

USING ELICITED CHOICE EXPECTATIONS TO PREDICT CHOICE BEHAVIOR
IN SPECIFIED SCENARIOS

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Partial Draft (Sections 1 - 4): July 21, 1997

1. Introduction

Revealed preference analysis and *hypothetical choice analysis* offer complementary approaches to prediction of choice behavior. Revealed preference analysis yields predictions by combining observations of realized choices with assumptions about underlying decision processes. Hypothetical choice analysis yields predictions by combining observations of elicited choice expectations with assumptions about underlying processes of expectations formation and communication.

A longstanding concern of research in economic theory and in econometrics has been to illuminate the logic of revealed preference analysis. Work in economic theory has focused mainly on cases in which the behavior of one person is observed in multiple choice settings and the objective is to predict that person's behavior in other settings (e.g., Afriat, 1967; Varian, 1982). Work in econometrics has focused mainly on cases in which a sample of persons is drawn from a population of interest, each sampled person's behavior is observed in one choice setting, and the objective is to predict the population distribution of choices in other settings (e.g., McFadden, 1973; Manski, 1988).

The logic of hypothetical choice analysis has not received comparable attention. As a consequence, the practice of hypothetical choice analysis has lacked the rigor and coherency characteristic of applied revealed preference analysis.

This paper continues the study of the logic of hypothetical choice analysis begun in Manski (1990; 1995, Chapter 5). There I

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examined the predictive power of *intentions* data (responses to questions asking for unconditional point predictions of future choices) under the "best-case" hypothesis that individuals have rational expectations and that their stated intentions are best point predictions of their future choice behavior. Even under this best-case hypothesis, stated intentions generally will not be perfect predictors of future behavior. Divergences between intentions and behavior may occur whenever behavior depends on events that are not yet realized when intentions are elicited but that will be realized before behavior is determined. Contrary to a common assertion in the empirical literature analyzing intentions data, divergences between stated intentions and subsequent behavior do not imply that individuals give flawed predictions of their futures.

I went on to show that, if future choice behavior depends on events not yet realized when intentions are elicited, intentions data obtained from a random sample of a population of interest do not identify the future population distribution of choices. At most, such data can bound the fraction of the population who will choose any action. Contrary to another common assertion in the literature analyzing intentions, individual-level divergences between stated intentions and subsequent behavior generally do not "average-out" in the aggregate.

Whereas Manski (1990) was concerned with the use of intentions data to predict unconditional future choice behavior, here I am concerned with the use of probabilistic expectations data to

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predict behavior in scenarios posed by the researcher. To illustrate these distinctions, consider these questions eliciting fertility expectations:

Looking ahead, do you expect to have any (more) children?

Looking ahead, what is the percent chance that you will have any (more) children?

Suppose that the government were to enact a child-allowance program providing women with fifty dollars per month for each dependent child. If this program were in effect, what is the percent chance that you would have any (more) children?

The first question, which has appeared in the June fertility supplement to the Current Population Survey, calls for a statement of fertility intentions. The second question calls for an unconditional probabilistic prediction of future fertility. The third question specifies a scenario and calls for a probabilistic prediction of future fertility in that scenario.

Section 2 lays out basic concepts of empirical choice analysis that enable formal study of the revealed preference and hypothetical choice approaches to prediction. Section 3 performs a best-case study of probabilistic choice expectations in the spirit of my earlier work on intentions. The researcher fully describes a choice scenario and elicits probabilistic choice

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expectations from respondents. Respondents have rational expectations and, when expectations are elicited, possess information that nests the information available to the researcher. Under this Rational Expectations with Nested Information (RENI) assumption, elicited probabilistic choice expectations reveal the distribution of population behavior in the specified scenario.

Sections 4 and 5 step away from the best-case setting in two respects. In Section 4, I call attention to a common problem in the practice of hypothetical choice analysis, which is that researchers may pose an incomplete scenario to respondents. I consider how respondents with rational expectations might answer questions posing incomplete scenarios and I characterize the predictive power that elicited choice expectations then have.

Section 5 questions the strong form of rational expectations assumed in much economic analysis and maintained in Sections 3 and 4. Persons seeking to predict their own futures in specified scenarios face fundamental inferential problems akin to those faced by researchers seeking to predict choice behavior. As a consequence, rational expectations is often an implausible assumption and sometimes an incredible one. I consider some weaker, perhaps more palatable, assumptions and characterize the predictive power that elicited choice expectations then have. The alternative assumptions examined here retain the basic economic perspective that persons think coherently and purposefully about their futures, using whatever limited information is available to them. I explain why this perspective is useful even if it should

turn out to be unrealistic.

Section 6 gives conclusions.

2. Basic Concepts of Empirical Choice Analysis

Section 2.1 introduces a set of primitives and derived constructs that enable formal study of the revealed preference and hypothetical choice approaches to prediction. Section 2.2 characterizes econometric revealed preference analysis in terms of these concepts. Section 2.3 does the same for the traditional form of hypothetical choice analysis eliciting point predictions. This sets the stage for consideration of probabilistic elicitation in Section 3.

2.1. Individual Choice Functions, Scenarios, and Population Choice Probabilities

The primitives of our analysis are a space of potential choice sets and a population of decision makers. Associated with each member of the population are a choice function (or decision rule) specifying the action the person would select if he or she were to face any potential choice set, a realized choice set from which the person actually selects an action, and some covariates.

A scenario is a function assigning a potential choice set to each member of the population. If a specified scenario were to be

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realized, each person would apply his or her choice function to select some feasible action. The frequency with which members of the population choose a given action is that action's population choice probability in the specified scenario. The researcher's objective is to determine population choice probabilities in scenarios of interest. What makes achievement of this objective problematic is that the researcher does not observe the choice functions of the members of the population.

Formally, let A denote a universe of *actions* and let Γ be the space of non-empty subsets of A . Each element of Γ is a *potential choice set*. Let T denote the population of decision makers. It is standard to describe the population as a measure space (T, Ω, P) , with P a probability measure. This enables population choice probabilities to be defined.

Each person $t \in T$ has a *choice function* $y_t(\cdot): \Gamma \rightarrow A$, a realized choice set $C_{rt} \in \Gamma$, and covariates $x_t \in X$. The choice function specifies the action that person t would select if he were to face any potential choice set. Chosen actions must be feasible, so $y_t(C) \in C$ for all $C \in \Gamma$.

A *scenario* $s(\cdot): T \rightarrow \Gamma$ is a function assigning a potential choice set to each member of the population. Let $C_{st} \equiv s(t)$ denote the choice set faced by person t in scenario s . Then the action that t would choose in this scenario is $y_t(C_{st})$. The realized scenario is the function $r(\cdot): T \rightarrow \Gamma$ assigning realized choice sets to the population. Thus person t 's realized choice is $y_t(C_{rt})$.

Observe that, as defined here, a scenario affects a person's

behavior only through its determination of his own choice set, not through the choice sets assigned to other members of the population. This is a substantive assumption, which excludes social interactions in choice behavior.

The researcher's objective is to predict behavior in specified scenarios of interest. Given any action $i \in A$, the *population choice probability* for i in scenario s is the fraction of the population who would select i . This is

$$(1) \quad P[y(C_s) = i] \equiv P[t \in T: y(C_{st}) = i],$$

assuming that this set of population members is measurable. Thus the researcher's objective is to learn $P[y(C_s) = i]$ for actions and scenarios of interest. The researcher also may want to predict the behavior of persons with given covariates x . Then the objective is to learn population conditional choice probabilities of the form $P[y(C_s) = i|x]$.

2.2. Econometric Revealed Preference Analysis

Prediction of population choices in specified scenarios would be straightforward if the researcher were able to observe the choice functions of the members of the population. The revealed preference approach to prediction begins from the premise that, although entire choice functions are not observable, particular points on choice functions may be observable. The literature in

economic theory supposes that a given person may be observed to make choices in multiple scenarios. The main body of work in econometrics supposes that each member of the population may be observed to make a choice in one scenario, namely the realized scenario r . I shall describe only the econometric setup here.

Econometric revealed preference analysis supposes that the researcher can observe the (covariate, realized choice set, realized choice) triple $[x_t, C_{rt}, y_t(C_{rt})]$ for each member of the population, or at least for a random sample thereof. Hence the researcher can learn empirically the population distribution $P[x, C_r, y(C_r)]$ of covariates, realized choice sets, and realized choices.

The available choice data reveal the population choice probabilities $P[y(C_r) = i|x]$ in the realized scenario but do not identify choice probabilities in unrealized scenarios. The *latent population choice probabilities* $P[y(C_s) = i|x]$, $s \neq r$ can be identified if the available choice data are combined with assumptions restricting the population distribution of choice functions and realized choice sets. The econometric literature on random utility models assumes that choice functions are utility maximizing rules and goes on to impose restrictions on the population distribution of utility functions and realized choice sets. In particular, it is commonly assumed that realized choice sets are *exogenous*; that is, utility functions and realized choice sets are statistically independent, conditional on x .

I would note in passing that econometric revealed preference

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analysis fits within the large tent of the modern analysis of treatment response. In the language of research on treatment response, a scenario is a *treatment policy* or *program* and a choice set is a *treatment*. A choice function is a *response function* giving the outcome (here a chosen action) that a person would experience if he were to receive any specified treatment (here a choice set). The researcher's objective is to learn the population distribution of outcomes that would occur if a treatment policy of interest were in effect. There is some realized treatment policy and the researcher is able to observe the outcomes that persons experience under their realized treatments. The researcher's objective is to predict the outcomes that would be experienced under unrealized treatment policies of interest. Conclusions can be drawn if the available data on realized treatments and outcomes are combined with assumptions restricting the population distribution of response functions and realized treatments. See, for example, Manski (1995, 1997).

2.3. Traditional Hypothetical Choice Analysis

Traditional hypothetical choice analysis extends the conventional analysis of intentions data from unconditional prediction of choice to prediction in specified scenarios. One poses an unrealized scenario to the members of the population, or at least to a random sample thereof, and elicits point predictions of choice. A common form of hypothetical choice question seeks a yes/no response to the query:

Q1. In scenario s , would you choose action i ?

or, perhaps, a response to the question "In scenario s , what action would you choose?" Responses are commonly interpreted as identifying the choices that respondents would make if scenario s were to be realized. The fraction of the population stating that they would choose action i is interpreted as the population choice probability for this action in the scenario posed.

Formally, let h_{sti} be person t 's response to question Q1, with $h_{sti} = 1$ indicating a "yes" response and $h_{sti} = 0$ a "no" response. Assume that

$$(2) h_{sti} = 1 \Leftrightarrow y(C_{st}) = i.$$

Then

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$$(3) \quad P[y(C_s) = i|x] = P(h_{si} = 1|x)$$

for each $i \in A$ and $x \in X$. So choice probabilities in scenario s are identified.

Traditional hypothetical choice analysis shares with the conventional analysis of intentions data the logical problem described in Section 1. The central assumption -- that elicited choice expectations coincide with the actual choices that respondents would make if the posed scenario were to be realized -- is untenable if behavior in this scenario would depend on events not yet realized when expectations are elicited. Researchers have sometimes used hypothetical choice data in place of realized choice data to estimate random utility models (e.g., Beggs, Cardell, and Hausman, 1981; Fischer and Nagin, 1981; Manski and Salomon, 1987). Such pseudo revealed preference analysis is well-grounded if assumption (2) holds but not otherwise.

3. Elicitation of Choice Expectations Before Choice Functions are Known

The scenarios posed in hypothetical choice analysis commonly refer to future settings in which persons would possess more information than they have when expectations are elicited. A person's response to a question eliciting choice expectations can be based only on the information the person possesses when the

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question is posed. However the person's behavior if the scenario were later to be realized would be based on the information the person would possess when a choice must be made.

Consider, for example, voter surveys conducted in the United States early in the presidential primary campaign, before the major party nominees have been selected. Respondents may be asked a question of the form:

Suppose that persons A and B will be the presidential nominees of the Democratic and Republican Parties. Would you vote for person B in the upcoming election?

The respondent must reply using the information available when the question is posed, but actual voting behavior may depend on information -- about the candidates, the economic and political environment, and the person's own situation -- that becomes available between the time of the survey and the date of the election.

To formalize the problem, let $v_t \in V$ denote the information that person t possesses when choice expectations are elicited. The researcher tells respondents the choice sets they would face in scenario s , so v_t includes knowledge of C_{st} . In other respects, however, v_t may be a proper subset of the information that person t would possess if scenario s were later realized and he were actually required to choose an action. Person t would then necessarily know his choice function $y_t(\cdot)$. When expectations are

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elicited, he need not yet know $y_t(\cdot)$.

Let $P[v, y(\cdot)]$ denote the population distribution of information and choice functions. Let $P[y(\cdot)|v = v_t]$ be the distribution of choice functions among those persons who have the same information as does t when expectations are elicited. Unless $P[y(\cdot)|v = v_t]$ is degenerate with all its mass at one choice function, person t does not yet know his choice function when expectations are elicited. Hence this person generally cannot predict his future behavior with certainty.

How should hypothetical choice questions be formulated and the responses interpreted when there is reason to think that behavior will depend on information not available when expectations are elicited? In the case of voting surveys, researchers sometimes eliminate the difference in timing between elicitation and behavior by asking a *forced-choice* question of the form:

Suppose that persons A and B are the presidential nominees of the Democratic and Republican Parties. If the election were held today, would you vote for person B?

This question solves the informational problem only by replacing the scenario of interest, a real election to be held in the future, with a different scenario in which the timing of the election is somehow changed. In general, responses to forced choice questions do not enable prediction of future choice behavior (see Manski, 1990, Section 5).

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Whereas traditional hypothetical choice questions seek point predictions of choice, a researcher might instead pose probabilistic questions of the form:

Q2. In scenario s , what is the percent chance you would choose action i ?"

The use of probabilistic questions to elicit unconditional choice expectations was recommended over thirty years ago by Juster (1966), who argued that it would be more informative to ask consumers for their purchase probabilities than for their buying intentions. Recently, considerable empirical experience has been obtained in the elicitation of probabilistic expectations of various personal economic and health outcomes (e.g., Quadrel, Fischhoff, and Davis, 1993; Hurd and McGarry, 1995; Dominitz and Manski, 1997a, 1997b). These empirical studies do not specifically elicit hypothetical choice expectations, but they suggest that such elicitation should be feasible.

How might a person respond coherently and purposefully to a probabilistic question of the form Q2? If asked for the probability that he would choose action i in scenario s , person t might use the available information v_t to form a subjective distribution, say $Q_t[y(\cdot)]$, for his as yet unknown choice function. He might apply this distribution to the potential choice set C_{st} specified by the researcher and derive the *subjective choice probability*

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$$(4) \quad q_{st}(i) \equiv Q_t[y(\cdot): y(C_{st}) = i].$$

He might then give $q_{st}(i)$ as the response to the question posed.

Person t is said to have *rational expectations* if his subjective distribution of choice functions coincides with the objective population distribution of choice functions among persons with information v_t ; that is, if

$$(5) \quad Q_t[y(\cdot)] = P[y(\cdot)|v = v_t].$$

The rational-expectations response to the hypothetical choice question is

$$(6) \quad q_{st}(i) = P[y(C_{st}) = i|v = v_t].$$

Suppose that all persons give rational-expectations responses. Then the population expected value of the subjective choice probabilities $q_{st}(i)$ is

$$(7) \quad E[q_s(i)] = E\{P[y(C_s) = i|v]\} = P[y(C_s) = i].$$

So the elicited probabilistic choice expectations reveal the population choice probability for action i in scenario s . Going further, suppose that the information v possessed by members of the population includes at least knowledge of the covariates x observed by the researcher. Under this assumption of *rational expectations*



with nested information (RENI), the above derivation holds if we restrict attention to persons with given covariates x , in which case

$$(8) \quad E[q_s(i)|x] = E\{P[y(C_s) = i | v]|x\} = P[y(C_s) = i|x].$$

Thus the elicited probabilistic choice expectations combined with the RENI assumption reveal the population conditional choice probabilities and enable the researcher to predict choice behavior in scenario s .

4. Incomplete Specification of Scenarios

Section 3 presented a best-case study of prediction using elicited probabilistic choice expectations. A researcher who elicits such expectations in a scenario of interest and who is willing to invoke the RENI assumption can easily generate predictions of behavior by averaging subjective choice probabilities across the sampled respondents. The econometrics literature has developed corresponding best-case studies of prediction using revealed preference analysis. There the data requirements are sufficiently rich observations of realized choices and the assumptions enabling prediction are sufficiently strong restrictions on the population distribution of choice functions and realized choice sets.

Of course researchers contemplating application of hypothetical choice analysis or revealed preference analysis should not content themselves with best-case justifications for these approaches. Best-case studies may be most valuable as constructive starting points for consideration of the two approaches from more realistic perspectives. In the case of revealed preference analysis, researchers have been able to draw on a large econometric literature investigating the predictions that remain possible with weaker data and/or assumptions than those contemplated in best-case studies. There is a need for corresponding research expanding the domain of hypothetical choice analysis. In this spirit, I examine here and in Section 5 two respects in which applications of hypothetical choice analysis may deviate from the best-case assumptions.

4.1. The Problem

In practice, researchers eliciting choice expectations often specify the scenario of interest incompletely. Researchers posing traditional hypothetical choice questions may ask

Q1'. In a scenario with attributes z , would you choose action i ?

Similarly, probabilistic questions may take the form

Q2'. In a scenario with attributes z , what is the percent chance

you would choose action i ?

Incomplete specification of a scenario is not problematic if the researcher does tell each person t the choice set C_{st} that he would face in scenario s . I have assumed there are no social interactions in behavior, so it is superfluous for the researcher to tell person t the choice sets that others would face. My concern here is with situations in which the attributes z do not determine a unique choice set for each member of the population. Then the scenario of interest is ambiguous.

Consider, for example, the description of presidential candidates in the election question discussed in Section 3:

Suppose that persons A and B will be the presidential nominees of the Democratic and Republican Parties. Would you vote for person B in the upcoming election?

This statement does not specify the minor party candidates who will be on the ballot and, hence, does not fully describe the voting choices that respondents will have available. Or consider the description of the child-allowance program in the fertility question of Section 1:

Suppose that the government were to enact a child-allowance program providing women with fifty dollars per month for each dependent child. If this program were in effect, what is the

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percent chance that you would have any (more) children?

This statement does not specify when the program would be initiated and does not define the term “dependent child.” These and other ambiguities leave it unclear what child allowance a woman would receive if she were to have any (more) children.

To understand the problem created by incomplete specification of scenarios, we need to interpret the phrase “In a scenario with attributes z .” Earlier, a scenario s was defined to be a function $s(\cdot): T \rightarrow \Gamma$ assigning a choice set to each member of the population. A *scenario with attributes z* , or an *incomplete scenario*, is simply a collection of scenarios, each $s \in z$ sharing some common features. In Sections 2 and 3, we took the researcher’s objective to be inference on the population conditional choice probabilities $P[y(C_s) = i|x]$ in a scenario s of interest. The problem is that this objective is not well-defined when a researcher poses an incomplete scenario.

4.2. Using Elicited Expectations to Infer Lower and Upper Choice Probabilities

An objective that is well-defined when an incomplete scenario is posed is inference on the *lower* and *upper* population choice probabilities

$$(9a) \quad P_{Lz}(i|x) \equiv \inf_{s \in z} P[y(C_s) = i|x]$$

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$$(9b) \quad P_{uz}(i|x) \equiv \sup_{s \in z} P[y(C_s) = i|x].$$

In a scenario with attributes z , the fraction of persons with covariates x who choose action i can be no less than $P_{Lz}(i|x)$ and no greater than $P_{uz}(i|x)$. So knowledge of these quantities enables some predictions about behavior to be made even though a complete scenario has not been posed.

Suppose that the researcher uses a probabilistic question of the form $Q2'$ to elicit choice expectations in an incomplete scenario. How might persons with rational expectations respond to such a question and what do the responses then reveal about the lower and upper choice probabilities $P_{Lz}(i|x)$ and $P_{uz}(i|x)$?

The rational-expectations response to a question posing a complete scenario s was given in equation (6), namely $q_{st}(i) = P[y(C_s) = i|v = v_t]$. There is no well-defined rational-expectations response to a question posing an incomplete scenario z . Rather, there is a range of responses that are consistent with the rational expectations assumption. To be consistent with rational expectations, person t 's response should lie in the interval $[q_{Lzt}(i), q_{Uzt}(i)]$, where

$$(10a) \quad q_{Lzt}(i) \equiv \inf_{s \in z} P[y(C_s) = i|v = v_t]$$

$$(10b) \quad q_{Uzt}(i) \equiv \sup_{s \in z} P[y(C_s) = i|v = v_t]$$

are the lower and upper bounds on $q_{st}(i)$ over the scenarios $s \in z$.

If each person t 's response lies in the interval $[q_{Lzt}(i),$

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$q_{Uzt}(i)]$, then the mean response among persons with covariates x lies in the interval $[E\{q_{Lz}(i)|x\}, E\{q_{Uz}(i)|x\}]$. Under the RENI assumption, the information v available to a respondent when expectations are elicited nests the covariates x observed by the researcher. The “inf” and “sup” operations are respectively concave and convex. Hence, by Jensen’s Inequality,

$$(10a) \quad E\{q_{Lz}(i)|x\} \leq P_{Lz}(i|x)$$

and

$$(10b) \quad E\{q_{Uz}(i)|x\} \geq P_{Uz}(i|x).$$

Thus, under the RENI assumption, the mean response to a question posing an incomplete scenario need not lie between the lower and upper population choice probabilities. This is a disturbing finding, which may undermine the usefulness of probabilistic choice expectations elicited for incomplete scenarios.

Fortunately, inequalities (10a) and (10b) carry a constructive message as well. Rather than elicit probabilistic choice expectations, a researcher might elicit lower and upper subjective choice probabilities using questions of the form

Q3'. In a scenario with attributes z , what is the lowest (highest) percent chance you would choose action i ?

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A person with rational expectations should give $q_{Lzt}(i)$ and $q_{Uzt}(i)$ as the responses to these questions. Averaging these responses across persons with covariates x , the researcher can learn the interval $[E\{q_{Lz}(i)|x\}, E\{q_{Uz}(i)|x\}]$ which, by (10), encloses the (lower, upper) population probability interval $[P_{Lz}(i|x), P_{Uz}(i|x)]$. Thus, under the RENI assumption, elicitation of lower and upper subjective probabilities yields a bound on the population choice probabilities of interest.

I am not aware of empirical research that seeks to elicit lower and upper subjective probabilities, and so cannot say how persons might respond in practice to questions of form Q3'. See Walley (1991) for a comprehensive survey of the extensive theoretical literature studying lower and upper subjective probabilities from various perspectives.

4.3. Filling Out Incomplete Scenarios

The discussion of Section 4.2 imposed no restrictions on how each person responding to question Q2' selects a value within the interval $[q_{Lzt}(i), q_{Uzt}(i)]$. Indeed there is no objective way to select such a value. We might suppose that each person t *fills out* the incomplete scenario z by placing a subjective distribution on the scenarios in z . This done, person t might report the mean of $q_{st}(i)$ with respect to this subjective distribution.

If no restrictions are imposed on these subjective distributions, no new conclusions about responses to question Q2'

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can be drawn. There exist subjective distributions that make person t 's response as low as $q_{Lz_t}(i)$ or as high as $q_{Uz_t}(i)$. Suppose, however, that all persons in the population fill out incomplete scenarios in the same way, by placing a common subjective distribution on the scenarios in z . If so, the RENI assumption implies that the population mean response to question Q_2' lies in the interval $[P_{Lz}(i|x), P_{Uz}(i|x)]$.

5. Rational Expectations Assumptions

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6. Conclusion

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