MODELING PREPARATORY COMMITMENT AND NON-REPEATABLE DECISIONS

INFORMATION-PROCESSING, PREFERENCE FORMATION AND EDUCATIONAL ATTAINMENT

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ABSTRACT

For many decisions with uncertain outcomes, prior preparation determines the payoffs received following choices. The payoff to an investment in human capital, for example, is a function of the ability to benefit from the course of training undertaken, and this ability is at least partly a function of one's self-regulated prior preparation. How should we use rational choice theory to model a goal-directed individual's preparatory commitment toward a consequential future decision if we cannot assume that preferences are fixed, that individuals engage in perfect information-processing, and that their expectations obey statistical decision theory? Introducing the concept of prefigurative commitment while invoking a stochastic decision tree for forecasts of future behavior, I show how a bounded rationality information-processing and evaluation mechanism generates courses of preparatory commitment decisions that differ from those that would result from strict adherence to orthodox decision theory. Throughout the development of the model, I discuss how the stochastic decision-tree framework can enhance sociological models of educational attainment.

KEY WORDS • bounded rationality • decision theory • educational attainment • expectations

The decision of whether or not to enter college immediately following high school is perhaps the most crucial determinant of alternative lifecourse transitions from adolescence to adulthood in contemporary American society. Immediate college entry is especially consequential because it is a genuine non-repeatable decision. Delayed college entry, in contrast, yields different payoffs

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that result in alternative lifecourse outcomes. Nonetheless, for a substantial proportion of students on the margin of college entry (i.e. those for whom policy interventions are designed to encourage college enrollment; see Kane 1999, Kosters 1999), the immediate college entry decision is vexing. The alternative choices are clearly in view from early adolescence onward, but there is no simple normative guide for behavior. As a result, everyday commitment to preparation for college instruction varies across high school students, affecting resulting enrollment decisions and the potential gains from college instruction.

Can rational choice theory offer a useful framework for the analysis of non-repeatable decisions such as immediate college entry? On the one hand, the answer to this question must be 'yes'; rational choice theory offers a powerful framework for modeling instantaneous decisions, as best demonstrated long ago for the college choice example by Manski and Wise (1983). But, can rational choice theory offer more than just a framework for analyzing instantaneous decisions, one that can also enable the modeling of the social processes that generate the costs, benefits, and preferences on which individuals rely when making expected utility calculations? In this article, I argue that the answer to this question is 'yes' as well, provided that a tractable framework is developed that can be used to model the consequential everyday decisions that prepare individuals to enact and then benefit from alternative courses of future behavior, one that neither reduces the actors to myopic automatons who simply observe their peers nor inflates them to the status of über-decision-makers who have rational expectations and effortlessly process all possible information. Rather, the framework must be grounded on a flexible and plausible mechanism (see Hedström and Swedberg 1998) that can be used to carefully specify how one's beliefs about alternative potential futures determine one's current behavior.

For the college entry application, recognition of the need to explicitly model belief formation and its implications for everyday decisions is not new. At least since the mid-1970s sociologists of education have argued that there are important belief-based interactions between endogenous social influence mechanisms, exogenous social-structural mechanisms, and the behavior of adolescents (see Bourdieu 1973; Kerckhoff 1976; Gambetta 1987; Giddens 1984). For example, according to status socialization theory (Sewell et al. 1969), students' college plans are shaped by their own expectations and by how their expectations respond to the expectations of parents, teachers and peers. But this position merely begs the questions: On what basis do students and their significant others form their expectations? Do significant others, for example, transmit accurate information about one's likely success in the educational system? Or do significant others systematically mislead students, so that some students who could succeed in college are discouraged while others who would likely fail are encouraged? How do students then reconcile inconsistent expectations, especially when those formulated through self-reflection conflict with those offered by significant others?

Despite interest in these processes, little explicit development of the necessary theoretical machinery has been achieved in the sociology of education in the past two decades. The stochastic decision-tree model of commitment that I propose in this article responds to this analytic need, and hence is especially (though not exclusively) suited for the analysis of college entry decisions. In short, the stochastic decision-tree model presupposes that the everyday decisions of individuals are self-regulated by simple commitments toward the future. In particular, individuals who can easily envision themselves pursuing a specific future course of behavior will have high levels of commitment to that course of behavior and will accordingly put forth more effort in preparation for it. Adopting a weak form of decision evaluation that is justified by the bounded rationality literature on cognitive constraints, along with the necessity of relying on a simple stochastic decision tree in order to allow for uncertainties in the identification of everyday decisions that one will have to navigate in the interim, the model then provides a plausible and parsimonious mechanism to analyze the way in which individuals formulate forward-looking beliefs about their own behavior, as conditioned by their beliefs about the payoffs to alternative courses of potential behavior.

The model is grounded on some of the core principles of rational choice theory, and when applied narrowly to the college choice application is also strongly tied to the rational choice reconceptualization of status socialization theory that motivates the questions on significant others' influence outlined above (see Morgan 1998). Nonetheless, the framework can be used to model preparatory commitment to alternative courses of action for all non-repeatable decisions with outcomes that are properly seen by decision-makers as uncertain (i.e. decisions for which no direct learning-by-doing is possible and for which payoffs are generated by an independent and only partly observable stochastic process).

The remainder of the article is organized as follows. As a starting point for development of the model, I present three assumptions, and in so doing define the concepts of prefigurative commitment and preparatory commitment. Since the stochastic decision-tree model that I later propose is an elaboration of an orthodox one-shot decision tree for choice under uncertainty, I first introduce a simple decision tree, note its commendable analytic specificity, but then argue that as commonly invoked it cannot serve by itself as a complete framework for modeling preparatory commitment in advance of many non-repeatable decisions. I then introduce the stochastic decision-tree model and use a set of numerical simulations to demonstrate how it operates, in particular by showing how it allows commitment toward a future course of action to be a function of the amount of processed information available to an individual and the amount of effort expended to analyze it. Accordingly, I claim that, among individuals who eventually enact the same forward-looking, utility-maximizing decision, those who are not systematically misinformed but who are nonetheless not well informed will exhibit less effort in the short run and attain lower levels of the payoff to the decision in the long run. Following a discussion of how social influence effects can be built into the stochastic decision-tree model, I conclude the article with a discussion of the model's potential to enhance empirical and policy-relevant research on the mechanisms that generate educational attainment.

Basic Assumptions and Definitions

The stochastic decision-tree model of commitment is grounded on the specific assumption that in the period leading up to a consequential non-repeatable decision:

> *Assumption A1.* Intermediate everyday courses of behavior are self-regulated by the clarity of prefigurative commitments toward alternative future courses of behavior.

For example, the strength of a high school student's prefigurative commitment to the future course of behavior 'Go to college immediately following high school' is the ease with which he or she is able to envision entering and ultimately graduating from a college degree program.

In its abstract form, Assumption A1 is strongly supported by the social psychological literature, and in particular by a new literature on control and automaticity (see Pittman 1998; Wegner and Bargh 1998).[1] The selection or adoption of a prefigurative commitment to a future course of behavior, such as 'I will enroll in college', is roughly analogous to the selection of an initial control criterion. If the conscious control criterion is sufficiently strong, and if there is scope to minimize self-monitoring costs, then the control criterion is transformable over time into a self-regulating and only minimally conscious behavioral mechanism that automates appropriate everyday behavior.[2]

Prefigurative commitment is a decomposable control criterion for current behavior, and its dimensions are specific to each decision context. However, for many decisions, three underlying dimensions are sufficiently exhaustive: purposive-prefigurative commitment, normative-prefigurative commitment, and imitative-prefigurative commitment. For the non-repeatable decision 'Go to college' versus 'Do not go to college', these three types of prefigurative commitment are set in response to three forward-looking prediction rules: 'I will go to college if I perceive it to be in my best interest to do so', 'I will go to college if my significant others perceive it to be in my best interest to do so', and 'I will go to college if I expect other students similar to me will also go to college.' These three generative dimensions are roughly analogous to the self-reflection, adoption, and imitation mechanisms of status socialization theory (see Haller 1982; Morgan 1998).

All three dimensions of prefigurative commitment have salience for many decisions, but purposive-prefigurative commitment is both the most theoretically interesting (because it has the most power to subsume the other two) and the least developed. I therefore focus development of the stochastic decision-tree model on the construction of purposive-prefigurative commitment, reserving for the final portion of the article a discussion of possible ways to introduce reinforcing and destabilizing normative and imitative-prefigurative commitment into the model. Thus, I motivate the stochastic decision tree model by assuming that:

> *Assumption A2*. Individuals use a decision tree to identify and prefiguratively commit to the future course of behavior that they believe is in their best interest.

Having defined prefigurative commitment as a cognitive attachment to a future course of behavior, the potentially observable course of everyday behavior that positions an individual to realize his or her prefigurative commitment can then be defined as preparatory commitment. A student with maximal preparatory commitment toward the prefigurative commitment 'I will enroll in college' will enact all possible behavior that prepares him or her for enrolling in college and then successfully obtaining a college degree. While in high school, such students will take college preparatory classes, complete their homework diligently, focus their attention when taking tests, sign up early for college entrance examinations, and investigate their range of realistic college alternatives.

If prefigurative commitment can be weak or strong, then resulting preparatory commitment may be anywhere from non-existent to maximally intensive. I therefore assume that:

> *Assumption A3*. An individual's observable level of preparatory commitment to a future course of behavior is a direct function of the strength of his or her prefigurative commitment to that course of behavior.

If, as is the case with many non-repeatable decisions, the payoff to a utility-maximizing affirmative decision is a function of preparatory commitment, then prefigurative commitment determines an individual's future level of well-being, above and beyond simply pushing an individual over a decision threshold, as is discussed in the presentation of Figure 2 below.

In the next section, I justify Assumption A2, following a presentation of a basic one-shot decision tree. Thereafter, Assumption A2 is fortified by two further assumptions that stipulate the nature of the decision tree that individuals invoke to prefiguratively commit to a future course of behavior.

A Decision Tree for Choice under Uncertainty

The stochastic decision tree with which I propose to model the purposive dimension of prefigurative commitment borrows the specificity of statistical decision theory, and in particular its basic decision tree foundation. However, I abandon the elegance (i.e. constraining features) of orthodox decision theory and its empirical inversion as traditional discrete choice analysis – perfect information-processing, redundant belief formation, and permissive revealed preference.[3]

Figure 1 presents a standard one-shot decision tree for choice under uncertainty. Although the specific form of the tree is entirely generic, and hence resembles in form nearly all of the models presented in Pratt et al. (1995), this specific tree is isomorphic with the set of equations used to model students' enrollment decisions by Manski (1989). For this simple model, an individual must contemplate whether or not it is in his or her best interest to choose the course of action Up or Down. The course of action Up is analogous to the decision 'Enroll in the program' in Manski's application.

Assume that individuals consider two payoffs, High and Low, and that all individuals would rather receive High than Low. Given these preferences, individuals must judge which path through the decision tree will put them in the best possible position to obtain High rather

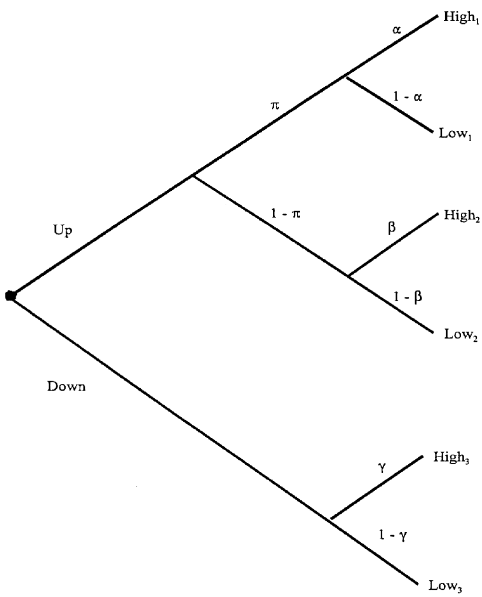

Figure 1. A Simple Decision Tree for Choice under Uncertainty

than Low. Individuals think of these paths as a series of lotteries that are controlled by success parameters π, α, β, and γ that are probabilities between 0 and 1.[4]

According to the decision tree, individuals recognize that if they choose Up they are subject to an intermediate hurdle. In Manski's application of this tree, initial enrollment does not guarantee successful completion of the course of instruction. Each individual's decision tree has a parameter π that represents each individual's subjective belief about the probability of surviving the intermediate lottery.[5]

Likewise, individuals maintain a set of beliefs about the relative likelihood of attaining High versus Low after traversing each of the three possible paths through the decision tree. They expect that if they choose Up and survive the intermediate lottery, they will attain High with probability α and Low with probability $(1-\alpha)$. If they choose Up but are eliminated by the intermediate lottery, then they expect that they will attain High with probability β and Low with probability $(1-\beta)$. And finally, if they choose Down, they expect that they will attain High with probability γ and Low with probability $(1-\gamma)$.

Rational choice theory offers the prediction that, under specific assumptions about optimization and consistency of choice (see Pratt et al. 1995; Sen 1997), individuals will choose Up as the expected-utility-maximizing choice if:

$$\pi \propto [u(\text{High}_1) - u(\text{Low}_1)] + (1-\pi)\beta[u(\text{High}_2) - u(\text{Low}_2)] < \gamma[u(\text{High}_3) - u(\text{Low}_3)] \quad (1)$$

where $u(.)$ is a utility function that, in its most general sense, assigns subjective values to the alternative payoffs High and Low.[6] If an individual's utility function is process-independent so that $u(\text{High}_1) = u(\text{High}_2) = u(\text{High}_3)$ and $u(\text{Low}_1) = u(\text{Low}_2) = u(\text{Low}_3)$, then both sides of Equation 1 can be divided by a common utility difference $u(\text{High}) - u(\text{Low})$, in order to obtain the simplified decision rule:

$$\pi \propto +(1-\pi)\beta > \gamma \quad (1a)$$

After individuals choose either Up or Down (i.e. enroll in college or enter the labor force immediately following high school), they are then subject to a set of real-life lotteries. Each lottery has a true probability, denoted respectively as $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$. Actual outcomes are therefore determined in large part by exogenous factors that structure these probabilities. For researchers, claims about the relative sizes of $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$ are usually domain-specific assumptions about institutional constraints on choosing Up or Down and the distribution of High versus Low payoffs. For the college entry decision, it is generally assumed that there are positive returns to schooling so that $\tilde{\alpha} \geq \tilde{\beta}$ and that $\tilde{\beta} > \tilde{\gamma}$. However, Manski (1989: 307) argues that 'analysis is trivial' unless, in the notation used here, for at least some students $\tilde{\beta} < \tilde{\gamma}$ and $\beta < \gamma$. If that were not the case, everyone would choose Up.[7]

Do individuals maintain reasonable beliefs about the lotteries that they face? In other words, for each individual and for a decision tree such as the one depicted in Figure 1, is there a close correspondence between π, α, β, and γ and $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$? The most common (indeed, almost universally invoked) assumption among rational choice researchers is that individuals, on average, have correct beliefs about $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$. Accordingly, the values of π, α, β, and γ that they rely upon when making decisions are assumed to be on average equal to the true probabilities that they will face in their futures. When this strong assumption is maintained, nothing is gained by preserving a distinction between true values for the parameters of the lotteries and beliefs about them.[8]

When the theoretical correspondence between true parameters and beliefs about them is asserted, grounded on the generally unevaluated assumption that individuals on average have accurate beliefs, a decision tree model can effectively motivate empirical analysis of individuals' observed choice behavior. However, a revealed preference assumption must be invoked first. In particular, one must be able to assume that what individuals are observed to do is precisely what they believed they should do. This assumption may be rather dubious in many applications, as I suspect it is for schooling decisions, for it is generally recognized that what one does is not necessarily what one wanted to do or could have done (see Sen 1982 [1977], 1997). The result is that a researcher can only learn, given data about what individuals did, what individuals' preferences and beliefs must have been if the proposed model and its associated assumptions are true.

Given the importance that subjective beliefs about the true decision-tree parameters play in determining action in rational choice models, it is surprising that the rational choice literature has developed so extensively since the 1940s without giving much explicit attention to mechanisms of belief formation. The core 20th-century foundations of the rational choice literature have almost nothing to say about how beliefs about parameters such as $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$ (that is, π, α, β, and γ) respond to differences in available information.[9] Strict Bayesian updating, though rigorously justified as the best normative approach to information-processing, reads more like a denial that belief formation is ever important, and for this reason is almost never explicitly invoked in empirical analyses of actual decision-making. Surely mean-spreading uncertainty is granted a place in rational choice models, but it is merely embedded in the concavity of assumed utility functions and then ignored.

The model I develop below attempts to provide a foundation for a more comprehensive approach. In so doing, I construct a model that is based in part on rational choice theory, but that also allows us to embrace the plea of Goldthorpe (2000: 132) that 'sociologists should aim to treat the information available to actors as a product of the social relations in which they are involved'.

A Stochastic Decision-Tree Model of Commitment

For many future decisions that are non-repeatable, individuals must also contemplate a series of consequential intermediate decisions. The action 'Go to college', for example, is a compound outcome of a series of underlying decisions, many of which must be enacted long before the first college tuition bill is due. In addition, the payoff to obtaining a college degree is a function not just of having enrolled in college but of how seriously one has prepared to master the college curriculum before being exposed to it. Thus, for many non-repeatable decisions, if not most, prior preparation can be as consequential for levels of ultimate well-being as whether or not one is able to carry out an *ex ante* utility-maximizing decision.

Figure 2 presents a simple graphical depiction of this claim, where the ultimate payoff is plotted against prior preparation, and where (for this depiction only) it is assumed that all individuals whose prior preparation is greater than a fixed decision threshold enact the affirmative decision. Often, in such analytic situations, one focuses on the mean levels of the payoffs by averaging over those who make affirmative and negative decisions (i.e. the levels represented by dashed lines in the figure). I assume that when choices

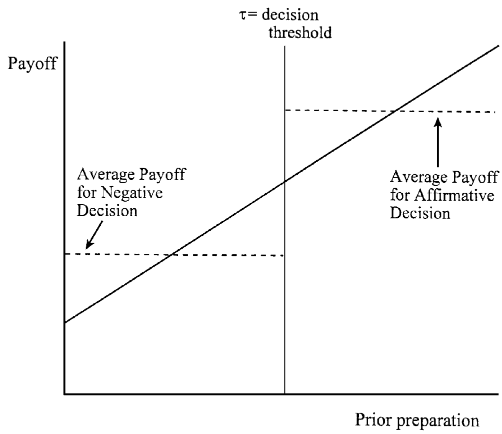

Figure 2. Payoff as a Linear Function of Prior Preparation

about a non-repeatable decision are made under uncertainty, the payoff distribution in social systems will exhibit patterned heterogeneity across the decision threshold because the level of preparation will differ. If this is the case, examination only of average differences is inadequate, both from theoretical and policy-relevant perspectives.

Can one model prior preparation, or what I have labeled preparatory commitment, using standard statistical decision theory? Yes, and the accepted procedure for incorporating underlying decisions into an existing decision tree is to add branches for all consequential intermediate decisions. Continuing with the college entry example, if the intermediate decision is whether or not to enroll in a trigonometry class in high school, then two alternative decision trees with the structure of the one presented in Figure 1 are then specified *in toto* as expected consequences (and possibly alongside other relevant consequences) for the decision on whether or not to enroll in the trigonometry class. An augmented decision tree of this form is justified if beliefs such as π or the utility evaluations of High and Low depend on whether or not one enrolls in the trigonometry class.

Although a single augmentation is easily achieved, further elaboration rapidly overwhelms the simplicity and power of the entire framework. For the decision of whether or not to go to college, the large number of preparatory commitment decisions that adolescents must navigate in middle school and high school would render their comprehensive decision trees massive and ever-changing as each intermediate decision is considered and then enacted.

Another possible solution to the impracticality of complete decision-tree augmentation is to limit individuals' time horizons (e.g. for the college choice example to only one year into the future). This is tantamount to assuming that individuals cannot forecast their futures in any meaningful way and that incentives and institutions determine action almost exclusively as unanticipated constraints on future behavior. Although possibly appropriate for some applications, I remain interested in important non-repeatable decisions (i.e. major life transitions) where this solution is unreasonable.

The modifications to the orthodox one-shot decision-tree structure that I propose below for the modeling of preparatory commitment are inspired by the approach to modeling bounded rationality outlined by Herbert Simon (see Simon (1996) for an overview), as opposed to recent attempts to harness bounded rationality within more traditional modes of rational choice analysis (such as Rubinstein (1998)). The modifications incorporate the cognitive constraints of actors, the implicit costs of analyzing available information, and the non-random distribution of information observed in real-world social systems. At the same time, however, I see no reason at this point of theoretical development of the proposed model to entirely abandon expected utility theory in favor of prospect theory (Kahneman and Tversky 1979), any of its subtle variants (see Camerer 1995), or aspiration adaptation theory (Selten 2001). Such drastic modifications may be called for in the future, especially in some specific decision contexts, but for now only modest departures from orthodox statistical decision theory suffice to demonstrate my proposed approach.

Decision-Tree Structure

I assume that for consequential non-repeatable decisions that lie on the horizon of individuals' futures, true comprehensive decision trees are fundamentally *ex ante* unknowable for individuals. Carrying on from the assumptions introduced earlier, I assume that:

Assumption A4. The decision tree that individuals use to prefiguratively commit to a future course of behavior is simpler in structure than that which would be required to explicitly model all consequential intermediate decisions.

Equivalently, I assume that preparatory commitment cannot be modeled as a long series of fully conscious, forward-looking decisions.

For the numerical demonstration of the framework that I offer below, I use the simple decision tree in Figure 1, and hence, when referring to the college choice example, adopt the position of Manski (1989) that for enrollment decisions four basic lotteries are considered by potential enrollees. For my framework, however, the decision tree serves only as a forecasting tool that individuals use when self-regulating everyday behavior in the long run-up to the instantaneous enrollment decision.

Belief Distributions

Instead of requiring individuals to construct comprehensive decision trees for all intermediate decisions, I allow the complexity of the everyday decisions that constitute preparatory commitment to be modeled as uncertainty about the parameters of a simple decision tree for a future course of behavior. Thus, I assume that:

> *Assumption A5*. The parameters of the decision tree that individuals use to prefiguratively commit to a future course of behavior are fundamentally stochastic.

This assumption is the major departure from standard practice.[10] For the evaluation of an orthodox one-shot decision tree, the usual maintained assumption is that parameters such as π, α, β, and γ in Equations 1 and 1a are regarded as constants by each individual. These constants may vary across individuals, but each individual evaluates a decision rule with point-values for its parameters.

Even though a decision rule is always evaluated with point-value beliefs in orthodox rational choice theory, in some cases rational choice researchers allow individuals to entertain more than one possible point-value for each decision-tree parameter. According to statistical decision theory, a decision-maker may recognize that he or she does not know $\tilde{\pi}$, $\tilde{\alpha}$, $\tilde{\beta}$, and $\tilde{\gamma}$ and therefore may attempt to estimate each of them. Under this more complex scenario, decision-makers may consult an entire distribution of estimates in their minds, but each decision-maker regards this distribution as a distribution of errors from an unknown true constant. In accordance with standard estimation principles, the decision-maker selects point-value beliefs for decision-rule evaluation from entire distributions of estimates, which in most cases results in the decision-maker selecting the means of the contemplated distributions (i.e. when assuming symmetric loss functions; see Lehman and Casella 1998).

The modification I propose for modeling how individuals think about a future non-repeatable decision is more fundamental. Individuals recognize that there is no true constant to be estimated because they understand that the decision tree they are consulting is simply a rough approximation to the complex set of real-life lotteries to which they will ultimately be subjected. Thus, individuals forecast their futures as if any ostensibly true parameters such as $\tilde{\pi}, \tilde{\alpha}, \tilde{\beta}$, and $\tilde{\gamma}$ have distributions. Accordingly, Assumption A5 stipulates that individuals maintain entire belief distributions for the parameters of a decision tree, such as π, α, β, and γ in Figure 1. As will be shown below, individuals may still wish to determine the most likely values implied by their belief distributions, but because they regard their belief distributions as only rough representations, they are unwilling to exert the analytic or numerical energy necessary to construct maximally precise estimates of the means of their belief distributions.

How are belief distributions constructed and revised? Although I discuss this question directly in the concluding section to the article when pointing the way toward further theoretical and empirical research, for now I assume that individuals simply store belief distributions in memory based on observations of individuals whom they regard as payoff models. And, in order to generate the analytic and numerical results offered below, I assume that these belief distributions allow the amount of information available to individuals to be expressed as variances of their belief distributions. Individuals with sparse information at their disposal will have uncertain belief distributions with large variances, and individuals with abundant information will have precise belief distributions with small variances.

For example, consider two high school students contemplating the decision tree presented in Figure 1 when forecasting their own future decision of whether or not to enter college immediately. Student A observes 20 college graduates and 10 college dropouts.

In contrast, Student B observes only 2 college graduates and 1 college dropout. The framework I adopt stipulates that Student A will have more confidence than Student B in eliminating extreme values from his or her belief distributions about his or her subjective probability of graduating from college if enrolled. Student A would consider values such as 0.66 much more likely than values such as 0.96 or 0.36. Student B would likewise consider 0.66 more likely than either 0.96 or 0.36 but would be less willing than Student A to discount the plausibility of 0.96 or 0.36. This position is consistent with the dominant literature on belief distributions, which for Bayesian decision theory (see Pratt et al. 1995) and information-integration theory in psychology (see Davidson 1995), similarly allows uncertainty and imprecision of beliefs to be a function of the amount of available information.

Decision-Tree Evaluation

When contemplating underlying decisions that contribute to an individual's preparatory commitment, individuals set their current level of prefigurative commitment by instantaneously evaluating their stochastic decision trees. As stipulated in Assumption A1, an individual's level of prefigurative commitment is thus analogous to a behavioral control condition that partially automates consistent everyday behavior. In selecting, or re-evaluating, a level of prefigurative commitment, how do individuals evaluate their stochastic decision trees?

By principles of statistical decision theory, the traditional answer (assuming symmetric loss functions and no option values) would be that they calculate the means of their belief distributions, declare them as their best estimates of their point-value beliefs, and use them to solve a decision rule such as Equation 1. Two evaluation methods are consistent with this position: (1) analytically solving for the means by integrating over the density functions of one's beliefs; (2) randomly sampling a large number of candidate point-value beliefs from one's belief distributions and then averaging over the candidate point-value beliefs. The first method seems entirely unreasonable for applications such as college choice, unless we are prepared to assume either that individuals know calculus or that they maintain degenerate belief distributions. The second method is more feasible, and yet begs the question: How effectively can individuals numerically solve for the means of their belief distributions? In the numerical simulations of the model offered below, I demonstrate the consequences of answering this latter question in different ways. But before showing the consequences of alternative answers, I draw upon the extant literature on bounded rationality to narrow the range of plausible answers.

In contrast to computers, humans operate under severe cognitive computational constraints, as has been argued within the rational action paradigm by Herbert Simon since the 1950s. Based on his own research, and his reading of the psychology of concept discrimination, Simon maintained that individuals can store only about seven 'chunks' in fast, short-term memory (e.g. the seven digits of a telephone number in the US), but when interrupted in the process of perceiving these chunks individuals can recall only two of them. Relatedly, he maintained that it takes approximately 8 seconds to fixate on a new chunk (but perhaps only 2 or 3 seconds to fixate on a confirmatory chunk) and transfer it from short-term to long-term memory (see Simon (1996) for an up-to-date summary of his views).

If individuals are subject to substantial cognitive constraints such as these, and hence cannot numerically evaluate density functions in order to quickly recover arbitrarily exact estimates of the means of their belief distributions, individuals must rely on some 'fast and frugal' strategies to evaluate their decision trees (see Gigerenzer and Selten 2001). Based on this reasoning, I assume that:

> *Assumption A6*. Individuals evaluate their stochastic decision trees by solving a decision rule with parameter values that are simple averages of a few randomly sampled candidate values drawn from their belief distributions.

In the numerical simulations of the framework offered below, I vary the total number of candidate draws that individuals use to evaluate their stochastic decision trees. Drawing directly from Simon's position on the cognitive constraints of the human mind, I (weakly) favor limiting the total number of candidate values drawn by individuals to seven, yet I also consider how the patterns of prefigurative commitment change as the number of randomly drawn candidate values increases, partly because it seems reasonable that individuals may differ in how many candidate draws they are able and willing to consult.

In particular, I allow individuals to randomly draw candidate parameter values for a decision tree of the structure presented in Figure 1 and then average over these values to form a set of candidate point-value beliefs $\{\pi', \alpha', \beta', \gamma'\}$. Assuming that utility evaluations are equivalent across paths and scaled to values of 1 for High and 0 for Low, an individual will set a dichotomous variable E equal to 1 if:

$$\pi'\alpha' + (1 - \pi')\beta' > \gamma'. \tag{1b}$$

Otherwise, E will be set equal to 0. E signifies an instantaneous prefigurative commitment to the future affirmative decision (e.g. the choice Up in Figure 1).[11]

Over a group of J individuals with equivalent beliefs, the average level of prefigurative commitment to the affirmative decision is simply:

$$\Pr(E = 1) = \frac{1}{J} \sum_{j=1 \ldots J} E_j.$$

$\Pr(E = 1)$ is therefore equal in expectation to the probability that E will be evaluated as 1 for a given set of beliefs and prespecified total number of candidate parameter draws selected for decision-tree evaluation. $\Pr(E = 1)$ is equivalent, as shown below, to the probability that the *ex ante* true distribution of expected utility for the affirmative future decision Up is greater than the *ex ante* true distribution of expected utility for the negative future decision Down, conditioned on the amount of information-processing and evaluation effort a decision-maker can marshal. Thus, whereas the binary orientation E represents the instantaneous level of prefigurative commitment that guides each preparatory commitment decision, $\Pr(E = 1)$ represents the average level of prefigurative commitment that is consistent with a set of stable beliefs and a procedure to analyze those beliefs in the process of constructing forward-looking prefigurative commitment. The distinction implies that for two individuals who at a specific point in time both set E equal to 1, the individual whose beliefs imply a lower value for $\Pr(E = 1)$ will be less likely to set E equal to 1 when contemplating subsequent preparatory commitment decisions. $\Pr(E = 1)$ is therefore the more fundamental quantity of interest.

Why would individuals use this form of decision evaluation? Individuals recognize that their stochastic decision trees are rough approximations to the future lotteries to which they will be subjected. Moreover, most individuals likely believe that each preparatory commitment decision is, in isolation, relatively unimportant. For both of these reasons, the opportunity costs of exerting heroic levels of computational power to formulate and then rigorously evaluate the most fine-grained decision tree possible are simply too high. In the college choice example, students wish to orient their current behavior to a long-run plan that is in their best interest, but doing so in a way that is as rigorous as stipulated by statistical decision theory is too costly, especially since students themselves must recognize that they cannot form comprehensive decision trees to capture all consequential intermediate decisions. Thus, while students are indeed to some extent myopic, they seek to avoid short-run mistakes in judgement by adopting a relatively frugal process of planning for their futures.

Analytic Results and Numerical Simulations

In this section, I offer analytic implications of the stochastic decision-tree framework, while at the same time demonstrating its contours with a set of numerical simulations. Throughout the section, I assume that differences in $\Pr(E = 1)$ have consequences for final levels of well-being by way of individuals' self-regulated preparatory commitment and the true responsiveness of the payoff distribution to levels of preparatory commitment. I first present an analytic result to establish the baseline value of prefigurative commitment, which applies to the case in which individuals have too little information to favor any particular range of potential beliefs for the parameters of their stochastic decision trees. I then provide a graphical depiction of 400 numerical simulations for the construction of $\Pr(E = 1)$ under alternative belief distributions about a stochastic decision tree of the structure presented in Figure 1. Following the demonstration, I then attribute the patterns observed in the simulations to specific analytic implications of the framework.

Uninformed Beliefs and Prefigurative Commitment

For a derivation of baseline levels of prefigurative commitment, assume that individuals use the simple decision tree in Figure 1 to forecast whether or not they should expect to take the decision Up instead of Down in the future. Utilizing the form of decision-tree evaluation proposed above, what are the consequences for $\Pr(E=1)$ of having no information at all on which to base one's beliefs? The following general proposition gives the answer.

Proposition 1. Uninformed Beliefs: Suppose that Assumptions A1 through A6 hold and that all individuals share the same utility function. If individuals have uninformed beliefs and are thus willing to accept as equally likely all theoretically possible values for each decision-tree parameter, then they will on average have identical levels of prefigurative and preparatory commitment to alternative future courses of action.

Proof Sketch for Proposition 1. Consider the stochastic decision tree with the same structure as the decision tree in Figure 1, and scale individuals' utility functions so that the utility of High is equal to 1 and the utility of Low is equal to zero, regardless of the path taken through the decision tree. Under this scenario, the belief distributions of individuals without any information are equivalent to uniform distributions over the 0 to 1 interval. Accordingly, for each individual, $\mathrm{E}[\pi]$, $\mathrm{E}[\alpha]$, $\mathrm{E}[\beta]$, and $\mathrm{E}[\gamma]$ equal 0.5. And, thus, because $\mathrm{E}[\pi]\mathrm{E}[\alpha]+(1-\mathrm{E}[\pi])\mathrm{E}[\beta]=\mathrm{E}[\gamma]$, for alternative candidate decision trees, $\{\pi',\alpha',\beta',\gamma'\}$, $\Pr[\pi'\alpha'+(1-\pi')\beta'>\gamma']$ is equal to $\Pr[\pi'\alpha'+(1-\pi')\beta'<\gamma']$. As a result, $\Pr[E=1]=\Pr[E=0]=0.5$. This result holds generally for all decision trees where the lottery parameters have the same range for each stage of the decision tree (i.e. including decision trees for which the first stage parameters are probabilities that are bounded by 0 to 1 and the final-stage parameters are interval-scaled utility functions that span the entire real line).

According to Proposition 1, for the decision tree in Figure 1, the baseline level of prefigurative commitment is 0.5. In general, with uninformed beliefs, prefigurative commitment will equal $1/n$, where n is the number of future courses of behavior that are contemplated. However, as shown in the next section, for informed belief distributions, prefigurative commitment will diverge from such baseline values.[12]

Informed Beliefs and Prefigurative Commitment

If individuals have informed beliefs, prefigurative commitment is a function of at least three different dimensions: (1) the amount of processed information (and hence precision of beliefs), (2) the effort expended to analyze processed information, and (3) the core expected utility difference between alternative choices. Before offering the specific proposition and proof sketch that explicates these claims, I provide a series of numerical simulations to demonstrate the basic patterns that they imply for the construction of $\Pr(E = 1)$.

Construction of Belief Distributions for the Simulations. With reference to a decision tree with the same structure as the one presented in Figure 1, I adopt beta distributions to encode individuals' beliefs about the probabilities π, α, β, and γ. The continuous beta distribution is the most natural one for modeling a probability, since the distribution is bounded by 0 and 1. Nonetheless, the claims that I develop below do not depend in any important way on this choice of distribution. Any non-degenerate distribution for which expectations and variances can be parameterized independently could be substituted for the beta distributions.

Denoted $Beta(s, f)$, the two-parameter beta density function for an unspecified random variable θ (which could be a parameter such as π, α, β, or γ) is:

$$\Pr(\theta) = \frac{\Gamma(s+f)}{\Gamma(s)\Gamma(f)}\theta^{s-1}(1-\theta)^{f-1}$$

where the first term is a constant of integration and where it is required that $s > 0$ and $f > 0$. The distribution of θ is the predictive distribution of the expected proportion of successes in an idealized series of independent Bernoulli trials, where the parameter s is the number of successes and the parameter f the number of failures in a prior series of identical independent trials. The density function can take a variety of shapes: When s equals f, the density function is symmetric with mean equal to 0.5; when s and f are greater than 1, the density function is unimodal; when s and f are both less than 1 (but still by restriction greater than zero), the density function is bimodal with spikes at 0 and 1; when both s and f equal 1, the density function is flat and therefore equivalent to a uniform distribution.

The belief distributions used for the following 400 numerical simulations are based on the heuristic that decision-makers observe alternative sets of individuals who serve as payoff models, and that these models can be encoded as the success and failure parameters of beta distributions, s and f. How does this work? Consider the four different distributions of payoff models in Table 1 applicable to the decision tree in Figure 1. For now, focus on the third column, where the distribution of payoff models indicates that there are large returns to choosing Up rather than Down.

For column 3, decision-makers can be thought of as looking in their immediate structural contexts and observing 5 models who have chosen Up and who have survived the intermediate lottery parameterized by π (i.e. 5 college graduates). Of these models, 3 receive the payoff High while 2 receive the payoff Low. Likewise, these same decision-makers observe 4 models who have chosen Up but who fail to survive the intermediate lottery (i.e. 4 college drop-outs), and of these models 1 receives the payoff High and 3 receive the payoff Low. And finally, they also observe 5 individuals who have chosen Down (i.e. 5 individuals who have never entered college), and of these models only 1 receives the payoff High while 4 receive the payoff Low.

These models can then be coded as the parameters of beta distributions, in particular a $Beta(3, 2)$ for α, a $Beta(1, 3)$ for β, and a $Beta(1, 4)$ for γ. Since the mean of a beta distribution is simply $s/(s+f)$, the resulting belief distributions have means of 0.6, 0.25 and 0.2 for α, β, and γ.

As will be shown below, the variances of belief distributions are crucial. For a beta distribution, the variance is $sf/[(s+f)^2(s+f+1)]$, which decreases as the number of models $(s+f)$ increases. When individuals observe abundant payoff models, the variances of their resulting belief distributions are small. In accordance with Bayesian theory, their beliefs can be considered precise. With beta distributions, when s and f increase by the same constant multiple, the mass of the density function shifts from the tails and accumulates at the mean. Accordingly, in the simulations, I vary the precision of beliefs by multiplying each of the parameters s and f by the same strictly positive constant, p, a manipulation of beliefs that is analogous to increasing the number of observed payoff models without changing their distributions across branches of the decision tree.

Table 1. Distributions of Payoff Models for the Simple Decision Tree in Figure 1

	Very Small Positive Returns (Figure 3)	*Small Positive Returns (Figure 4)*	*Large Positive Returns (Figure 5)*	*Very Large Positive Return (Figure 6)*
Successes for α lottery	1.5	2	3	4
Failures for α lottery	1	1	2	1
Implied mean of α	0.6	0.667	0.6	0.8
Successes for β lottery	1	1	1	3
Failures for β lottery	1	2	3	1
Implied mean of β	0.5	0.333	0.25	0.75
Successes for γ lottery	1	1	1	1
Failures for γ lottery	1	2	4	4
Implied mean of γ	0.5	0.333	0.2	0.2
Assuming backward induction:				
Derived successes for π	2.5	3	5	5
Derived failures for π	2	3	4	4
Implied mean of π	0.556	0.5	0.556	0.556
Implied expected gain in the probability of receiving High instead of Low when choosing Up instead of Down	0.056	0.167	0.245	0.578

Finally, I concentrate on differences in the belief distributions for the final-stage reward parameters α, β, and γ. The belief distributions for π will simply be derived by backward induction from the belief distributions for α and β, as described in the simulation algorithm below.

Algorithm for Each Simulation. Figures 3 through 6 summarize 400 simulated values of prefigurative commitment $\Pr(E = 1)$, over three different dimensions – the total amount of processed information available to decision-makers (parameterized by the variances of the belief distributions, holding their means constant), the total amount of effort expended to analyze processed information (parameterized by the total number of candidate draws selected for evaluation of Equation 1b), and the expected gain for choosing Up rather than Down if efforts to analyze processed information were maximally intensive (parameterized by the means of the belief distributions).

The specific algorithm for each of 400 simulations proceeds in five steps:

Step 1. Select a set of belief distributions:

A. Encode the payoff distributions from Table 1 as baseline beta distributions:

$$\alpha \sim Beta(s_{\text{High}_1}, f_{\text{High}_1}),$$

$$\beta \sim Beta(s_{\text{High}_2}, f_{\text{High}_2}),$$

$$\gamma \sim Beta(s_{\text{High}_3}, f_{\text{High}_3}),$$

using backward induction to stipulate that

$$\pi \sim Beta(s_{\text{High}_1} + f_{\text{High}_1}, s_{\text{High}_2} + f_{\text{High}_2})$$

B. Select a constant precision of belief multiplier, p, with which to scale the success and failure parameters of the baseline belief distributions:

$$\alpha \sim Beta(ps_{\text{High}_1}, pf_{\text{High}_1}),$$

$$\beta \sim Beta(ps_{\text{High}_2}, pf_{\text{High}_2}),$$

$$\gamma \sim Beta(ps_{\text{High}_3}, pf_{\text{High}_3}),$$

again, using backward induction to stipulate that

$$\pi \sim Beta(p(s_{\text{High}_1} + f_{\text{High}_1}),\ p(s_{\text{High}_2} + f_{\text{High}_2})).$$

Step 2. Let each of J simulated individuals randomly draw candidate values from the belief distributions specified in Step 1:

A. One from each of the belief distributions for π, α, β, and γ;
B. And then k additional draws from any of these distributions, where the determination of which belief distribution serves as the source for each additional draw is generated by a multinomial distribution with equal mass of 0.25 specified for each of the four belief distributions.

Step 3. Let each simulated individual take the simple average of the candidate values for each parameter. The result is a set of individual-specific candidate decision trees for each of J individuals: $\{\pi'_j, \alpha'_j, \beta'_j, \gamma'_j\}_{j=1}^{J}$.

Step 4. Let each simulated individual use his or her j-specific candidate decision tree, $\{\pi', \alpha', \beta', \gamma'\}$, to evaluate the decision rule in Equation 1b.

Step 5. Average over the J evaluations of the candidate decision trees of simulated individuals to form an arbitrarily precise numerical estimate of $\Pr(E = 1)$, which summarizes the level of prefigurative commitment associated with the set of beliefs that is specified in Step 1 and the amount of effort expended to analyze the information that is specified in Step 2.

As presented below, variations in the implementation of this algorithm arise from selection of exogenously specified baseline belief distributions, precision of beliefs, p, and the additional number of candidate draws, k. The distributions of payoff models presented in the four columns of Table 1 correspond to baseline sets of beliefs where there are very small, small, large, and very large returns to choosing the decision Up instead of the decision Down. The precision of beliefs parameter p varies over 10 logarithmically spaced values, from 0.0316, to 0.1, 0.316, 1, 3.16, 10, 31.6, 100, 316, and finally 1000. Likewise, the additional number of candidate draws k varies over 10 values from 0 to 9. Finally, each simulation is performed with J equal to 10,000, which stipulates that 10,000 independent individuals evaluate identical stochastic decision trees.

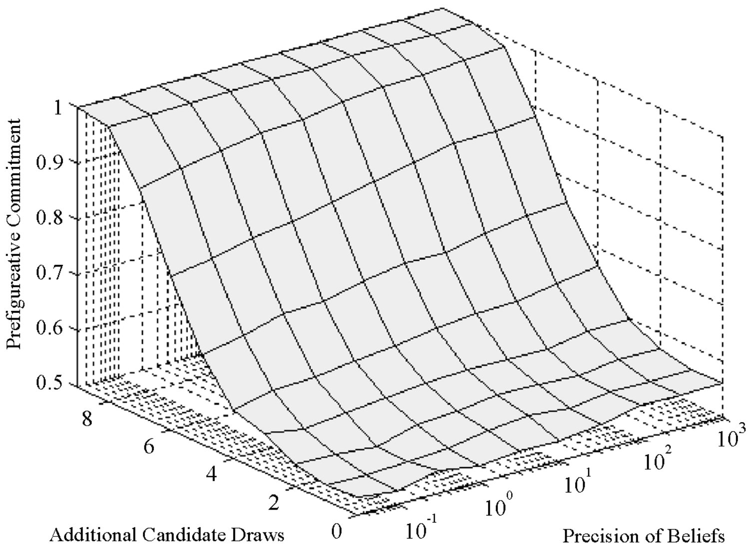

Figure 3. Simulated Values of Prefigurative Commitment for Very Small Returns to Choosing the Decision Up

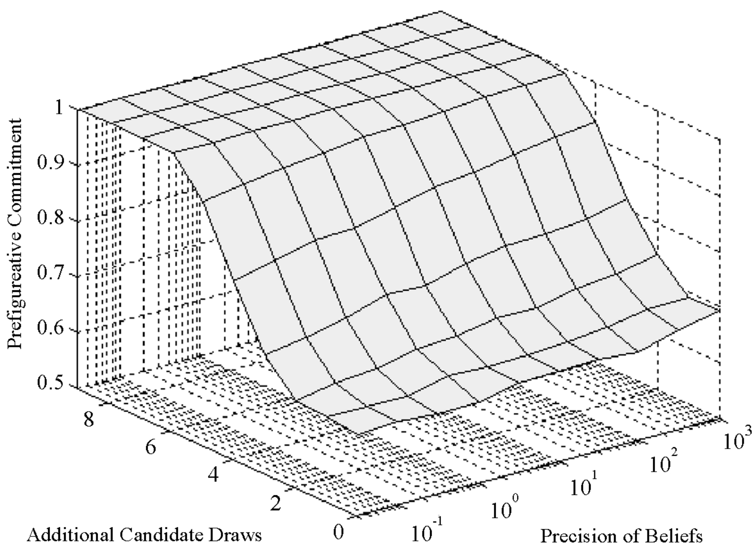

Figure 4. Simulated Values of Prefigurative Commitment for Small Returns to Choosing the Decision Up

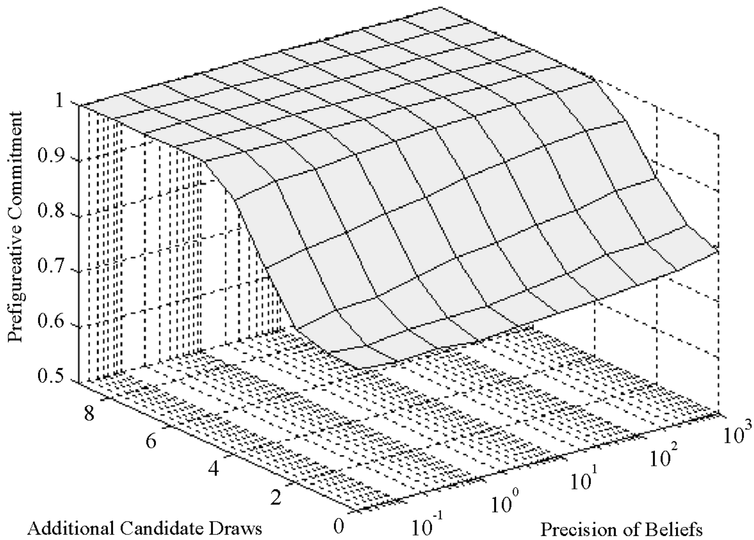

Figure 5. Simulated Values of Prefigurative Commitment for Large Returns to Choosing the Decision Up

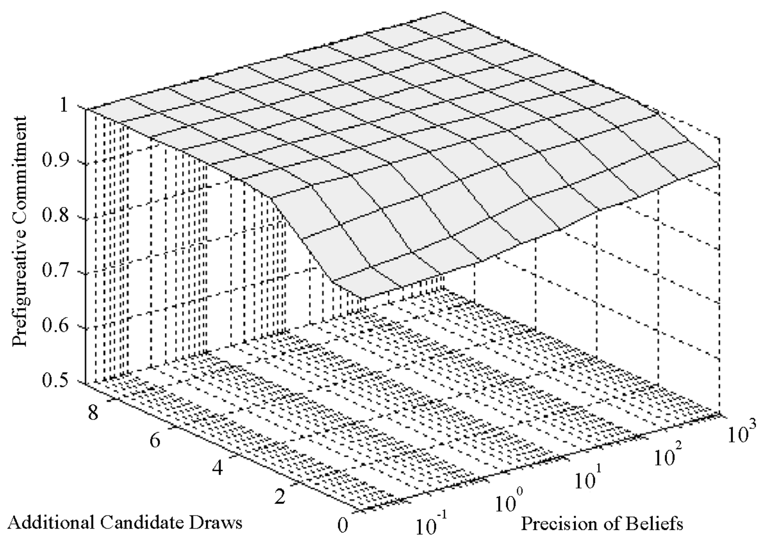

Figure 6. Simulated Values of Prefigurative Commitment for Very Large Returns to Choosing the Decision Up

Simulation Results. Each of the four surface plots of $\Pr(E = 1)$ in Figures 3 through 6 correspond to 100 independent implementations of the simulation algorithm, cross-classified by each of the 10 prespecified values of p and k. Beyond random simulation noise, which would disappear if J increased to infinity, the four figures differ only in the baseline belief distributions selected from Table 1 in Step 1 of the simulation algorithm.

For each of the surface plots of $\Pr(E = 1)$, the right-horizontal axis is the precision of beliefs, p, scaled logarithmically. The left-horizontal axis is the additional number of candidate draws, k. Moreover, the fourth contour line (when counting along the left-horizontal axis) corresponds to the set of simulations where individuals make three total additional draws beyond the four requisite draws. This set of simulations corresponds to my reading of Simon's claim that individuals can store only seven chunks of information in short-term memory. Finally, the vertical axis is $\Pr(E = 1)$, scaled from the baseline value of 0.5 to its maximum of 1.

Three robust patterns emerge from inspection of the figures:

1. At all 100 points of direct comparison, the surface in Figure 3 is either lower than or no higher than the surfaces in Figures 4, 5, and 6. Likewise, the surface in Figure 4 is either lower than or no higher than the surfaces in Figures 5 and 6, and so on. This pattern suggests that $\Pr(E = 1)$ increases as returns to choosing Up increase, though only weakly so, since $\Pr(E = 1)$ attains its upper bound for a sufficiently large value of k in each of the figures. In particular, as shown in the last row of Table 1, the implied expected gain in probability of capturing High instead of Low when choosing Up instead of Down increases from 0.056, to 0.167, 0.245, and 0.578 across Figures 3 through 6. This shift in the expected returns to choosing Up increases $\Pr(E = 1)$ until it reaches its maximum of 1, where it then remains.
2. As shown in all four surfaces, $\Pr(E = 1)$ increases with the precision of beliefs, though, again, only weakly so since it cannot exceed its upper bound of 1. Increases in the precision of beliefs are equivalent to decreases in the variances of belief distributions. For example, for Figure 3, the belief distribution for α is stipulated to be a $Beta(p{*}1.5, p{*}1)$, where p increases from 0.0316 to 1000. Accordingly, the belief distribution for α goes from a $Beta(0.0474, 0.0316)$ to a $Beta(1500, 1000)$ along the

right-horizontal axis of Figure 3. This change is analogous to dramatically increasing the amount of information available to an individual without changing the distribution of that information. Thus, the mean of the belief distribution for α remains fixed at 0.6, while the variance of the belief distribution for α declines from 0.222 to 0.000096. Over all four figures, $\Pr(E = 1)$ increases weakly in p because the mean candidate draws generated in Step 3 of the simulation algorithm approach the true means of the belief distributions, which themselves imply (to varying degrees) that taking the decision Up is in each individual's future best interest. In particular, for Figures 3 through 6, respectively, and with k equal to 0, $\Pr(E = 1)$ increases from 0.5328 to 0.5619, 0.6465 to 0.6921, 0.7540 to 0.7905, and 0.8845 to 0.9534 as p increases from 0.0316 to 1000. Similarly, for k equal to 3, $\Pr(E = 1)$ increases from 0.5698 to 0.5878, 0.7127 to 0.8182, 0.8571 to 0.9258, and 0.9905 to 0.9995.

3. As shown for all four surfaces, $\Pr(E = 1)$ increases with constant increases in the effort expended to analyze information, in particular the number of total candidate values drawn for construction of a candidate decision tree, $\{\pi', \alpha', \beta', \gamma'\}$. For each surface, simulated values of $\Pr(E = 1)$ increase as k increases from 0 to 9 (and hence the total number of candidate draws increases from 4 to 13) until $\Pr(E = 1)$ reaches the upper bound of 1. For all four figures, the simulated value of $\Pr(E = 1)$ is equal to 1 when k is equal to 9. But, as shown across the figures, the rate at which $\Pr(E = 1)$ approaches 1 in k is a function of both the precision of beliefs and the returns to choosing Up.

General Analytic Implications. The patterns revealed in the simulations suggest the following proposition.

Proposition 2. Informed Beliefs: Suppose that Assumptions A1 through A6 hold and that all individuals share the same utility function. If individuals have informed belief distributions, prefigurative commitment to the course of action with the largest implied expected utility is

(a) increasing (or non-decreasing) in the common precision of all beliefs,

(b) increasing (or non-decreasing) in the common amount of effort expended to analyze all beliefs, and
(c) increasing (or non-decreasing) in the implied expected utility gain for choosing the action.

Proof Sketch for Proposition 2. Consider a stochastic decision tree with same structure as the decision tree in Figure 1, and scale individuals' utility functions so that the utility of High is equal to 1 and the utility of Low is equal to zero, regardless of the path taken through the decision tree.

Proof sketch for part (a): For mean preserving and proportional increases in the precision of all beliefs (i.e. increases in p in the simulations above), Var[π], Var[α], Var[β], and Var[γ] decline while E[π], E[α], E[β], and E[γ] remain fixed. Because the mean is an efficient estimator of the expectation of a random variable, the expected variance of each element of $\{\pi', \alpha', \beta', \gamma'\}$ is declining, respectively, in the precision of each of the belief distributions for π, α, β, and γ. Thus, as precision increases by the same constant multiple across all four belief distributions, $\text{Var}[\pi', \alpha' + (1-\pi')\beta']$ and $\text{Var}[\gamma']$ approach zero and the amount by which any individual's $\pi'\alpha' + (1-\pi')\beta'$ and γ' differ from $\text{E}[\pi\alpha + (1-\pi)\beta]$ and E[γ], respectively, becomes arbitrarily small. Accordingly, if $\text{E}[\pi]\text{E}[\alpha] + (1-\text{E}[\pi])\text{E}[\beta] > \text{E}[\gamma]$, then $\Pr[\pi'\alpha' + (1-\pi')\beta' > \gamma']$ and $\Pr[E = 1]$ go to 1 as beliefs increase in precision.

Proof sketch for part (b): Given a set of fixed, non-degenerate belief distributions (i.e. where E[π], E[α], E[β], and E[γ] are constant and where Var[π], Var[α], Var[β], and Var[γ] are strictly positive and constant), the law of large numbers implies that the expected variance of each element of $\{\pi', \alpha', \beta', \gamma'\}$ is declining in the expected number of candidate draws for each parameter (which is equal to $1 + k/4$ in the simulations above). As the average number of candidate draws increases for each individual, the amount by which any individual's $\pi'\alpha' + (1-\pi')\beta'$ and γ' differ from $\text{E}[\pi\alpha + (1-\pi)\beta]$ and E[γ], respectively, becomes arbitrarily small. Accordingly, if $\text{E}[\pi]\text{E}[\alpha] + (1-\text{E}[\pi])\text{E}[\beta] > \text{E}[\gamma]$, then $\Pr[\pi'\alpha' + (1-\pi')\beta' > \gamma']$ and $\Pr[E = 1]$ go to 1 as the total number of random candidate draws increases.

Proof sketch for part (c): By the linearity of expected utility theory, if E[π] remains fixed, then E[$\pi\alpha + (1-\pi)\beta$] is increasing in both E[α] and E[β]. Accordingly, any increase in E[α] or E[β] relative to E[γ] will increase both E[$\pi\alpha + (1-\pi)\beta$] and Pr[$\pi'\alpha' + (1-\pi')\beta' > \gamma'$] for all candidate decision trees. Likewise, if E[α] is greater than E[β] and both remain fixed, then any increase in E[π] will increase both E[$\pi\alpha + (1-\pi)\beta$] and Pr[$\pi'\alpha' + (1-\pi')\beta' > \gamma'$], and so on. For all similar shifts in the expectations of belief distributions, Pr[$E = 1$] goes to 1 as {E[π]E[α] + (1 − E[π])E[β]} − {E[γ]} increases. Moreover, the rate at which Pr[$E = 1$] goes to 1 is a direct function of both the average precision of beliefs and the amount of effort expended to analyze beliefs, as shown in the proof sketches of parts (a) and (b) above.

Similarly structured proof sketches can be generated for all decision trees, since the efficiency of the mean as an estimator, the law of large numbers, and the linearity of expected utility theory remain valid for all decision trees. But, if individuals do not share the same utility function, then Proposition 2 holds only within strata of individuals who share the same utility function, although a conditional version of Proposition 2 could be offered taking exogenous utility differences into account.

The following four qualifications to Proposition 2 demonstrate the flexibility of the framework:

1. Although part (a) of Proposition 2 claims that prefigurative commitment is increasing in common increases in the precision of all component belief distributions, uneven increases in precision across different belief distributions will not necessarily increase prefigurative commitment. For example, if E[π]E[α] + $(1 - E[\pi])E[\beta] > E[\gamma]$, and if the moments of the belief distributions for π, α, and β remain fixed, Pr($E = 1$) is weakly decreasing in the precision of the belief distribution for γ. Thus, the underlying analytic structure implied by Assumptions A1 through A6 is more general than the simple Proposition 2 implies. The gross effect of precision of beliefs on prefigurative and preparatory commitment is a function of both the amount and the distribution of imprecision across belief distributions for the branches of a stochastic decision tree, and hence part (a) of Proposition 2 holds only for

common increases in precision, p, across all of the component belief distributions. Accordingly, one should not conclude from the arguments above that in order to effectively model prefigurative commitment, all one needs to do is add another term for uncertainty to a generic linear expected utility model (essentially, by building more concavity into the expected utility calculation of Up versus Down in the backward induction process). The relative distribution of precision across the stochastic decision tree is the relevant determinant.

2. As for the first qualification, if analysis effort is not evenly distributed across each of the component belief distributions (i.e. if the distribution of effort specified by the multinomial distribution in Step 2A of the simulation algorithm instead assigned different probability mass to additional draws from alternative belief distributions), then prefigurative commitment is not necessarily increasing in the total amount of analysis effort enacted by a decision-maker. The gross effect of analysis effort on prefigurative and preparatory commitment is a function of both the amount and the distribution of effort across belief distributions, and hence part (b) of Proposition 2 holds only for common increases in analysis effort across all of the component belief distributions.
3. When the belief distribution for π is formed by simple backward induction, as in the simulations above, $E[\pi]$ will remain fixed only if the distribution of information across α and β remains constant (as is the case only for Figures 3, 5, and 6). Since this may not necessarily be the case, movements of $E[\pi]$, $E[\alpha]$, and $E[\beta]$ in response to shifts in the distribution of payoff models must be tracked simultaneously. Likewise, as discussed in the concluding section to the article, the belief distributions for intermediate lotteries of a stochastic decision tree, such as π, may be entirely independent of the belief distributions for lottery parameters further down the tree, such as α and β. Presumably, for the college choice example, belief distributions at different stages would not be entirely independent, since payoff models are also college graduation and non-graduation models. But, since students may look at relatively young college graduates and non-college graduates (and think about the futures of peers whom they expect to be college graduates and non-college graduates), they most likely form belief distributions for π based on some observations of individuals

who have not received payoffs in the labor market, or whose lifetime payoffs are unknown.

4. Proposition 2 suggests that $\Pr(E = 1)$ will not reach 1 if k is sufficiently small and the mass of the belief distributions for π, α, β, and γ continue to overlap. This indirect implication in turn implies that for any set of overlapping belief distributions, there exists a low enough level of analysis effort that decision-makers *could* enact such that prefigurative commitment would not be universally and maximally intensive. This claim holds no matter how strongly the distribution of available information suggests that a future course of behavior is in an individual's best interest, as long as belief distributions overlap.

Taken together, the simulations and the analytic implications that are responsible for producing them demonstrate that when the uncertainty of beliefs is allowed to explicitly enter a decision evaluation, preparatory commitment to a future course of behavior is sensitive to the amount and type of uncertainty in one's beliefs as well as the effort expended to analyze one's beliefs. Thus, for example, even in a world where the returns on investments in higher education are massive, if beliefs are the least bit uncertain, and if students have limited information-processing and analysis capacities, some high school students some of the time will perceive it to be in their future best interest to forgo a college education. In these episodic and contrarian instances, they will adjust their current behavior accordingly. Since final levels of well-being are a function of preparation for college, even among those who ultimately do not attend college, such information-induced behavioral orientations in high school are potentially very important.

Discussion

I have proposed in this article a stochastic decision-tree model of commitment for use in research on non-repeatable decisions and also argued that the model is especially appropriate for analyzing preparatory commitment among adolescents toward the future course of behavior 'Go to college'. Alongside a set of simulations and analytic results, I have argued that individuals' prefigurative and preparatory commitments are functions of how clearly their stochastic decision trees identify a preferred course of future action. In particular, individuals whose beliefs are based on abundant information are more likely to clearly identify and then commit to a favored course of action. A primary implication of the framework is that individuals with accurate but sparse information on the potential benefits of an affirmative future decision may not prepare themselves adequately to attain what they suspect is in their best interest. Even if they do enact the affirmative decision, they may not be well positioned to harvest all of the returns of having made a utility-maximizing decision because of a lack of prior preparation.

In the remainder of the article, I offer some indirect but context-appropriate evidence for the adoption and further development of the stochastic decision-tree model. I then discuss elaborations of the model that allow for the incorporation of normative and imitative sources of prefigurative commitment. I conclude with a discussion of how the adoption of the proposed stochastic decision-tree framework can enhance research on educational attainment.

Evidence in Support of a Stochastic Decision-Tree Model for Preparatory Commitment

When seen as a cognitive attachment, prefigurative commitment shares essential features with the concept of an attitude in the social psychology literature. Attitudes toward an object, which can be a type of behavior, are a function of (1) an individual's positive and negative evaluations of possible component characteristics of the object and (2) probability judgments of whether or not each component characteristic is genuinely reflective of the object. Numerous studies show that individuals who lack information are unable to maintain strong probabilistic judgments and are more likely to have ambivalent attitudes (see Eagley and Chaiken 1998). This literature is broadly supportive of the claim that prefigurative commitment is a joint function of the accuracy and amount of available information (see also Davidson 1995; Petty and Krosnick 1995).

Despite this general evidence, the suitability of the framework must be evaluated for each domain in which it might be invoked. For the illustrative example utilized throughout this article, preparatory commitment to the course of action 'Go to college', there is some relevant evidence. Educational expectations – answers to questions such as 'How far in school do you think you will get?' –

represent the only commonly available measure of students' subjective beliefs about their future educational attainments. Morgan (1998) presents trend lines for the family-background-adjusted educational expectations of high school seniors from 1976 to 1990 and trend lines for the same years of the rate of return on years of educational attainment for young labor market participants. Across race, sex, and time, educational expectations roughly trace the same pattern as rates of return, lending some support to the assumption that students form attachments to levels of educational attainment that they would judge to be in their best interest. Albeit weakly, these patterns support the contention that prefigurative commitment is a function of the labor market returns that contribute to plausible belief distributions for parameters such as, α, β, and γ of the specific stochastic decision tree considered in this article (and hence support for part (c) of Proposition 2).[13]

If prefigurative commitment is a function of precision of beliefs, and if educational attainment is a function of prefigurative commitment by way of preparatory commitment, then there should be positive correlations between perceived uncertainty during adolescence, forecasts of future educational attainment, and educational attainment as an adult. It can be shown with many data sources, such as the *High School & Beyond* survey, that internal locus of control (Rotter 1982 [1966]) is positively related to both educational expectations and educational attainment. Such correlations provide some indirect support for the assertion that *ceteris paribus* prefigurative commitment is a function of precision of beliefs and that these effects may propagate through levels of preparatory commitment all the way to educational attainment and eventual labor market position.

Finally, there is also some indirect evidence that preparatory commitment may be a function *ceteris paribus* of precision of beliefs, if it is the case that increases in the amount of available information increase the precision of beliefs. Morgan and Sørensen (1999) present evidence that mathematics achievement among high school students is positively related to the network connections of a school community to independent sources of information, as proxied by the number of connections parents have to adults outside of the school community. Such network bridges generate horizon-expanding environments that have the potential to increase student effort and preparatory commitment to the utility-maximizing future course of behavior 'Go to college'.

Incorporating Normative and Imitative Sources of Prefigurative Commitment

When introducing the stochastic decision-tree model of commitment, I focused attention on the purposive source of prefigurative commitment, but I conceded that imitative and normative sources of prefigurative commitment deserve attention as well. For example, the purposive dimension that arises in response to the prediction rule 'I will go to college if I perceive it to be in my best interest to do so' may be reinforced or undermined by normative and imitative dimensions that arise in response to the additional prediction rules 'I will go to college if my significant others perceive it to be in my best interest to do so' and 'I will go to college if I expect other students similar to me will also go to college'. Can one grant explanatory power to these additional dimensions and still maintain that the stochastic decision-tree model has merit?

Yes, such incorporation can be accomplished in two ways, one external to the structure of the model and one internal to its explicit mechanisms. One could model normative-prefigurative commitment as external coercion. For example, a student might reason: 'Regardless of whether or not I think that going to college is in my best interest, I will go to college because my parents say that I must do so.' In this case, prefigurative commitment would primarily be a response to the normative influence of parents and only secondarily of an evaluation of a stochastic decision tree. Similarly, imitative-prefigurative commitment could be modeled externally as a pure contextual effect. A student might reason: 'Regardless of whether or not I think that going to college is in my best interest, I will go to college if I observe other students similar to me going to college.' Students from low social origins, for example, observe many fewer students entering college immediately following high school than students from high social origins. Thus, for this reason alone, students from low social origins might be less likely to expect to attend college and thus less likely to prepare themselves to do so.

Although external to the decision evaluation mechanism I propose here, incorporating normative and imitative sources of prefigurative commitment in these ways is consistent with much past sociological literature. There is, however, an alternative approach, one that is internal to the structure of the stochastic decision-tree model itself. For this approach, one would first stipulate that purposive-prefigurative commitment is the controlling guide for forward-looking behavior, but then specify lower-order mechanisms for the generation of the parameters on which forward-looking decision evaluation is based. In particular, one could specify that the beliefs with which students formulate prefigurative commitment are subject to lower-order normative and imitative pressures which themselves must be explicitly modeled.

From my perspective, this approach is entirely sensible in some decision contexts, such as modeling preparatory commitment for college. It seems undeniable that students' belief distributions are shaped in response to the views and actions of their significant others. For example, students' beliefs about the probability of graduating from college if initially enrolled are very likely a function of the views and actions of their parents, teachers, siblings and peers. Supportive parents are able to convince their children that they will receive adequate financial support. Teachers are able to convince students that they are smart enough to survive college instruction. Relatedly, students may see their older siblings and friends thriving in college environments and may thus eliminate low values as permissible probabilities for their own likelihood of graduating from college if enrolled. In principle, the same sort of social influence processes may operate for beliefs about the returns to alternative pathways through the educational system.

Potential of the Framework to Enhance Research on Educational Attainment

It was once fashionable for sociologists to delineate their field from economics by claiming that: 'Economics is about the choices people make while sociology is about the choices people don't get to make.' Although perhaps rhetorically effective, such statements are unfair to both disciplines, for in almost every substantive area in which economics and sociology are jointly engaged the best research has always sought to find a middle ground. For research on educational attainment, adoption of a stochastic decision-tree framework for modeling preparatory commitment may help to develop this middle ground more completely.

On the one hand, its adoption would amount to the deployment of a flexible form of rational choice theory that can loosen up the rigidity of discrete choice analysis in the economics of education. For example, it would enable a formalization of the tantalizing speculation of Cameron and Heckman (1999: 85) that 'Children who grow up in inferior environments may expect less of themselves and may not fully develop their academic potential because they see little hope for ever being able to complete college or use their schooling in any effective way.' The framework might also allow an additional avenue for the development of the arguments offered by Manski (1993a, b) that processes of expectation-formation are crucial for correctly modeling educational attainment, by adding precision of component beliefs to the criteria that determine decision evaluation.

And for sociology, in addition to enabling the pursuit of answers to the questions outlined in the introduction to this article (following upon Morgan 1998), the framework also allows for the formalization and empirical evaluation of ideas that have captivated the sociological imagination but which have been too vague to effectively implement in empirical research. For example, Bourdieu's argument that educational attainment should be modeled at the aggregate social class level as a mechanism of social reproduction has remained popular, and adoption of the stochastic decision-tree framework may allow us to explicitly develop his claim that educational attainment could be modeled as an 'anticipation, based upon the unconscious estimation of the objective probabilities of success' (Bourdieu 1973:83).[14] Likewise, there may be scope to develop the similarly captivating claim of Willis (1977: 172) that in studying educational attainment we ought to adopt a framework that 'gives the social agents involved some meaningful scope for viewing, inhabiting and constructing their own world', in particular by observing adult working-class culture and responding to individualist perceptions of typical institutional trajectories into it.

Beyond the independent utility of the stochastic decision-tree framework for both sociology and economics, adoption of the framework may help to unite dominant approaches to the study of educational attainment within sociology and economics, drawing on their appropriately complementary strengths. For example, sociologists have succeeded in delineating many of the potential mechanisms that generate the psychic costs and taste for education that economists must assume exist in order to explain why college enrollment rates are lower than narrow cost and benefit calculations of tuition and labor market benefits would imply. However, economists have achieved a comparative advantage by deploying threshold crossing models for instantaneous enrollment behavior, and the sociology of education could benefit from engaging these techniques more deeply. The stochastic decision-tree model, by giving formal expression to sociological mechanisms of the past, has the potential to bring sociology into decision-tree modeling and hence enable sociologists to join (or counter) economists in offering sharp policy-relevant predictions about enrollment behavior.

The next step in developing the stochastic decision-tree model is to specify explicit mechanisms of belief formation and belief revision that are responsive to social influence processes and to exogenous information differences. In constructing models of belief formation, I would argue that we first declare that the traditional belief formation and belief revision mechanisms based on Bayes' theorem represent the gold standard for such processes (which is the implicit assumption beneath the belief construction procedures detailed in the descriptions of the simulations above). We would then proceed in two directions: (1) relate direct measures of beliefs to predicted belief distributions from empirical analyses of outcomes from real-life payoff distributions; (2) develop alternative models based on non-Bayesian mechanisms for belief formation and belief revision. For models of college going, for example, such a research agenda is the natural and proper legacy of the general status socialization approach that is the foundation of most attempts by sociologists to model patterns of educational attainment. Indeed, the status attainment research from the 1970s that focused on racial differences in the formation of educational expectations and subsequent realizations of educational attainment can be seen as the first steps in this research agenda (see Morgan 2002). Such analyses represent the first tractable attempts to explain outcomes for distinct groups of actors who it is readily accepted are located within information fields that are defined by alternative social structural arrangements.

NOTES

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1. My concepts of prefigurative and preparatory commitment differ from the sort of forward-loooking strategies for guaranteeing self-control and overcoming weakness of will which, in the work of Elster and others (see 1984, 2000), have acquired the label of precommitments. Rather, my notion of commitment resonates with an older sociological tradition, as best exemplified by Parsons' notion of 'the transition from acceptance to commitment' (1951: 332). For the college choice example, I maintain that accepting the simple guide for action, based on an accurate set of beliefs, that obtaining a college degree may be in one's future best interest does not also imply that one will exhibit the commitment necessary to realize what is known to be in one's future best interest.
2. See the automatization mechanism in Wegner and Bargh (1998: 465).
3. Although I abandon such elegance for genuine modeling reasons, it is worth noting that some of the pioneers of discrete choice analysis are also finding good and very general justifications for relaxing these foundational assumptions (see McFadden 1999, 2001).
4. Although seemingly very limited, this setup of the alternative returns to different pathways through the decision tree is actually very general. We could easily add intermediate payoffs such as Middle. Or we could replace High, Low, and the associated success parameters α, β, and γ with rankings on a separate continuous distribution of payoffs. In this case, rather than maintaining different values for α, β, and γ, we would allow the quantiles of the payoff distributions to vary across the three pathways (and in line with the following argument base expected utility calculations on three different expected values of the continuous distribution function of rewards).
5. Keep in mind that this is a model of decision-making and thus precedes the behavior that it models. The parameter π is not, for example, the conditional probability of surviving the intermediate lottery among those who actually choose Up. Rather, π is the subjective belief that each individual – including those who ultimately choose Down – maintains for his or her own personal probability of surviving the intermediate lottery if he or she chooses Up.
6. Although not explicitly addressed in this presentation, I do not wish to exclude the possibility that option values (as for the college choice example was first modeled by Weisbrod (1962) and Comay et al. (1973)) could be embedded in the utility function explicitly (i.e. by including components above and beyond the valuation of High versus Low) or could be factored into the means of belief distributions about the final-stage lottery parameters. The first type of modification would prevent the simple elimination of the utility function as I move from Equation 1 to Equation 1a in the main text of the article, but it would not otherwise complicate analysis. The second form or revision, which I would prefer, does not change the model in any fundamental way, other than changing the meaning of High and Low (which are nothing other than nominal labels in any case).
7. As shown below, the stochastic decision-tree model that I propose yields non-trivial predictions even in such cases.
8. There is a hidden assumption here as well. In order for individuals to have accurate beliefs about the parameters of a decision tree, it must also be the case that their decision trees are accurate representations of the real-life set of lotteries that they will face. Thus, there can be no branching points that are ignored for the

sake of simplicity (or that cannot be integrated out by collapsing an option into a relevant parameter for a prior branching point).

9. Pioneering rational choice theorists were aware that beliefs are important (since utility functions are merely functions of component beliefs), but they became convinced that it is prohibitively difficult to measure individuals' beliefs. Axioms of revealed preference were thus regarded as tremendous breakthroughs, since decisions could be analyzed by observing behavior without having to look inside actors' heads.
10. Related stochastic utility and random preference models have been proposed in economics and psychology (see Becker et al. 1963; Hey and Orme 1994; Loomes and Sugden 1995; and Machina 1985). The main idea of this literature is that disturbance terms should be added to core fixed utility functions so that observed choices can be modeled as a function of errors in preferences, broadly construed. None of the proposed models are concerned with forecasts of a decision yet to be made, and hence with the idea that preparatory commitment is a function of the clarity of forecasts of the future. And thus, although they are related to my proposals, they have no straightforward connection with my stochastic decision-tree model of commitment.
11. In this set-up, prefigurative commitment to the course of behavior Up is modeled (i.e. 'Go to college'). But, since an increase in prefigurative commitment to the course of behavior Up is exactly equivalent to a decrease in prefigurative commitment to the course of behavior Down, one could obtain the same results offered below by flipping around the parameterizations and modeling prefigurative commitment to the course of behavior Down.
12. I continue to assume that utility functions and beliefs are so finely calibrated that no ties occur in the process of evaluating decision rules. Hence, I use strict inequalities for all decision rules, as is also the case for the college choice example analyzed by Manski and Wise (1983). Using weak inequalities and allowing for ties would merely force trivial modifications to the propositions and simulations.
13. That educational expectations are always shown to be a function of test scores supports the contention that prefigurative commitment is also a function of at least the mean of the belief distributions for π.
14. Despite the apparent clarity of this statement, which I regard as a sign that some of Bourdieu's ideas could be explicitly modeled, it is important that I concede that this reading of Bourdieu is likely not shared by his most ardent admirers. Many of these scholars cherish the heroic ambiguity of Bourdieu's scholarship, which Wacquant, for example, celebrates as a bold attempt to 'capture the intentionality without intention, the knowledge without cognitive intent, the prereflective, infraconscious mastery that agents acquire of their social world by way of durable immersion within it' (Bourdieu and Wacquant 1992: 19).

REFERENCES

Becker, Gordon; Morris H. DeGroot and Jacob Marschak. 1963. 'Stochastic Models of Choice Behavior.' *Behavioral Science* 8: 41–55.

Bourdieu, Pierre. 1973. 'Cultural Reproduction and Social Reproduction.' In *Knowledge, Education, and Cultural Change: Papers in the Sociology of Education*, ed. Richard Brown, pp. 71–112. London: Tavistock Publications.

Bourdieu, Pierre and Loïc J.D. Wacquant. 1992. *An Invitation to Reflexive Sociology*. Chicago, IL: University of Chicago Press.

Comay, Y.; A. Melnik and M. A. Pollatschek. 1973. 'The Option Value of Education and the Optimal Path for Investment in Human Capital.' *International Economic Review* 14: 421–35.

Camerer, Colin. 1995. 'Individual Decision Making.' In *Handbook of Experimental Economics*, eds John H. Kagel and Alvin E. Roth, pp. 587–703. Princeton, NJ: Princeton University Press.

Cameron, Stephen V. and James J. Heckman. 1999. 'Can Tuition Combat Rising Wage Inequality?' In *Financing College Tuition: Government Policies & Educational Priorities*, ed. Marvin H. Kosters, pp. 76–124. Washington, DC: AEI Press.

Davidson, Andrew R. 1995. 'From Attitudes to Actions to Attitude Change: The Effects of Amount and Accuracy of Information.' In *Attitude Strength: Antecedents and Consequences*, eds Richard. E. Petty and Jon. A. Krosnick, pp. 315–36. Mahwah: Erlbaum.

Eagley, Alice H. and Shelly Chaiken. 1998. 'Attitude Structure and Function.' In *The Handbook of Social Psychology,* 4th ed., vol. 1, eds Daniel T. Gilbert, Susan T. Fiske, and Gardner Lindzey, pp. 269–322. Boston, MA: McGraw-Hill.

Elster, Jon. 1984. *Ulysses and the Sirens,* rev. ed. Cambridge: Cambridge University Press.

Elster, Jon. 2000. *Ulysses Unbound: Studies in Rationality, Precommitment, and Constraints*. Cambridge: Cambridge University Press.

Gambetta, Diego. 1987. *Were They Pushed or Did They Jump?* Cambridge: Cambridge University Press.

Giddens, Anthony. 1984. *The Constitution of Society*. Berkeley, CA: Cambridge University Press.

Gigerenzer, Gerd and Reinhard Selten (eds). 2001. *Bounded Rationality: The Adaptive Toolbox*. Cambridge, MA: MIT Press.

Goldthorpe, John H. 2000. *On Sociology: Numbers, Narratives, and the Integration of Research and Theory*. Oxford: Oxford University Press.

Haller, Archibald O. 1982. 'Reflections on the Social Psychology of Status Attainment.' In *Social Structure and Behavior: Essays in Honor of William Hamilton Sewell,* eds Robert M. Hauser, David Mechanic, Archibald O. Haller, and Taissa S. Hauser, pp. 328. New York, NY: Academic Press.

Hedström, Peter and Richard Swedberg. 1998. *Social Mechanisms: An Analytical Approach to Social Theory*. Cambridge: Cambridge University Press.

Hey, John D. and Chris Orme. 1994. 'Investigating Generalizations of Expected Utility Theory Using Experimental Data.' *Econometrica* 62: 1291–326.

Kahneman, Daniel and Amos Tversky. 1979. 'Prospect Theory: An Analysis of Decision Under Risk.' *Econometrica* 47: 263–91.

Kane, Thomas J. 1999. *The Price of Admission: Rethinking How Americans Pay for College*. Washington, DC: Brookings.

Kerckhoff, Alan C. 1976. 'The Status Attainment Process: Socialization or Allocation?' *Social Forces* 55: 368–81.

Kosters, Marvin H. ed. 1999. *Financing College Tuition: Government Policies & Educational Priorities*. Washington, DC: AEI Press.

Lehman, E. L. and George Casella. 1998. *Theory of Point Estimation,* 2nd ed. New York, NY: Springer.

Loomes, Graham and Robert Sugden. 1995. 'Incorporating a Stochastic Element into Decision Theories.' *European Economic Review* 39: 641–8.

Machina, Mark J. 1985. 'Stochastic Choice Functions Generated from Deterministic Preferences Over Lotteries.' *The Economic Journal* 95: 575–94.

Manski, Charles F. 1989. 'Schooling as Experimentation: a Reappraisal of the Post-secondary Dropout Phenomenon.' *Economics of Education Review* 8: 305–12.

Manski, Charles F. 1993a. 'Adolescent Econometricians: How Do Youth Infer the Returns to Schooling?' In *Studies of Supply and Demand in Higher Education*, eds C. Clotfelter and M. Rothschild. Chicago, IL: University of Chicago Press.

Manski, Charles F. 1993b. 'Dynamic Choice in Social Settings.' *Journal of Econometrics* 58: 121–36.

Manski, Charles F. and David A. Wise. 1983. *College Choice in America*. Cambridge, MA: Harvard University Press.

McFadden, Daniel. 1999. 'Rationality for Economists?' *Journal of Risk and Uncertainty* 19: 73–105.

McFadden, Daniel. 2001. 'Economic Choices.' *The American Economic Review* 91: 351–78.

Morgan, Stephen L. 1998. 'Adolescent Educational Expectations: Rationalized, Fantasized, or Both?' *Rationality and Society* 10: 131–62.

Morgan, Stephen L. 2002. *Methodologist as Arbitrator: Multi-Model Deliberations for a Classic Unresolved Question on Educational Attainment*. Ithaca, NY: Cornell University.

Morgan, Stephen L. and Aage B. Sørensen. 1999. 'Parental Networks, Social Closure, and Mathematics Learning: A Test of Coleman's Social Capital Explanation of School Effects.' *American Sociological Review* 64: 661–81.

Parsons, Talcott. 1951. *The Social System*. Glencoe, IL: Free Press.

Petty, Richard. E. and Jon. A. Krosnick, eds. 1995. *Attitude Strength: Antecedents and Consequences*. Mahwah: Erlbaum.

Pittman, Thane S. 1998. 'Motivation.' In *The Handbook of Social Psychology,* 4th ed., vol 1, eds Daniel T. Gilbert, Susan T. Fiske, and Gardner Lindzey, pp. 549–90. Boston, MA: McGraw-Hill.

Pratt, John W., Howard Raiffa, and Robert Schlaifer. 1995. *Introduction to Statistical Decision Theory*. Cambridge, MA: MIT Press.

Rotter, Julian B. 1982 [1966]. 'Generalized Expectancies for Internal Versus External Control of Reinforcement.' In *The Development and Applications of Social Learning Theory: Selected Papers*, ed. Julian B. Rotter, pp. 171–214. New York, NY: Praeger.

Rubinstein, Ariel. 1998. *Modeling Bounded Rationality*. Cambridge, MA: MIT Press.

Selten, Reinhard. 2001. 'What is Bounded Rationality?' In *Bounded Rationality: The Adaptive Toolbox*, eds Gerd Gigerenzer and Reinhard Selten, pp. 13–36. Cambridge, MA: MIT Press.

Sen, Amartya. 1982 [1977]. 'Rational Fools: A Critique of the Behavioural Foundations of Economic Theory.' In *Choice, Welfare and Measurement*, ed. Amartya Sen, pp. 84–106. Cambridge, MA: Harvard University Press.

Sen, Amartya. 1997. 'Maximization and the Act of Choice.' *Econometrica* 65: 745–79.

Sewell, William H.; Archibald O. Haller, and Alejandro Portes. 1969. 'The Educational and Early Occupational Attainment Process.' *American Sociological Review* 34: 82–92.

Simon, Herbert A. 1996. *The Sciences of the Artificial*. Cambridge, MA: MIT Press.

Wegner, Daniel M. and John A. Bargh. 1998. 'Control and Automaticity in Social Life.' In *The Handbook of Social Psychology,* 4th ed. vol. 2, eds Daniel T. Gilbert, Susan T. Fiske, and Gardner Lindzey, pp. 446–96. Boston, MA: McGraw-Hill.

Weisbrod, Burton A. 1962. 'Education and Investment in Human Capital.' *Journal of Political Economy* 70(5): S106–23.

Willis, Paul. 1977. *Learning to Labour: How Working Class Kkids Get Working Class Jobs*. New York, NY: Columbia University Press.

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