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MEASURING EXPECTATIONS[1]

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To predict choice behavior, the standard practice of economists has been to infer decision processes from data on observed choices. When decision makers act with partial information, economists typically assume that persons form probabilistic expectations for unknown quantities and maximize expected utility. Observed choices may be consistent with many alternative specifications of preferences and expectations, so researchers commonly assume particular sorts of expectations. It would be better to measure expectations in the form called for by modern economic theory; that is, subjective probabilities. Data on expectations can be used to relax or validate assumptions about expectations. Since the early 1990's, economists have increasingly undertaken to elicit from survey respondents probabilistic expectations of significant personal events. This article discusses the history underlying the new literature, describes some of what has been learned thus far, and looks ahead towards making further progress.

KEYWORDS: Choice analysis, beliefs, subjective probabilities, survey research.

1. INTRODUCTION

ECONOMISTS HAVE LONG SOUGHT to predict choice behavior. The standard practice, often called *revealed preference analysis*, has been to infer decision processes from data on observed choices. These inferences are then used to predict behavior in other settings.

The form of revealed preference analysis introduced by Samuelson (1938, 1948) supposes that a researcher observes the consumption bundles that a single person chooses when facing different budget sets with varying relative prices. Samuelson showed that observation of multiple (consumption, price, income) realizations, when combined with basic assumptions of consumer theory, implies restrictions on the consumption bundles that this person would choose when facing other budget sets. This idea, while beautifully simple, is more a thought experiment than a practical proposal; empirical researchers rarely observe the person-specific data that Samuelson envisioned.[2] Research in axiomatic decision theory similarly rests on a thought experiment in which one can observe the decisions that one person would make when facing many alternative choice sets (e.g., Savage (1954)).

The more practical form of revealed preference analysis developed by McFadden (1974) supposes that a researcher observes the decisions made by a

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[2]Economists applying Samuelson's idea usually have used data for multiple persons and have assumed that their preferences are homogeneous in some respects. Blundell (2003) reviews the literature and explores the extent to which heterogeneity in preferences can be accommodated.

random sample of heterogeneous persons, each of whom faces one discrete choice problem. McFadden showed that these data, combined with assumptions on the population distribution of preferences, enable estimation of probabilistic choice models. He then showed how probabilistic choice models may be used to predict population choice behavior in other settings.

Use of the term *revealed preference analysis* to describe econometric analysis of choice data has become imprecise. The meaning of the term is clear when decision makers know the outcomes of alternative actions. However, most empirical research today concerns choice problems in which decision makers act with partial information. Economists commonly assume that persons form probabilistic expectations for unknown quantities and maximize expected utility. Hence, the research problem is to infer the subjective probability distributions that express expectations and the utility functions that embody preferences.[3]

The difficulty is that observed choice behavior may be consistent with many alternative specifications of preferences and expectations. Hence, identification of decision processes from choice data must rest on strong maintained assumptions. The prevailing practice has been to assume that decision makers have specific expectations that are objectively correct (i.e., *rational*). This practice reduces the task of empirical inference to revelation of preferences alone, but has contributed to a crisis of credibility. Researchers performing econometric analysis of choice data often have enormous difficulty defending the expectations assumptions they maintain and, as a consequence, have similar difficulty justifying the findings they report.

I have concluded that econometric analysis of decision making with partial information cannot prosper on choice data alone. However, combination of choice data with other data should mitigate the credibility problem and improve our ability to predict behavior. The data I have in mind are self-reports of expectations elicited in the form called for by modern economic theory; that is, subjective probabilities. Researchers can use data on expectations to relax or validate assumptions about expectations.

Since the early 1990's, economists engaged in survey research have increasingly asked respondents to report probabilistic expectations of significant personal events. Expectations have been elicited for macroeconomic events (stock market returns), for risks that a person faces (job loss, crime victimization, mortality), for future income (earnings and Social Security benefits), and for choices that persons make (durable purchases and voting choices). In this article, I discuss the history underlying this new literature, describe some of what has been learned thus far, and look ahead towards making further progress.

[3]Here and elsewhere, I use the single word "preferences" to mean preferences over outcomes. This usage has been standard in applications of the expected utility model, but not in the literature on decision theory. Decision theorists often use the unadorned word "preferences" to mean preferences over actions.

Sections 2 and 3 make the case that choice data alone do not provide an adequate empirical foundation for econometric analysis of decision making with partial information. Section 2 uses two specific decision problems to illustrate how alternative combinations of preferences and expectations can produce the same choice data. Section 3 considers the conventional assumption that persons have rational expectations. Observing that persons forming expectations face the same inferential problems that empirical economists confront in their research, I find it generally implausible to assume rational expectations.

Section 4 traces the emergence of the modern economic literature eliciting probabilistic expectations from survey respondents. I critique the verbal expectations questions posed in attitudinal research and discuss elicitation of probabilistic expectations in cognitive psychology. I call attention to the early work in economics of Juster (1966).

Section 5 describes some of what I have learned from my own collaborative research measuring probabilistic expectations. I discuss worker perceptions of job insecurity and student perceptions of the returns to schooling. I present findings on expectations of income in the year ahead, Social Security benefits, and returns to mutual-fund investments. I suggest probabilistic polling to measure voting expectations.

Section 6 describes three ways in which researchers have sought to evaluate the accuracy of elicited expectations. In each case, I summarize available findings. I also suggest that probabilistic questioning may improve traditional survey research practices asking respondents about facts.

Section 7 considers two ways in which expectations data may be used to predict choice behavior. One approach directly asks respondents to predict their own behavior. The other combines elicited expectations with choice data to estimate econometric decision models. I observe that use of an econometric model to predict behavior may require an understanding of how persons would form expectations in the setting of interest.

By and large, Sections 2–7 do not question the psychological realism of probabilistic expectations, nor that measured expectations faithfully describe persons' internal beliefs.[4] Section 8 entertains the idea, considered in research on *ambiguity*, that beliefs have some but not all the structure of a probability distribution. To enable persons to express ambiguity, I suggest elicitation of ranges of probabilities rather than precise probabilities for events of interest.

Measurement of expectations is not the only possible way to enrich choice data. Collection of other subjective data may be useful as well. The possibilities range from elicitation of preferences to verbal probes asking persons to describe how they make decisions. I do not discuss these other forms of subjective data here, because I have not had experience with them.

[4]One exception is Section 4.2, which discusses a controversy within cognitive psychology as to whether humans process information using verbal or numerical modes of thinking. Another is the introduction to Section 5, which discusses concerns that probabilistic questioning may not reveal persons' thinking.

Nor do I discuss *neuroeconomics*. Interpretation of responses to subjective questions has always run up against the problem that a researcher cannot directly observe a person's thinking. However, neuroscientists have recently begun to use brain imaging technology to observe aspects of the biological processes that accompany decision making (e.g., McCabe et al. (2001), Smith et al. (2002)). It is too early to judge how neuroeconomics may eventually contribute to the prediction of behavior.

2. INFERENCE USING CHOICE DATA ALONE: TWO ILLUSTRATIONS

The illustrations in this section are drawn from Manski (1993a, 2002a). The former article critiques practices in the econometric analysis of schooling choice, and the latter calls attention to identification problems in experimental economics. Both articles assume that persons maximize subjective expected utility. Within this paradigm, both explore how preferences and expectations may combine to yield observed choices.

2.1. *Schooling Choices and Perceptions of the Returns to Schooling*

Economists analyzing schooling decisions assume that youth, having formed expectations for the returns to schooling, choose between schooling and other options. Given the centrality of the returns to schooling in economic thinking on schooling behavior, it might be anticipated that economists would make substantial efforts to learn what expectations youth hold. However, the standard practice has been to make assumptions without the benefit of data on expectations.

Economic studies of schooling behavior have generally supposed that all youth condition their beliefs on the same variables and process information in the same way. However, the hypothesized conditioning variables and information processing rule vary considerably across studies. For example:

(a) In his analysis of the major field decisions of male college students, Freeman (1971) assumed that each student observes the incomes realized by earlier cohorts of male students and believes that, should he select a given college major, he would obtain the mean income realized by the members of a specified earlier cohort who made that choice.

(b) In their study of college enrollment, Willis and Rosen (1979) supposed that youth condition their expectations on sex, armed forces status, and ability. They assumed that youth know the actual process generating life-cycle incomes conditional on these personal covariates, and thus are able to form rational expectations for the returns to college enrollment.

(c) In their analysis of college choice, Manski and Wise (1983, Ch. 6) assumed that youth condition their expectations for the utility of enrolling in a given college on their own SAT score and on the average SAT score of students enrolled at the college. Youth do not necessarily know either the outcomes realized by earlier cohorts nor the actual process generating outcomes. Rather, they believe the returns to enrolling to be a function of their own SAT score and the average at the college.

The expectations assumptions in these studies differ in many respects, one of which is the way in which youth are assumed to use ability information to form expectations. Whereas Freeman (1971) assumed that youth do not condition their expectations on ability, Willis and Rosen (1979) assumed that they do condition on ability and that they have rational expectations. Manski and Wise (1983) assumed that they use SAT score, which may be associated with ability, to form expectations that may or may not be rational.

This variation in expectational assumptions is consequential. Manski (1993a) used a simple human capital model to demonstrate that interpretation of data on schooling choices can depend critically on how youth actually use ability information to form expectations of the returns to schooling. A particularly striking finding was that, if youth do not condition their expectations on ability, a researcher who assumes they do so may mistakenly conclude from observed choices that youth are unconcerned with the returns to schooling.

2.2. *Identification of the Decision Rules of Proposers in Ultimatum Games*

The behavior of subjects playing the ultimatum game has been of considerable interest to experimental economists. The ultimatum game is a game of proposal–response in which the proposer offers a division of a specified sum of money. The responder either accepts the offer, in which case the division is realized, or rejects it, in which case both players receive nothing. Roth (1995, Ch. 4) reviews the empirical findings. A particularly common finding has been that proposers often offer responders an even division of the money. Experimental economists have taken this as evidence of a prevalent preference for *fairness*. However, the decision to offer an even division can also arise when a proposer who wants to maximize private utility has appropriate expectations about the behavior of responders.

To illustrate, suppose that a proposer is given K dollars and that $C = [0, K]$ is the set of offers he can make to the responder. For $c \in C$, let $d(c) = 1$ if the responder would accept an offer of size c and let $d(c) = 0$ if he would reject the offer. Then the payoffs to the proposer and responder are $y(1, c, d) = (K - c)d(c)$ and $y(2, c, d) = cd(c)$, respectively.

Assume that agents playing the role of proposer are known to be of six types, each having one of two utility functions and one of three forms of expectations. The possible utility functions are:

$$U_1[y(1, c, d), y(2, c, d)] = y(1, c, d) = (K - c)d(c),$$

$$\begin{aligned} U_2[y(1, c, d), y(2, c, d)] &= y(1, c, d) \cdot y(2, c, d) \\ &= [(K - c)d(c)]cd(c). \end{aligned}$$

Agents with the first utility function aim to maximize their own payoff. Those with the second exhibit a strong form of *fairness* in which they care equally about their own payoff and that of the other player.

Suppose that the three forms of expectations are

$$Q_1[d(c)=1] = \frac{1}{2} + \min(c/K, 1/2),$$
$$Q_2[d(c)=1] = \min[c/(K-c), 1],$$
$$Q_3[d(c)=1] = \min(c/K, 1).$$

Agents with the first form of expectations believe that the probability with which a responder would accept a proposal rises from $1/2$ to 1 as the size of the offer rises from 0 to $K/2$. Those with the second form believe that the chance of acceptance rises from 0 to 1 as the offer rises from 0 to $K/2$. Those with the third form believe that the chance of acceptance rises from 0 to 1 as the offer rises from 0 to K.

Let $c(i, j)$ be the action chosen by a proposer who has the ith utility function and the jth form of expectations. Maximization of expected utility by the six types of agents yields these chosen actions:

$$c(1,1) = K/4, \quad c(1,2) = K/2, \quad c(1,3) = K/2,$$
$$c(2,1) = K/2, \quad c(2,2) = K/2, \quad c(2,3) = 2K/3.$$

Observe how preferences and expectations combine to determine the chosen actions. Fully four of the six types offer the responder an even division of the money. Agents with both utility functions offer an even division if they have the second form of expectations. Thus, choice data do not reveal the preferences of agents playing proposer in the ultimatum game. They reveal only that preferences and expectations combine to yield the observed offers.

3. RATIONAL EXPECTATIONS ASSUMPTIONS

The above illustrations exemplify a familiar abstract problem of decision making with partial information. Let C be a choice set, Γ be a space of feasible states of nature, $\gamma^* \in \Gamma$ denote the true state of nature, and $f(\cdot,\cdot): C \times \Gamma \rightarrow R$ be an objective function. Assume that a decision maker wants to choose an action that solves

$$(1) \qquad \max_{c \in C} f(c, \gamma^*).$$

The problem is that the decision maker does not know the value of γ^*. In the schooling-choice illustration, the unknown state of nature was the return to schooling. In the ultimatum-game illustration, it was the function $d(\cdot)$ expressing how the responder would react to offers of different sizes.

A person who does not know γ^* can solve problem (1) only if there is a dominant action; that is, a $c \in C$ such that $f(c, \gamma) \geq f(d, \gamma)$, all $(d, \gamma) \in C \times \Gamma$. Decision theorists have sought to prescribe how persons should behave when there is no dominant action, but no consensus has emerged. One normative principle is that a person should not choose a weakly dominated action; action d is weakly dominated if there exists another action, say c, such that $f(d, \gamma) \leq f(c, \gamma)$ for all $\gamma \in \Gamma$ and $f(d, \gamma) < f(c, \gamma)$ for some $\gamma \in \Gamma$.

Economists regularly assume that decision makers place subjective probability distributions on the feasible states of nature and maximize subjective expected utility. It is routine to assume that a person who cannot solve problem (1) instead solves the problem

$$(2) \qquad \max_{c \in C} \int u[f(c, \gamma)]\, dQ,$$

where Q denotes the subjective distribution on Γ and where $u(\cdot): R \to R$ is an increasing transformation of f. Economists also regularly assume that γ^* is the realization of a random variable and that decision makers have *rational expectations*; that is, they know the objective probability distribution that generates γ^*.[5]

Although economists routinely assume rational expectations, they only occasionally ask how persons could know the objective distribution, say P, generating γ^*. Researchers have shown that particular learning processes reveal some features of P in specific circumstances. See, for example, Cyert and DeGroot (1974), Blume and Easley (1982), Bray and Kreps (1987), Marcet and Sargent (1989), Kalai and Lehrer (1993), and Manski (1993b). However, the plausibility of rational expectations has been questioned sharply by authors such as Pesaran (1987), who writes (p. 2) that the rational expectations hypothesis "is based on extreme assumptions and cannot be maintained outside the tranquility of a long-period steady state." Considering the problem of expectations formation, I too have concluded that rational expectations assumptions often are implausible in the extreme.

Suppose that the true state of nature actually is the realization of a random variable distributed P. A decision maker attempting to learn P faces the same inferential problems—identification and induction from finite samples—that empirical economists confront in their research. Whoever one is, decision

[5]To justify the assumption that persons solve (2), economists may cite the Savage (1954) axiomatic derivation of the subjective-expected utility criterion. Savage assumed that a person has a complete preference ordering on a universe of actions and showed that if this ordering satisfies certain other axioms, the preference ordering can be obtained by maximization of subjective expected utility. The normative appeal and empirical realism of the Savage axioms have long been debated. Whatever one's view on these matters may be, it is important to understand that the axioms imply no restrictions on the substantive form of probabilistic expectations. In particular, they do not imply that expectations are rational.

maker or empirical economist, the inferences that one can logically draw are determined by the available data and the assumptions that one brings to bear. Empirical economists seldom are able to completely learn objective probability distributions of interest, and they often cannot learn much at all. It therefore seems hopelessly optimistic to suppose that, as a rule, expectations are either literally or approximately rational.

To illustrate, consider again the problem of schooling choice. In Manski (1993a), I observed that youth who form earnings expectations confront the same inferential problems as do labor economists when they study the returns to schooling. The literature in labor economics exhibits much debate on the credibility of assumptions and many disagreements about findings. If experts disagree on the returns to schooling, is it plausible that youth have rational expectations? I think not.

I would particularly stress that decision makers and empirical economists alike must contend with the logical unobservability of counterfactual outcomes. Much as economists attempt to infer the returns to schooling from data on schooling choices and outcomes, youth may attempt to learn through observation of the outcomes experienced by family, friends, and others who have made their own past schooling decisions. However, youth cannot observe the outcomes that these people would have experienced had they made other decisions. The possibilities for inference, and the implications for decision making, depend fundamentally on the assumptions that youth maintain about these counterfactual outcomes.

Even if the assumption of rational expectations were plausible, this assumption per se does not specify the expectations that persons hold; it asserts only that persons hold objectively correct expectations conditional on the information they possess. Economists typically assume much more than this. The standard practice has been for a researcher to pose a model of the economy, to assert that this model is correct, and also to assert knowledge of the information on which agents condition their expectations. The rational expectations hypothesis in combination with these additional assumptions closes the model.

Why do economists so often assume that they and the decision makers they study share rational expectations? Part of the reason may be the elegant manner in which these assumptions close an economic model. A researcher specifies his own vision of how the economy works, and he assumes that the persons who populate the economy share this vision. This is tidy and self-gratifying.

Another part of the reason must be the data used in empirical research. As illustrated in Section 2, choice data do not necessarily enable one to infer the expectations that decision makers hold. Hence, researchers who are uncomfortable with rational expectations assumptions can do no better than invoke some other unsubstantiated assumption. Rather than speculate on how expectations actually are formed, they follow convention and assume rational expectations.

4. ELICITATION OF EXPECTATIONS FROM SURVEY RESPONDENTS

If choice data alone do not suffice to infer how persons make decisions with partial information, one might anticipate that economists would ask persons about their preferences and expectations. However, economists have been deeply skeptical of subjective statements; they often assert that one should believe only what people do, not what they say. As a result, the profession for many years enforced something of a prohibition on the collection of subjective data.

It is reasonable to ask whether the conventional economic wisdom on collection of subjective data is well grounded. I sought to determine the scientific basis underlying economists' hostility to measurement of expectations, but found it to be meager. One influential event appears to have been the Machlup (1946) criticism of then ongoing efforts by economists to interview businessmen about their cost and revenue expectations. Another important part of the story occurred in the 1950's and early 1960's, when economists reported negative evidence on the usefulness in predicting consumer purchase behavior of verbal assessments of expected household finances (National Bureau of Economic Research (1960), Juster (1964)). These specific events appear to have predisposed academic economists to draw the broad but unsubstantiated conclusion that all data on expectations are suspect.[6]

Other social scientists have not shared economists' inhibitions about collection of expectations data. Section 4.1 critiques the verbal expectations questions posed in attitudinal research. Section 4.2 discusses elicitation of verbal and probabilistic expectations in cognitive psychology. I then turn to the economics literature from Section 4.3 onward.

[6]Dominitz and Manski (1997a, 1999) describe this history. In the 1940's, the Federal Reserve Board began to fund an annual Survey of Consumer Finances, conducted by the University of Michigan Survey Research Center (SRC), that elicited verbal assessments of expected household finances. The usefulness of responses to the SRC questions was controversial and the Board of Governors appointed a committee to assess their value. The Federal Reserve Consultant Committee on Consumer Survey Statistics (1955) questioned the predictive value of subjective data, with the exception of purchase intentions. The conclusions were at odds with the views of SRC researchers, notably George Katona, a leading proponent of research on consumer attitudes (Katona (1957)). A contentious conference on expectations data at the National Bureau of Economic Research (1960) was followed by an intensive study by Juster (1964) that drew largely negative conclusions on the usefulness of verbal expectations data in predicting individual behavior.

Although academic economists retreated from collection and analysis of personal expectations data by the early 1960's, SRC has continued to elicit verbal expectations in its Survey of Consumers and to report aggregate findings in its Index of Consumer Sentiment (Curtin (1982)). Other nonacademic organizations, such as the Conference Board (Linden (1982)) have since initiated their own surveys of consumer confidence. Moreover, the Livingston Panel and the Survey of Professional Forecasters elicit point predictions of macroeconomic variables from experts; see Caskey (1985) and Keane and Runkle (1990).

4.1. *Attitudinal Research*

Attitudinal researchers have long used verbal questions to measure expectations. When asked to predict some outcome, respondents may be asked to report whether they "think" or "expect" that the event will occur. Sometimes they are asked to report the strength of this belief by attaching one of a choice of modifiers, such as "very," "fairly," "not too," or "not at all" likely that the event will occur. A prominent example is this Michigan Survey of Consumers question on business conditions (Curtin (1982)):

> *Survey of Consumers Business-Conditions Question*: Now turning to business conditions in the country as a whole—do you think that during the next 12 months we'll have good times financially, or bad times, or what?

Another is this question on job loss in the General Social Survey (Davis and Smith (1994)):

> *General Social Survey Job-Loss Question*: Thinking about the next twelve months, how likely do you think it is that you will lose your job or be laid off—very likely, fairly likely, not too likely, or not at all likely?

These questions illustrate a persistent problem that researchers face in interpreting verbal expectations data—assessment of the interpersonal comparability of responses. How do respondents to the Michigan survey interpret the phrases "business conditions" and "good times financially?" Do different respondents to the General Social Survey interpret the phrases "very likely, fairly likely, not too likely, or not at all likely" in the same way? Cognitive research does not give reason to think that responses should be or are comparable. Indeed, the available empirical evidence indicates that interpretations of verbal expectations questions vary substantially between persons (Lichtenstein and Newman (1967), Beyth-Marom (1982), Wallsten et al. (1986)). One may also question whether responses are intra-personally comparable; that is, a given respondent may interpret verbal phrases in different ways when asked about different events.

A second persistent problem is that the coarseness of the response options limits the information contained in the responses. Consider, for example, the fertility question asked female respondents in the annual June Supplement to the Current Population Survey of the U.S. Bureau of the Census:

> *Current Population Survey Fertility Question*: Looking ahead, do you expect to have any (more) children?
> Yes No Uncertain.

The three response options express little of the richness of the uncertainty that women may perceive about their future childbearing.

The influential Fishbein-Ajzen model of intentions illustrates the loose manner in which attitudinal researchers have thought about expectations. Fishbein and Ajzen (1975) propose that "intention" is a mental state that causally precedes behavior and that can be elicited through questionnaires or interviews.

According to Ajzen and Fishbein (1980), a person's "behavioral intention" is his subjective probability that the behavior of interest will occur. (They refer to the response to a yes/no intentions question as "choice intention.") It seems, however, that social psychologists do not use the term "subjective probability" as a Bayesian statistician would. Ajzen and Fishbein (1980, p. 50) state: "we are claiming that intentions should always predict behavior, provided that the measure of intention corresponds to the behavioral criterion and that the intention has not changed prior to performance of the behavior." In a review of attitudinal research, Schuman and Johnson (1976, p. 172) write that the Fishbein–Ajzen model implies that "the correlation between behavioral intention and behavior should approach 1.0, provided that the focal behavior is the same in both cases and that nothing intervenes to alter the intention." It is difficult to reconcile these statements with the idea that behavioral intention is a subjective probability, unless that probability is always zero or one.

4.2. *Probabilistic Expectations in Cognitive Psychology*

If persons can express their expectations in probabilistic form, elicitation of subjective probability distributions should have compelling advantages relative to verbal questioning. Perhaps the most basic attraction is that probability provides a well-defined absolute numerical scale for responses; hence, there is reason to think that responses may be interpersonally comparable. Another attraction is that empirical assessment of the internal consistency of respondents' expectations is possible. A researcher can use the algebra of probability (Bayes Theorem, the Law of Total Probability, etc.) to examine the internal consistency of a respondent's expectations about different events.

When probability has a frequentist interpretation, a researcher can compare elicited subjective probabilities with known event frequencies and reach conclusions about the correspondence between subjective beliefs and frequentist realities. Such *calibration studies* have a long history in cognitive psychology. Lichtenstein, Fischhoff, and Phillips (1982) review findings from 1906 on, and McClelland and Bolger (1994) update the review with findings from 1980 through 1994. Whereas the older studies mostly examined the accuracy of experts (e.g., weather forecasters' reported probabilities of precipitation), much recent research analyzes the expectations of nonexperts, especially students in a cognitive laboratory.

Within cognitive psychology, there has been controversy about the way in which humans internally represent their beliefs, and their ability and willingness to express their beliefs as numerical probabilities. Koriat, Lichtenstein, and Fischhoff (1980) and Ferrell and McGoey (1980) posed models in which individuals may have some difficulty expressing beliefs as numerical probabilities, but nevertheless concluded that elicitation of numerical subjective probabilities is feasible. However, Zimmer (1983, 1984) argued that humans process information using verbal rather than numerical modes of thinking, and he concluded that expectations should be elicited in verbal rather than numerical forms.

Erev and Cohen (1990) and Wallsten et al. (1993) have reported that a majority of respondents prefer to communicate their own beliefs verbally and to receive the beliefs of others in the form of numerical probabilities. This asymmetry is intriguing but only marginally relevant to the design of expectations questions. The relevant question is not what communication mode respondents prefer to use, but rather what modes they are willing and able to use. Wallsten et al. (1993) report that virtually all of their respondents were willing to communicate their beliefs numerically, should the situation warrant it.

Another ongoing controversy concerns the manner in which persons process objective probabilistic information. In an influential article, Tversky and Kahneman (1974) summarized some randomized experiments in which subjects were presented with statistics of various forms and were asked for probabilistic predictions of specified events. They interpreted the findings as showing that persons tend to use certain heuristic rules to process data, rather than Bayes theorem. To the extent that the Tversky and Kahneman experiments shed light on expectations formation in real life, they cast doubt on the assumption of rational expectations, not on the representation of expectations through subjective probability distributions.[7]

The controversy concerns the degree to which the Tversky–Kahneman and similar experiments do shed light on subjects' use of Bayes theorem to process data. Gigerenzer (1991) argued that the reported empirical regularities result not from respondents' use of heuristics but from the manner in which statistical information was presented to them. Here and elsewhere (e.g., Hoffrage et al. (2000)), Gigerenzer and his colleagues have reported experimental evidence indicating that respondents perform much better in applying probability theory when statistics are presented in the form of natural frequencies rather than objective probabilities (e.g., "30 out of 10,000 cases," rather than ".3 percent of cases").

[7]Some researchers have used Tversky and Kahneman (1974) to argue that expectations should be elicited in verbal rather than probabilistic form (e.g., Jamieson and Bass (1989)). However, the experimental evidence does not relate to this question. Tversky and Kahneman did not report experiments with verbal elicitation of expectations. The deviations from correct application of probability theory that they found were discoverable only because they elicited expectations in probabilistic form.

Indeed, Tversky and Kahneman (1974) argued for the psychological realism of subjective probabilities. Considering the propensity of decision theorists to view subjective probabilities as constructs that may be inferred from choices, they wrote (p. 1130): "It should perhaps be noted that, while subjective probabilities can sometimes be inferred from preferences among bets, they are normally not formed in this fashion. A person bets on team A rather than on team B because he believes that team A is more likely to win; he does not infer this belief from his betting preferences. Thus, in reality, subjective probabilities determine preferences among bets and are not derived from them, as in the axiomatic theory of rational decision."

4.3. *Probabilistic Expectations in Economics*

Among economists, the idea that measurement of probabilistic expectations might improve on the verbal approaches of attitudinal research appears to have originated with Juster (1966). Considering the case in which the behavior of interest is a binary purchase decision (buy or not buy), Juster considered how responses to traditional yes/no buying intentions questions should properly be interpreted. He wrote (Juster (1966, p. 664)): "Consumers reporting that they 'intend to buy A within X months' can be thought of as saying that the probability of their purchasing A within X months is high enough so that some form of 'yes' answer is more accurate than a 'no' answer." Thus, he hypothesized that a consumer facing a yes/no intentions question responds as would a statistician asked to make a best point prediction of a future random event. Working from this hypothesis, Juster concluded that it would be more informative to ask consumers for their purchase probabilities than for their buying intentions.[8] In particular, he proposed questions that associate verbal expressions of likelihood with numerical probabilities to elicit purchase expectations for automobiles and other household appliances:

Juster Purchase Probability Questions: Taking everything into account, what are the prospects that some member of your family will buy a ____ sometime during the next _____ months, between now and ____ ?

Certainly, Practically Certain (99 in 100); Almost Sure (9 in 10); Very Probably (8 in 10); Probably (7 in 10); Good Possibility (6 in 10); Fairly Good Possibility (5 in 10); Fair Possibility (4 in 10); Some Possibility (3 in 10); Slight Possibility (2 in 10); Very Slight Possibility (1 in 10); No Chance, Almost No Chance (1 in 100).

He went on to collect data and found that elicited purchase probabilities are better predictors of subsequent individual purchase behavior than are yes/no intentions data.

Some market researchers were attracted to Juster's proposal (e.g., Morrison (1979)). The idea that expectations might be elicited probabilistically from survey respondents did not, however, draw the immediate attention of economists. By the time Juster's article was published, economists were preaching that empirical research on decision making should be based on choice data alone. A quarter century passed before economists began to systematically collect and analyze probabilistic expectations data.

The conventional economic wisdom unraveled in the 1990's. Various large-scale sample surveys now use probabilistic formats to elicit expectations, and a new field of empirical research on expectations has emerged. The major platforms for methodological exploration and substantive research include the Health and Retirement Study (Juster and Suzman (1995), Hurd and McGarry

[8]Tobin (1959) interpreted intentions data in much the same way, but he did not go on to propose elicitation of probabilities. More recently, I derived a formal upper bound on the information about probabilistic expectations that a researcher can extract from responses to Yes/No intentions questions (Manski (1990)).

(1995)), the Bank of Italy's Survey of Household Income and Wealth (Guiso, Jappelli, and Terlizzese (1992), Guiso, Jappelli, and Pistaferri (2002)), the Survey of Economic Expectations (Dominitz and Manski (1997a, 1997b)), the Dutch VSB Panel Survey (Das and Donkers (1999)), and the 1997 cohort of the National Longitudinal Survey of Youth (Fischhoff et al. (2000), Dominitz, Manski, and Fischhoff (2001), Walker (2001)). Even the venerable Michigan Survey of Consumers now includes some probabilistic questions along with its traditional verbal questions (Dominitz and Manski (2003, 2004)).[9]

5. A SELECTION OF FINDINGS

This section describes some of what I have learned from my collaborative research eliciting probabilistic expectations from respondents to surveys in the United States. This work has mainly sought to answer basic empirical questions: How willing and able are respondents to reply to such questions? What expectations do persons hold for their futures?

Although a long-term objective is to use expectations data to predict behavior, it has been natural to focus first on elementary matters. Showing that respondents are willing and able to respond to probabilistic questions is an obvious prerequisite for substantive interpretation of the data. When I began to collect expectations data in the early 1990's, I encountered considerable skepticism from researchers who asserted that probabilistic questioning would not "work." One common assertion was that respondents would either refuse to answer the questions or would only give the responses 0, 50, and 100 percent. This concern has largely been laid to rest as empirical evidence has accumulated. I and other researchers have repeatedly found that respondents are as willing to respond to probabilistic questions as they are to traditional attitudinal questions on the same subjects. Moreover, they use the full expanse of the 0–100 percent chance scale, typically rounding to the nearest 5 percent.[10]

[9]These are all surveys of individuals or households. I am aware of only one survey of firms that has used probabilistic questioning to elicit business expectations. This is the Italian Survey of Investment in Manufacturing, which has asked firms to provide probabilistic predictions of product demand. See Guiso and Parigi (1999).

[10]Respondents tend to report values at one-percent intervals at the extremes (i.e., 0, 1, 2, and 98, 99, 100) and at five-percent intervals elsewhere (i.e., 5, 10, ..., 90, 95). Responses tend to be more bunched at 50 percent than at adjacent round values (40, 45, 55, 60), but not excessively so. The studies summarized in this section provide detailed information on the distributions of response to specific questions.

To encourage full use of the percent chance scale, it helps to familiarize respondents with the scale before commencing substantive questioning. The Survey of Economic Expectations, which will be discussed in Sections 5.1–5.3, uses this introductory statement and opening question about the weather:

Survey of Economic Expectations Introduction and Opening Question: Now I will ask you some questions about future, uncertain outcomes. In each case, try to think about the

Another common assertion was that, in the absence of incentives for honest revelation of expectations, responses to expectations questions might not reveal the expectations that persons truly hold.[11] It is not possible to directly observe respondents' thinking; hence, this assertion is not formally refutable. However, it is possible to informally judge the *face validity* of responses by examining the degree to which persons give internally consistent, sensible responses to the questions posed. The studies described in this section and in Section 6 mainly, although not always, conclude that responses do possess face validity when the questions concern well-defined events that are relevant to respondents' lives.

Having demonstrated that probabilistic questioning does "work," straightforward description of respondents' risk perceptions, income and employment expectations, and beliefs about other events has been interesting per se to economists who heretofore have only been able to speculate about the expectations that people hold. Thus, the work described below is descriptive rather than applied directly to the analysis of decision making. I discuss aspects of my

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whole range of possible outcomes and think about how likely they are to occur during the next 12 months. In some of the questions, I will ask you about the percent chance of something happening. The percent chance must be a number from 0 to 100. Numbers like 2 or 5 percent may be 'almost no chance,' 20 percent or so may mean 'not much chance,' a 45 or 55 percent chance may be a 'pretty even chance,' 80 percent or so may mean a 'very good chance,' and a 95 or 98 percent chance may be 'almost certain.' The percent chance can also be thought of as the number of chances out of 100.

Let's start with the weather where you live. What do you think is the percent chance (what are the chances out of 100) that it will rain tomorrow?

[11]An absence of incentives is a common feature of all survey research, not a specific attribute of expectations questions. I am aware of no empirical evidence that responses to expectations questions suffer more from incentive problems than do responses to other questions commonly asked in surveys.

The literature on *proper scoring rules* develops incentive mechanisms for honest revelation of expectations concerning observable events (e.g., Shuford, Albert, and Massengill (1966), Savage (1971)). These mechanisms encourage honest revelation under the assumption that respondents maximize expected utility and are risk neutral. Perhaps the simplest one, applicable when the event is binary, gives the respondent a reward whose magnitude decreases with the squared deviation between the event realization (0 or 1) and the elicited probability. The mean of a distribution is the optimal prediction under square loss, and the mean of a binary event is the probability that the event will occur. Hence, with this reward function, a person's optimal forecast is his subjective probability for the event.

Proper scoring rules have been applied in experimental research (e.g., Nyarko and Schotter (2002)) and in educational testing (see Section 6.4), but not in survey research eliciting expectations. An important reason is that application of a proper scoring rule requires the researcher to verify what events do and do not occur. Verification commonly is not practical and sometimes is not possible in principle. Another reason may be doubt about the validity of the assumption that respondents are risk-neutral expected-utility maximizers who are able to correctly deduce what response is optimal given the specified reward function.

research on perceptions of job insecurity (Section 5.1), income expectations (Section 5.2), Social Security expectations (Section 5.3), mutual-fund investment expectations (Section 5.4), probabilistic polling (Section 5.5), and expectations of the returns to schooling (Section 5.6).

5.1. *Perceptions of Job Insecurity*

Worker perceptions of *job insecurity* have been hypothesized to be determinants of economic outcomes ranging from wages and employment to consumption and savings. Meaningful empirical conclusions about the effects of job insecurity can be drawn only if the concept is defined clearly and measured appropriately. Writers often use the expression *job insecurity* without formal definition, but usage indicates that the expression is commonly intended to convey the chance that a worker will lose his present job and subsequently not obtain a position of comparable value.

Until recently, the only measures of perceptions of job insecurity available in the United States were the responses to verbal questions such as the General Social Survey question about job loss cited in Section 4.1.[12] For the period 1994–2002, probabilistic measures of job insecurity are available through the nationwide Survey of Economic Expectations (SEE), a repeated cross-sectional survey designed by Jeff Dominitz and myself. The survey procedures are described in Dominitz and Manski (1997b).[13]

Following an introductory segment familiarizing respondents with the *percent chance* scale, persons holding jobs were asked these questions eliciting expectations of job loss and search outcomes:

> *SEE Job-Loss Question*: I would like you to think about your employment prospects over the next 12 months. What do you think is the percent chance that you will lose your job during the next 12 months?

> *SEE Search-Outcome Question*: If you were to lose your job during the next 12 months, what is the percent chance that the job you eventually find and accept would be at least as good as your current job, in terms of wages and benefits?

Respondents were also asked for the percent chance that they would voluntarily quit in the next 12 months.

[12]The General Social Survey also asks this verbal question about search outcomes: "About how easy would it be for you to find a job with another employer with approximately the same income and fringe benefits that you now have? Would you say very easy, somewhat easy, or not easy at all?"

[13]SEE was administered as a module in WISCON, a continuous national random-digit telephone survey conducted by the University of Wisconsin Survey Center. The data for the 5432 SEE interviews completed from 1994 through early 1998 have been archived by the Data and Program Library Service of the University of Wisconsin-Madison, and are available on the web at http://dpls.dacc.wisc.edu/econexpect/index.html. The data for all interviews completed from 1994 through 2002 are available from the author.

TABLE I

Job Loss				Search Outcome			
	Quantile				Quantile		
Mean	.25	.50	.75	Mean	.25	.50	.75
14.7	0	5	20	57.0	30	60	89

Source: Manski and Straub (2000).

Manski and Straub (2000) examine 3561 responses to these questions obtained from 1994 through early 1998.[14] As shown in Table I, the distribution of responses to the job-loss question is highly skewed. Most respondents perceive little or no chance of job loss in the year ahead, but some view themselves as facing a moderate to high risk. The distribution of responses to the search-outcome question has a very different shape. This distribution is approximately symmetric and quite dispersed.

The shape of the empirical distribution of search-outcome responses has an interesting interpretation in terms of the theory of job search. Standard models of job search with time-invariant reservation wages imply that the responses to the search-outcome question should be distributed uniformly on $[0, 1]$. The empirical distribution of responses is reasonably close to uniform.

The responses to the job-loss and search-outcome questions can be combined to yield a composite measure of job insecurity. Let L denote the response to the job-loss question and S denote the response to the question on search outcome conditional on job loss. Then $L \times (100 - S)/100$ gives the percent chance that a worker will lose his job in the year ahead and subsequently not obtain a position of comparable economic value. Examination of the cross-sectional and time-series variation across respondents in their perceptions of job insecurity yields several interesting findings: (a) Expectations of job loss tend to decrease markedly with age, but so do expectations of a good outcome should job search become necessary. The net result is that the measure of composite job insecurity tends not to vary at all with age. (b) Subjective probabilities of job loss tend to decrease with schooling, and subjective probabilities of good search outcomes tend to increase with schooling. Hence composite job insecurity tends to decrease with schooling. (c) Perceptions of job insecurity vary little by sex but vary substantially by race. The main differences are in expectations of job loss, with the subjective probabilities of blacks tending to be nearly double those of whites.

[14]These questions were posed to the 3812 respondents who reported that they were working at the time of the interview. Of these, 3561 provided basic demographic information and answered the job-loss, search-outcome, and voluntary-quit questions.

5.2. *Income Expectations*

Economic analysis of household behavior assigns a central role to income expectations as a determinant of consumption/savings decisions. Not having data on income expectations, economists studying consumption/saving have made assumptions. Consider, for example, Hall and Mishkin (1982), Skinner (1988), Zeldes (1989), Caballero (1990), and Carroll (1992). Each study assumes that persons use their own past incomes to forecast their future incomes. Perhaps so, but how do persons form expectations of future income conditional on past income? Each study assumes that persons know the actual stochastic process generating their income streams; thus, they have rational expectations. Perhaps so, but what is this stochastic process? Each study specifies some parametric model of the income process and uses available data on income realizations to estimate the parameters.

Dominitz and Manski (1997a) analyzed household income expectations reported by respondents to a preliminary version of the Survey of Economic Expectations in 1993.[15] In principle, expectations for a continuous variable such as income could be elicited in various ways. Respondents might be asked to report quantiles of their subjective distributions, moments of the distribution, or points on the cumulative distribution function. Morgan and Henrion (1990) discuss the practical pros and cons of different procedures for eliciting subjective distributions. Their recommendations formed the basis for our approach, with some tailoring of the procedures to fit the survey medium (telephone interview) and subject matter. In a telephone survey it is infeasible to present visual aids that may help respondents to understand questions and to think probabilistically. Use of the telephone medium led us to reject elicitation of quantiles or moments of the subjective income distribution in favor of eliciting points on the distribution function.[16]

Respondents were first asked to report the lowest and highest levels of income that they think possible in the year ahead. The responses to these preliminary questions were used to set thresholds (Y) for a series of four probabilistic questions, of this form:[17]

[15]Expectations for household income were elicited only in the 1993 version of SEE. Expectations of personal income were elicited from 1994 onward.

[16]We did elicit the medians of subjective income distributions in an explanatory study of the returns-to-schooling expectations of high school and college students (Dominitz and Manski (1996)). That study used an interactive computer program to elicit expectations. See Section 5.6 for further discussion.

[17]We did not interpret the answers to the preliminary questions literally as minimum and maximum incomes; the phrases "lowest possible" and "highest possible" are too vague to warrant this formal interpretation. Instead, we used the responses to suggest the support of the respondent's subjective distribution. Our reasoning was that responses to questions about a range of thresholds spanning the support of a respondent's subjective distribution should yield more information about the shape of the distribution than would the same number of questions asked about a narrower or wider range of thresholds. Morgan and Henrion (1990) offer two

SEE Household Income Expectations Questions: What do you think is the percent chance (or what are the chances out of 100) that your total household income, before taxes, will be less than Y over the next 12 months?

After division by 100, the responses give four points on a person's subjective distribution for household income in the year ahead. Thus, for each respondent i, we observe $F_{ik} \equiv P(y < Y_{ik} | \Psi_i)$, $k = 1, 2, 3, 4$, where y denotes future income, Ψ_i is the information available to respondent i, and $(Y_{i1}, Y_{i2}, Y_{i3}, Y_{i4})$ are the income thresholds about which this respondent is queried.[18]

The subjective probabilities $(F_{ik}, k = 1, \dots, 4)$ elicited from respondent i imply bounds on his subjective income distribution but do not identify the distribution. To facilitate analysis, we used the expectations data to fit a respondent-specific parametric distribution. Let $F(Y; M, Q)$ denote the log-normal distribution function with median M and interquartile range (IQR) Q, evaluated at any point Y. Let (M_i, Q_i) solve the least-squares problem

$$\inf_{M,Q} \sum_{k=1}^{4} [F_{ik} - F(Y_{ik}; M, Q)]^2.$$

We used M_i and Q_i to estimate respondent i's subjective median and IQR for income in the year ahead.

Assuming that subjective distributions are log-normal, analysis of the cross-sectional distribution of (M, Q) enables assessment of the expectations assumptions made in research on consumption/savings behavior. It has been common to assume a fixed relationship between the spread and central tendency of income expectations; some authors assume that spread does not vary with central tendency and others that spread is proportional to central tendency.[19] We found that Q tends to rise with M, but more slowly than propor-

additional, psychological, reasons for asking such preliminary questions. One is to decrease overconfidence problems wherein respondents focus too heavily on central tendencies, down-weighting their uncertainty about outcomes. Another is to decrease anchoring problems wherein respondents' beliefs are influenced by the questions that interviewers pose. Suppose, for example, that a respondent expects his income to be no less than \$30,000. If the first question asked concerns the probability that income will be less than \$20,000, the respondent may perhaps be influenced to think that this amount is objectively reasonable. Thus, asking respondents to provide their own minimum and maximum income levels, and basing subsequent thresholds on these values, replaces interviewer-induced anchoring with respondent self-anchoring. See Section 6.4 for further discussion of anchoring.

[18]The thresholds $Y_{i1}, \dots, Y_{i4}$ were posed in increasing order. The interviewer informed the respondent if a probability elicited at threshold Y_{i2}, Y_{i3}, or Y_{i4} was smaller than one elicited earlier. This ensured that the sequence of responses was always coherent. The one exception to the protocol occurs if a response of "100 percent chance" is given when the first, second, or third threshold is posed. Then it is not necessary to elicit further responses as a coherent distribution must give "100 percent chance" to all subsequent thresholds.

[19]In Hall and Mishkin (1982), the subjective distribution of next year's income is assumed normal with household-specific median and constant IQR. Skinner (1988) and Zeldes (1989)

tionately. We also found substantial variation in Q among respondents with the same value of M.

Many authors studying consumption/savings behavior have sought to explain the substantial cross-sectional variation in savings, conditional on observable attributes, documented by Avery and Kennickell (1991) and others. Hubbard, Skinner, and Zeldes (1995), for example, argue that some cross-sectional variation in savings reflects the incentive effects of asset-based, means-tested social insurance programs on precautionary savings. Other studies attribute cross-sectional variation in savings to heterogeneous preferences or to liquidity constraints. Our empirical finding of substantial variation in Q among persons with the same M suggests that cross-sectional variation in the spread of income expectations may account for at least some of the observed cross-sectional variation in savings.

5.3. *Social Security Expectations*

Americans may be uncertain of their future Social Security retirement benefits for several reasons, including uncertainty about their future labor earnings, the formula now determining benefits, and the future structure of the Social Security system. Research aiming to understand the impact of Social Security policy on labor supply, retirement savings, and other household decisions has long been hampered by a dearth of empirical evidence on Social Security expectations. Respondents to the Retirement History Survey and to the Health and Retirement Study (HRS) provided point predictions of their future benefits (Bernheim (1988), Gustman and Steinmeier (1999, 2001)), but uncertainty about benefits was not measured.

Probabilistic expectations of Social Security retirement benefits have been elicited from respondents to the Survey of Economic Expectations from 1999 through 2002. Respondents of ages 18–69 were read a brief description of the Social Security program and were then asked to predict their eligibility for benefits when 70 years old, as follows:

> *SEE Social Security Eligibility Question*: Politicians and the news media have been talking recently about the future of the Social Security retirement system, the federal program providing benefits to retired workers. The amount of benefits for which someone is eligible is currently determined by the person's retirement age and by earnings prior to retirement. There has been much discussion of changing the form of the Social Security system, so the future shape of the system is not certain. With this in mind, I would like you to think about what kind of Social Security retirement benefits will be available when you are older. In particular, think ahead to when you are about to turn 70 years old and suppose that you

assume the subjective distribution of next year's log-income to be normal with household-specific mean $\log(M_i)$ and constant variance δ^2. Equivalently, the subjective distribution of income is log-normal with median M_i and IQR $M_i[\exp(.6745\delta) - \exp(-.6745\delta)]$. Thus, the IQR is proportional to the median in these studies.

are not working at that time. What is the percent chance that you will be eligible to collect any Social Security retirement benefits at that time?

Respondents who report a positive probability of eligibility were asked a series of questions eliciting their subjective distribution of benefits, conditional on eligibility. This series follows the format of the income-expectations questions described in Section 5.2. That is, respondents were first asked to report the lowest and highest possible levels of their future benefits. The responses to these preliminary questions were then used to set thresholds (Y) for up to six probabilistic questions about the level of benefits, as follows:

SEE Social Security Benefit Questions: Suppose you are eligible to collect Social Security benefits when you turn 70. Please think about how much money you would be eligible to collect each year. When considering the dollar value, please ignore the effects of inflation or cost-of-living increases. That is, please respond as if a dollar today is worth the same as a dollar when you turn 70. What do you think is the lowest amount of Social Security benefits, per year, that you would be eligible to receive? What do you think is the highest amount of Social Security benefits, per year, that you would be eligible to receive? What is the percent chance (or chances out of 100) that you would be eligible to receive over $\$\{Y\}$,000 of Social Security benefits per year, when you turn 70?

Dominitz, Manski, and Heinz (2003) study the responses to these questions. The eligibility question was posed to 2457 SEE respondents. Of the 2384 who reported a valid probability of eligibility for benefits at age 70, the mean subjective probability of eligibility was .57 and the median was .60. Figure 1 presents kernel-smoothed quantiles of eligibility probabilities conditional on age. The overall pattern is striking, with older respondents tending to report much higher probabilities of eligibility than do younger ones. For example, the estimated median subjective probability of eligibility is .40 at age 30, .50 at age 40, .70 at age 50, .90 at age 60, and 1.00 at age 65. Thus, older Americans tend to be almost certain that, in one form or another, the Social Security system will survive at least ten more years. However, younger Americans have no such confidence in the continuation of the system until their retirement.

The 2161 persons who reported a positive chance of eligibility were asked the questions eliciting lowest/highest possible benefits and the probabilities of benefits exceeding specified thresholds, conditional on eligibility. Of these 2161 persons, 1398 gave a complete set of responses that could be used to fit person-specific log-normal subjective distributions.[20] As in Section 5.2, we characterize the fitted distributions through their medians M and interquartile ranges Q.

[20]The overall response rate of .65 (i.e., 1398/2161) to the sequence of Social Security benefit questions is considerably lower than those experienced asking SEE respondents to forecast simple binary events (typically .95 or more) and somewhat lower than the experience eliciting income expectations one-year-ahead (typically .80), reported in Dominitz and Manski (1997a). About 80 percent (664 out of 836) of the nonresponse occurs when respondents do not report lowest/highest possible benefits. Another 14 percent did not respond to all of the probability questions asked, and the remaining 6 percent gave complete reports that could not be used to estimate person-specific subjective distributions. The rate of response to the SEE Social Security

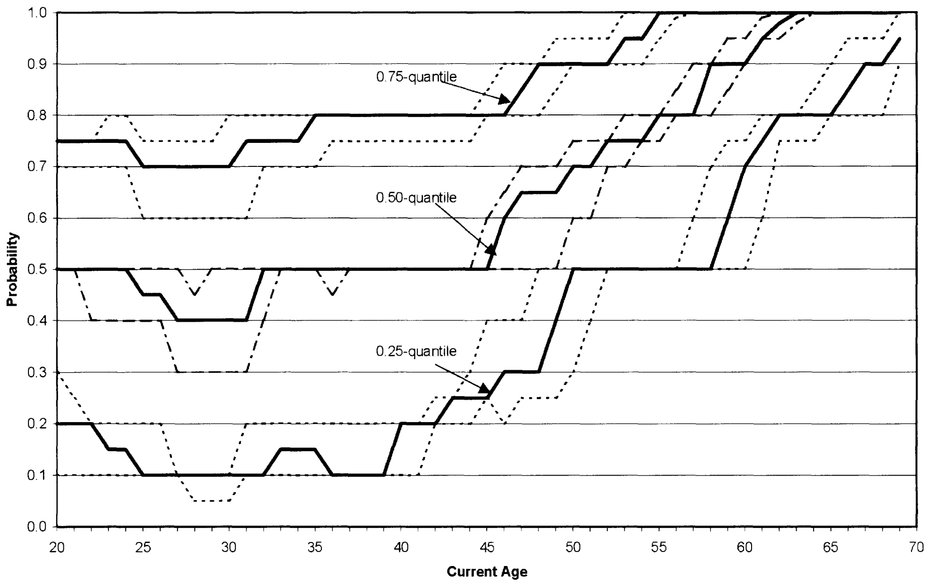

FIGURE 1.—Quantiles of subjective probability of social security eligibility at age 70, conditional on current age.

Conditional quantiles estimated using Gaussian kernel with bandwidth of two years (2384 observations). Solid curves depict point estimates. Dashed curves depict bootstrap 90% confidence intervals. Source: Dominitz, Manski, and Heinz (2003).

Figure 2 presents kernel-smoothed .25, .50, and .75-quantile regressions of M on age. The main impression is that the central tendencies of persons' expectations of benefit levels vary relatively little with age, but for a tightening of the cross-sectional distribution of M above age 45.[21] In contrast, Figure 1 showed that expectations of eligibility rise dramatically with age. Juxtaposing these findings, we conclude that the prevalent concern among younger persons appears to be that the Social Security system will collapse entirely, not that benefits will be reduced to keep the system going.

Figure 3 presents kernel-smoothed .25, .50, and .75-quantile regressions of Q on age. The figure shows that subjective uncertainty about the magnitude of

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benefit questions, while troubling to some degree, nevertheless compares favorably with the rate of response to the Social Security benefit question posed in the HRS. The HRS question asks for a point estimate of benefits, not a subjective distribution.

[21]Figure 2 also shows that expectations of benefit levels vary substantially among persons of any given age. This heterogeneity in expectations presumably reflects a combination of real and perceptual factors. On the real side, the current system makes benefits vary with a person's own earnings and, in the case of survivor benefits, with the earnings of spouses; hence expectations should vary with personal and spousal past and expected labor earnings. On the perceptual side, persons may vary in their knowledge of how the Social Security system currently operates and in their expectations for the future structure of the system.

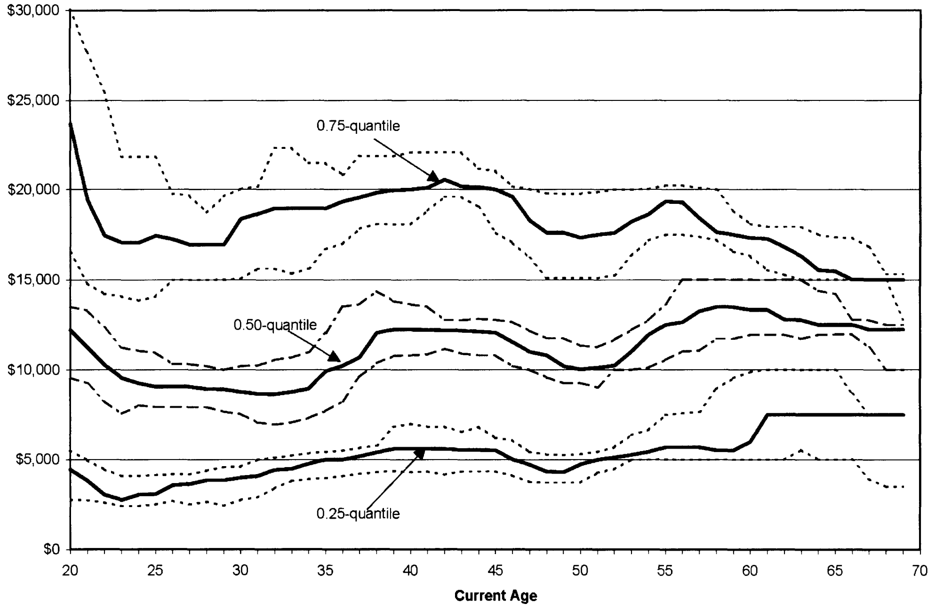

FIGURE 2.—Quantiles of subjective median of benefits at age 70, conditional on current age. Conditional quantiles estimated using Gaussian kernel with bandwidth of two years (1398 observations). Solid curves depict point estimates. Dashed curves depict bootstrap 90% confidence intervals. Source: Dominitz, Manski, and Heinz (2003).

Social Security benefits is very substantial among young persons but decreases with age. That uncertainty about benefit levels should decrease with age makes much sense, because uncertainty about future labor earnings and about the future structure of Social Security should decrease as retirement nears. However, we take the main message of Figure 3 to be that even middle-aged persons who are nearing retirement tend to be rather uncertain of their future benefit levels, conditional on eligibility. For example, the median value of Q is $6100 among respondents of age 55, who are typically only ten years from retirement.

It is of interest to learn how different sources of uncertainty—about future labor earnings, the formula now determining benefits, and the future structure of the Social Security system—combine to produce the findings about benefit expectations displayed in Figures 2 and 3. With this in mind, Dominitz, Manski, and Heinz (2003) performed an exploratory face-to-face interview of a small random sample of 49 staff members at a midwestern university. These respondents were administered the SEE questions. Then, to shed some light on formula uncertainty, they were asked for their perceptions of the current maximum annual Social Security benefit. In particular, respondents were asked for their subjective probabilities that the maximum benefit exceeds various thresholds Y, ranging from $5000 to $25,000:

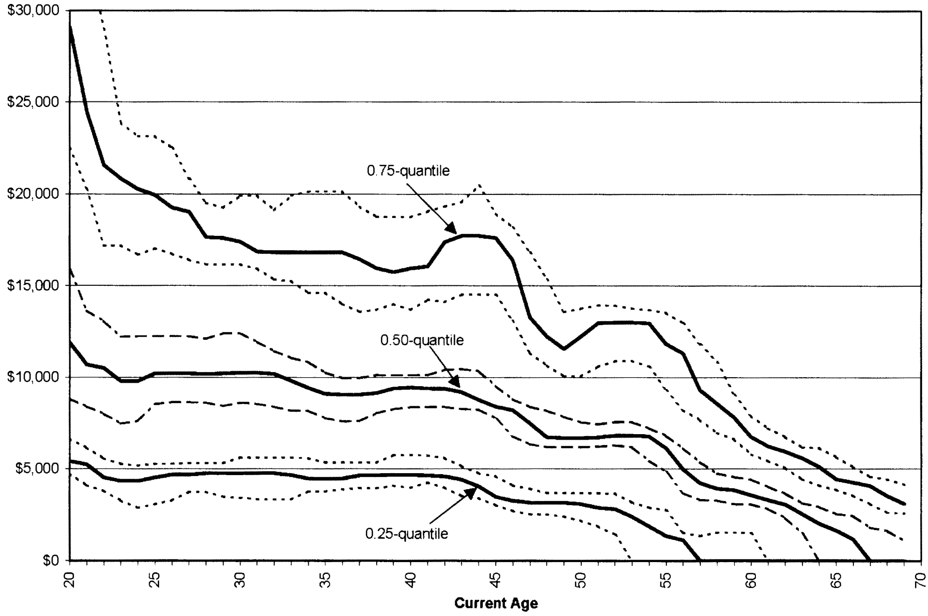

FIGURE 3.—Quantiles of subjective IQR of benefits at age 70, conditional on current age.
Conditional quantiles estimated using Gaussian kernel with bandwidth of two years (1398 observations). Solid curves depict point estimates. Dashed curves depict bootstrap 90% confidence intervals. Source: Dominitz, Manski, and Heinz (2003).

> *Social Security Maximum Benefit Questions*: Now think about Social Security benefits today. In particular, imagine a person who is now 70 years old. Suppose that this person retired from work at age 65 and began collecting benefits after working full time for 40 years. Suppose that, while working, this person had high enough income to be eligible for the maximum Social Security benefit that is currently paid. What is the percent chance that this person currently receives *over* \${Y},000 of Social Security benefits per year?

The maximum Social Security benefit is a fact whose value can be determined through scrutiny of Social Security Administration documents; in 2001, when the interviews were performed, the maximum benefit was $16,860 per year. Of the 49 respondents, 6 reported a 100 percent chance that the maximum benefit exceeds $25,000. We were able to estimate subjective distributions for the remaining 43 respondents.

The cross-sectional median value of their subjective medians was about $18,500, which is reasonably close to the actual maximum benefit. However, respondents tended to exhibit substantial uncertainty. The subjective interquartile range was above $5000 for most respondents, and above $10,000 for many. These findings, albeit for a small and special sample of respondents, suggest that much of the uncertainty that SEE respondents displayed about the magnitudes of their own future Social Security benefits may reflect uncertainty about the current Social Security formula.[22]

5.4. *Mutual-Fund Investment Expectations*

The Michigan Survey of Consumers has long used verbal questions to measure expectations for personal finances and for the economy as a whole. Beginning in June 2002, the Survey of Consumers has also included some probabilistic questions derived from the Survey of Economic Expectations. One elicits expectations concerning the performance of a mutual-fund investment in the year ahead:

> *SEE/Michigan Mutual-Fund Investment Question*: The next question is about investing in the stock market. Please think about the type of mutual fund known as a diversified stock fund. This type of mutual fund holds stock in many different companies engaged in a wide variety of business activities. Suppose that tomorrow someone were to invest one thousand dollars in such a mutual fund. Please think about how much money this investment would be worth one year from now. What do you think is the percent chance that this one thousand dollar investment will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?

This question may be contrasted with the verbal question on business conditions cited in Section 4.1. Whereas that question asked about a vague event and did not permit respondents to express uncertainty, the present one asks about a well-specified event and enables respondents to express uncertainty through their subjective probabilities.

Dominitz and Manski (2003, 2004) analyzed the responses to the SEE-based questions in the Survey of Consumers. A particularly intriguing finding was the existence of substantial heterogeneity in responses to the mutual-fund investment question. A total of 3543 persons were asked this question from June 2002 through May 2003, and 3257 responded. Table II describes the cross-sectional variation in responses.

We conjecture that most people have no meaningful private information about mutual funds. If so, the observed variation in expectations mainly reflects differences in the way people process the available public information. The mean response was a 42.0 percent chance of an increase in the value of

[22]To learn something about respondents' knowledge of the current formula, we followed the question about the maximum benefit with this open-ended question: "Describe as best you can the current system that the government now uses to determine social security benefits. What are the main factors in calculating the size of the benefit? And so on." More than half of the respondents indicated a link between earnings histories and benefits, but the responses rarely suggested a full understanding of the formula. Some persons expressed a belief that benefits are based on earnings at retirement or over the preceding few years, as is common in defined-benefit pension plans. Six respondents expressed a belief that benefits are mean-tested. These responses suggest that respondents not only have heterogeneous beliefs about the magnitude of current benefits but also vary in their understanding of the structure of the Social Security system.

TABLE II
PERCENT CHANCE MUTUAL-FUND INVESTMENT WILL INCREASE IN VALUE

	Responses	Mean	Std. Dev.
Total	3257	42.0	28.6
Male	1480	45.4	29.3
Female	1777	39.1	27.7
White	2633	42.5	28.5
Black	260	39.2	28.6
Hispanic	183	40.9	29.7
American Indian	25	30.4	25.6
Asian	65	43.3	31.4
Age 18–34	808	46.3	26.1
Age 35–49	1151	43.2	27.9
Age 50–64	788	41.1	30.4
Age 65+	510	33.5	29.4
0–12 years schooling	1113	38.4	27.8
13–15 years schooling	878	41.9	28.4
16+ years schooling	1251	45.3	29.1

Source: Dominitz and Manski (2004).

the mutual fund, and the standard deviation of the responses was 28.6. Some of this heterogeneity was systematic, in the sense that persons with different demographic attributes tended to have different expectations. Males tended to be more optimistic than females. Optimism increased with schooling. Younger persons were more optimistic than older ones, and most of this decline occurs at the highest age group (65 and older). The empirical existence of such strong heterogeneity in investment expectations runs counter to the usual rational expectations assumption that all persons access and process public information in the same way.[23]

These findings raise important questions: Why do investment expectations vary so sharply and systematically across the population? How does the observed variation in expectations affect investment behavior? The data available

[23] An economist who is predisposed to the rational expectations hypothesis might interpret the heterogeneity displayed in Table II as evidence that responses to the SEE/Michigan mutual-fund question do not accurately measure the expectations persons "truly" hold. However, an empirical finding not shown in Table II makes me skeptical of the assertion. The finding is that individual responses to the probabilistic questions asked in the Survey of Consumers exhibit considerable temporal stability.

The Survey of Consumers has a rotating panel design, in which approximately 70% of first-time respondents are re-interviewed six months later. Dominitz and Manski (2003) report linear autoregressions of individual expectations on the same expectations lagged six months. We find that all auto-regressions have substantial predictive power. In particular, the estimated autoregression of individual mutual-fund responses on responses six months earlier is $Y_t = 24.14 + .43Y_{t-6}$.

in the Survey of Consumers do not enable us to answer these questions, which should be subjects for future research.

5.5. *Probabilistic Polling*

Public opinion researchers have long performed election polls asking citizens to predict their future voting behavior. Standard polling questions do not enable respondents to express uncertainty about whether they will vote and, if so, for whom. Consider, for example, this Gallup Poll question administered early in the American 2000 Presidential campaign:[24]

> *Gallup Poll Question*: Next, we'd like you to think about the general election for President to be held in November. If Vice-President Al Gore were the Democratic Party's candidate and Texas Governor George W. Bush were the Republican Party's candidate, who would you be more likely to vote for—[Al Gore, the Democrat (or) George W. Bush, the Republican]?

Observe that this question specifies only the Democratic and Republican candidates, making no mention of possible minor party candidates. Also observe that the question does not mention the possibility that the respondent may choose not to vote.

Even if all respondents vote and no other candidates are on the ballot, responses to the Gallup question do not reveal much about whether sample members will vote for Gore or Bush. They only reveal whether persons perceive themselves as more likely to vote for one candidate or the other. Thus persons who respond "Gore" are saying that the chance they will vote for Gore is at least 50 percent and the chance they will vote for Bush no more than 50 percent; analogous reasoning applies to persons who respond "Bush."

In Manski (1990), I showed that questions of the Gallup form logically only imply a bound of width .5 on the fraction of voters who would vote for each candidate. Consider Gore, the reasoning for Bush being analogous. The lower bound on the fraction voting for Gore occurs if all the sample members who respond "Gore" have 50 percent chance of voting for Gore and all those who respond "Bush" have no chance of voting for Gore. The upper bound occurs if all the sample members who respond "Gore" have 100 percent chance of voting for Gore and all those who respond "Bush" have 50 percent chance of voting for Gore. Suppose, for example, that the fraction of persons who respond "Gore" is .6. Then one can logically conclude only that the fraction who would vote for Gore is between .3 and .8.

Manski (2000b, 2002b) suggests that *probabilistic polling* would improve on standard polling practices by permitting citizens to express uncertainty about

[24]CNN/USA Today/Gallup Poll, February 20–21, 2000, questions 5 and 5a, available online at www.gallup.com/poll/surveys/2000/Topline000220/index.asp.

how they will vote.[25] Pollsters could ask respondents to state, in percentage terms, how likely it is that they will vote in an upcoming election. They could then ask respondents how likely it is that they would vote for each candidate. For example, pollsters could have asked these probabilistic questions during the 2000 American presidential campaign:

Probabilistic Polling Questions:

P1. What do you think is the percent chance that you will cast a vote for President?

P2. Suppose now that you will vote for President. I will read five voting possibilities, and then ask you the percent chance that you would vote for each one. Please listen to the choices, allocating 100 percentage points total among all five: Al Gore, the Democrat; George W. Bush, the Republican; Ralph Nader, the Green Party candidate; Pat Buchanan, the Reform Party candidate; another candidate.

I performed a small pilot study in the weeks preceding the year 2000 American presidential election. Using conventional random-digit telephone sampling methods, an interviewer contacted fifty respondents in Evanston, Illinois and posed the above probabilistic polling questions, as well as these traditional questions taken from the CBS-New York Times poll:[26]

CBS-New York Times Questions:

Q1. How likely is it that you will vote in the 2000 election for President—would you say that you will definitely vote, probably vote, probably not vote, or definitely not vote in the election for President?

Q2. If the 2000 election were being held today and the candidates were Al Gore, the Democrat, George W. Bush, the Republican, Ralph Nader, the Green Party candidate, and Pat Buchanan, the Reform Party, would you vote for Al Gore, George Bush, Ralph Nader, or Pat Buchanan?

All 50 respondents answered these questions. Juxtaposition of the responses to P1 and Q1 shows how respondents answer questions requesting verbal and probabilistic measures of the likelihood of voting. The responses, shown in Table III, correspond well ordinally.

[25]Probabilistic polling is too simple and appealing an idea to have been thought of only once. From the time that I initially critiqued traditional polling questions in Manski (1990) through the recent period in which I wrote Manski (2002b), I was unaware of related research. However, after the latter paper was complete, I learned of some related studies analyzing data across the world. Burden (1997) analyzed data collected in Ohio in 1986 and 1988 eliciting probabilities that persons would vote for particular candidates in upcoming state and federal elections. Hoek and Gendall (1993, 1997) elicited voting probabilities in elections in New Zealand. Maas, Steenbergen, and Saris (1990) analyzed probabilities of voting for particular parties reported by Dutch voters in 1986. Earlier still, Meier (1980) and Meier and Campbell (1979) used a seven-point scale to elicit voting expectations.

[26]Questions P1 and Q1 ask for verbal and probabilistic responses about the same event, whether the respondent will vote. However, questions P2 and Q2 do not inquire about the same event. Whereas P1 asks a respondent to predict his choice of candidate conditional on voting, Q2 is a *forced-choice* question, asking a respondent how he would vote if the election were held today. See Manski (1990) for analysis of the conceptual difference between expectations and forced-choice questions.

TABLE III

	P1 Response (Percent Chance)					
Q1 Response	0	[1–10]	[11–50]	[51–90]	[91–99]	100
Definitely vote	0	0	0	4	5	27
Probably vote	0	0	1	3	0	6
Probably not vote	0	0	0	0	0	0
Definitely not vote	4	0	0	0	0	0

Source: Manski (2002b).

The really interesting finding is that probabilistic elicitation of the likelihood of voting reveals quantitative differences in expectations that verbal questioning misses entirely. It turns out that the thirty-six persons who state that they will "definitely" vote when responding to Q1 are not uniformly certain that they will vote. Responding to P1, most of these persons state a 99 or 100 percent chance of voting but one states only an 80 percent chance of voting and another reports an 85 percent chance. We also learn that the ten persons who state that they will "probably" vote in response to Q1 actually vary widely in the chance that they will vote. One member of this subgroup states a 40 percent chance, one states a 78 percent chance, and six state a 100 percent chance of voting.

Juxtaposition of the responses to P2 and Q2 (Table IV) shows how respondents answer questions requesting verbal and probabilistic measures of the prospects of voting for particular candidates. Again, the responses correspond well ordinally.

Again, the really interesting finding is that probabilistic polling reveals quantitative differences in voting expectations that verbal questioning misses entirely. Thirty-three of the fifty respondents state a 100 percent chance that they will vote for the candidate they named in response to Q2, but five respondents state no more than a 50 percent chance of voting for this candidate. Two respondents seem the very model of the "undecided" voter. Both state "Bush" when asked how they would vote if the election were held today, but

TABLE IV

	P2 Response for the Candidate Named in Q2 (Percent Chance)				
Q2 Response	[0–50]	[51–80]	[81–90]	[91–99]	100
Gore	1	2	2	4	26
Bush	2	1	1	1	6
Nader	1	1	0	0	0
Buchanan	1	0	0	0	0
Other	0	0	0	0	1

Source: Manski (2002b).

they then go on to express much uncertainty in their *percent chance* responses. One states (Gore—40, Bush—60), while another states (Gore—30, Bush—40, Nader—10, Buchanan—20).

5.6. *Student Expectations of the Returns to Schooling*

As discussed in Section 2.1, knowledge of how students perceive the returns to schooling is a prerequisite for informed analysis of schooling decisions. However, only the barest empirical evidence has been available. Freeman (1971) and Betts (1996) asked college undergraduates about the average earnings of persons in various occupations or major fields—they did not ask respondents about the earnings they themselves would expect to receive if they were in these fields. Smith and Powell (1990) asked a sample of college seniors for point predictions of their "anticipated annual income in 10 years" and their "expected earnings" in the first year of their first job. Blau and Ferber (1991) asked a sample of college seniors to forecast "how much they would expect to earn initially and after 10 and 20 years if they were to be *continuously* employed in their preferred occupation after leaving school."

Dominitz and Manski (1996) report an exploratory study eliciting probabilistic expectations of the returns to schooling from high school and university students in Madison, Wisconsin. The substantive findings are of some interest, but the most innovative aspects of this study were its design and implementation. I focus on these aspects here.

Whereas the surveys described earlier in this section were administered by telephone, this one was implemented on personal computers at schools using computer-assisted self-administered interview (CASI) software. We found the CASI medium to be well-suited to the task of eliciting probabilistic expectations. CASI software enabled us to design a survey that appears straightforward to respondents but that actually incorporates an extensive question-branching algorithm. CASI also enabled us to incorporate several tools intended to aid respondents in expressing meaningful expectations. These included *training screens* which explain basic probabilistic ideas through examples before the respondent begins the actual survey, *help screens* which could be accessed by the respondent at any time, *error checks* informing the respondent if a response to a probabilistic question is not a proper probability or if the response is logically inconsistent with earlier responses, and *review-and-revise* screens showing the respondent his responses to each completed sequence of questions and allowing the respondent to revise these responses if desired. I describe here the version of the survey administered to high school students.

Let s denote a level of completed schooling. Let $y(s, x)$ denote the income that a respondent would earn at age x if he were to complete schooling level s. Let Ψ denote the information available to a respondent at the time of the survey. Labor economists would ideally like to learn $Q[y(s, x), \text{all } x|\Psi]$, the subjective distribution of lifecycle earnings that the respondent associates with schooling option s. Elicitation of entire distributions of lifecycle earnings was impractical, so we focused on earnings at ages 30 and 40 and limited attention to two schooling options: $s = 0$ indicating attainment of a high school diploma but no further schooling, and $s = 1$ indicating attainment of at least a bachelor's degree. Thus, we sought to learn $P[y(s, x)|\Psi]$ for $x = 30, 40$ and $s = 0, 1$.

To elicit these distributions, we first gave respondents this on-screen introduction:

> The next sets of questions ask you to put yourself in one of two hypothetical situations. In the first situation, you assume that you continue in school until you finish your senior year of high school and obtain your diploma, and you do not continue in school after that. In the second hypothetical situation, you assume that you continue in school at least until you finish your senior year of college and obtain your college diploma (a bachelor's degree). When responding to these questions, please attempt to fully place yourself in the hypothetical situation as it is described.

After this, respondents received these more detailed instructions concerning the first scenario (i.e., $s = 0$):

> In the first hypothetical situation, assume that you continue in school until you complete your senior year of high school and obtain your high school diploma. Please respond under the assumption that you do not return to school at any time after high school. Remember, this is a hypothetical situation. Just think about the kinds of jobs that would be available for you and that you would accept. Think about the amount of money you would make on these jobs. Again, you should ignore the effects of price inflation on earnings.[27]

Following this, respondents were asked to state their probabilities that earnings at age 30 or 40 would exceed several thresholds. The thresholds were determined by the answers that students gave to a preliminary question eliciting their subjective median earnings at ages 30 and 40.[28]

Observe that the wording used to describe the two schooling scenarios offers respondents no reason why one or the other scenario might be realized. This was intentional—we did not want respondents to draw from the descriptions of

[27] Respondents received this on-screen instruction before the first earnings question was posed: "Also, please ignore the effects of price inflation on earnings. That is, assume that one dollar today is worth the same as one dollar when you are 30 years old and when you are 40 years old." Our debriefings of respondents make us confident that this instruction was understood and adhered to by most students.

[28] The question on the median here takes the place of the preliminary questions on maximum and minimum income or benefits used in the SEE telephone-administered survey. Eliciting the median determines the probabilistic center of a respondent's expectations and provides a natural self-anchor for subsequent selection of threshold values in probability elicitation. At the beginning of the survey, respondents received this on-screen instruction defining the median of a distribution: "The first question will ask you about the median amount of money that you think you will earn at some time in the future. The median is the amount of money for which there is a 50 percent chance that you will earn more than it and a 50 percent chance that you will earn less than it. So, to answer this question and others like it, you should try to pick the amount of money that you think there is just as good a chance you will earn more than it as less than it."

the scenarios information that might influence their expectations. In particular, we did not want respondents to state earnings expectations conditional on a specified choice of schooling level.

To understand this point, let c indicate the schooling level that a respondent will eventually realize. Respondents do not know c at the time of the survey; that is, c is not part of the information Ψ. Suppose that, in describing a scenario, we had instructed respondents to assume that they choose schooling level s. Then a rational respondent would have reported earnings expectations $Q[y(s, x)|\Psi, c = s]$ rather than $Q[y(s, x)|\Psi]$. However, the subjective returns to schooling are given by the latter distribution, not the former. Although the distinction between $Q[y(s, x)|\Psi, c = s]$ and $Q[y(s, x)|\Psi]$ is well appreciated by economists familiar with the selection problem in the analysis of treatment response, we are not certain whether the wording of our questions on the returns to schooling succeeded in explaining the distinction to our student respondents.

6. EVALUATING THE ACCURACY OF ELICITED EXPECTATIONS

Researchers have many reasons to be interested in the correspondence between subjective expectations and objective realities. Economists invoking rational expectations assumptions should want to know how well such assumptions describe real decision makers. Social planners contemplating provision of information to the public on the risks associated with detrimental behaviors (e.g., smoking, drug use, school dropout) should want to know how accurately persons presently perceive such risks.

Sections 6.1–6.3 describe three ways that researchers have evaluated the accuracy of elicited expectations, and summarizes some substantive findings. In Section 6.4, I suggest that probabilistic questioning may improve survey research practices asking respondents about facts.

6.1. *Comparison of Individual Expectations and Realizations*

The most direct way to evaluate the accuracy of elicited expectations is to follow respondents over time and compare the events that they experience with the expectations elicited from them. Fifty years ago, Federal Reserve Consultant Committee on Consumer Survey Statistics (1955) argued that "reinterviews provide the only satisfactory way to test the usefulness or relevance of statistics on expectations and intentions." Subsequently, Juster (1966) used data on individual expectations and realizations to evaluate the predictive power of consumer purchase expectations.

Dominitz (1998) used a one-year follow-up to a preliminary 1993 version of SEE to evaluate the accuracy of respondents' expectations of their weekly earnings. He reasoned as follows. Suppose that subjective earnings distributions are continuous and that realizations are statistically independent across respondents; thus, there are no aggregate shocks. Then rational expectations implies that, for any $\alpha \in (0, 1)$, a fraction α of respondents should report realized weekly earnings in 1994 that are less than or equal to the subjective α-quantile of the expectations that they reported a year earlier. Applying this criterion, he found that expectations and realizations matched up reasonably well, but not entirely so. They differed in that expectations "tended to be too optimistic (i.e., central tendency of expectations exceeds central tendency of realizations) and too confident (i.e., spread of realizations exceeds spread of expectations) ex post."

Hurd and McGarry (2002) used mortality realizations to evaluate expectations of survival to ages 75 and 85 elicited from respondents to the HRS in 1992. They reported that, among the HRS respondents who died between 1992 and 1994, the average subjective survival probability to age 75 elicited in 1992 was .45. Among those who survived to 1994, the survival probability elicited in 1992 was .65. These and other findings led them to conclude that subjective survival probabilities have predictive power for actual survival.

6.2. *Comparison of Mean Expectations and Realizations*

The above approach to evaluation of accuracy requires longitudinal data. When data are collected in repeated cross-sectional surveys, one may compare the expectations elicited from respondents in one wave of the survey with the events realized by respondents in a later wave. Suppose that persons randomly selected are asked at date t to provide expectations for events that will be realized at date $t+1$. Suppose that a new random sample from the same population is drawn following date $t+1$, and those individuals are questioned about their realizations at $t+1$. If realizations are statistically independent across respondents, then rational expectations implies that the distribution of realizations at date $t+1$ is the same as the cross-sectional mean distribution of expectations elicited at date t.

Dominitz and Manski (1997b) used this approach to evaluate the one-year-ahead expectations of SEE respondents interviewed in 1994, comparing their expectations with the realizations reported by the new sample of respondents interviewed in 1995. All SEE respondents were asked these questions eliciting expectations of health insurance coverage and crime victimization, as well as the job-loss question cited in Section 5.1:

> *SEE Health-Insurance Question*: What do you think is the percent chance that you will have health insurance coverage 12 months from now?

> *SEE Burglary Question*: What do you think is the percent chance that someone will break into your home and steal something, during the next 12 months?

In addition, all respondents were asked these questions inquiring about realized events:

> *SEE Health-Insurance Realization Question*: Do you have any health insurance coverage?

TABLE V

SEE EXPECTATIONS IN 1994 AND REALIZATIONS IN 1995

	No Health Insurance		Victim of Burglary		Job Loss	
	Exp	Real	Exp	Real	Exp	Real
Male	.15	.15	.16	.05	.15	.18
	(.01)	(.02)	(.01)	(.01)	(.01)	(.02)
Female	.16	.13	.17	.03	.21	.18
	(.01)	(.02)	(.01)	(.01)	(.01)	(.02)

Note: The estimates for 1994 and 1995 are based on the 1036 and 1024 SEE respondents in the labor force in those years. Standard errors are in parentheses.

Source: Dominitz and Manski (1997b).

SEE Burglary Realization Question: During the past 12 months, did anyone break into or somehow illegally get into your home and steal something?

SEE Job-Loss Realization Question: Have there been any times during the past 12 months when you did not have a job and were looking for work?

The health-insurance and burglary questions elicit realizations of the same events about which the expectations questions ask. The job-loss question does not correspond as well to the expectations question.

Suppose that realizations of health insurance, burglary, and job loss are statistically independent across respondents. Subject to this assumption, we can evaluate the accuracy of elicited risk perceptions by comparing population mean subjective probabilities reported in 1994 with corresponding realized rates of occurrence reported in 1995. Table V presents this comparison using data from the 1036 SEE labor force participants in 1994 and the 1024 labor force participants in 1995.

The table shows that mean expectations and realizations of health insurance match up closely, for males and females. Mean expectations and realizations of job loss also match up closely, notwithstanding that the expected and realized job-loss questions differ somewhat in the event of interest. The picture is rather different with respect to crime victimization, where respondents tend to substantially overpredict the risk of burglary. This finding corroborates those of attitudinal researchers, who have reported that Americans perceive crime to be far more prevalent than it actually is (Bursik and Grasmick (1993, Chapter 4)).

6.3. *Comparison of Mean Expectations with Historical Realizations*

The most common way that researchers have evaluated accuracy has been to compare mean expectations with historical realizations. Such comparisons assume that successive cohorts of persons have the same distribution of realizations for the event of interest. If so, the logic of Section 6.2 may be applied when realizations are observed for earlier cohorts than the one from which expectations were elicited.

Several studies have used historical mortality data to evaluate the accuracy of probabilistic expectations of survival to specified ages. In a notably early effort, Hamermesh (1985) used historical mortality data to assess the accuracy of expectations of survival to ages 60 and 80. He reported reasonable correspondence between expectations and life-table data on mortality conditioned on various risk factors. However, his small sample was not randomly drawn from the population to which available life tables pertain.

Hurd and McGarry (1995) used life-table data to evaluate expectations of survival to ages 75 and 85 elicited from 51–61 year-old respondents to the HRS in 1992. They concluded that the elicited subjective probabilities approximate well the historical survival rates given in a life table from 1990. However, they cautioned that life expectancy in the United States has been increasing over time. Hence, it may not be appropriate to assume that the HRS respondents interviewed in 1992 have the same objective survival probabilities as those shown in life tables.

Whereas the HRS elicited the expectations that middle-aged adults hold for survival well into old age, the 1997 National Longitudinal Study of Youth (NLSY97) elicited the expectations of 15–16 year-old adolescents for survival one-year-ahead and to age 20. In this case, the expectations were wildly pessimistic relative to the life table evidence. Fischhoff et al. (2000) report that the mean and median subjective percent chance of death before age 20 were 20.3 and 10 percent respectively, whereas the historical death rate of youth during this period was .4 percent.

The NLSY97 mortality findings are startling, but one should not extrapolate to the conclusion that youth generally are so inaccurate when queried about their expectations. The NLSY97 respondents were asked to report probabilistic expectations of various events, including school completion by age 20, employment at age 30, pregnancy and parenthood in the year ahead and by age 20, crime victimization and arrest in the year ahead, and confinement in jail or prison by age 20. Comparing the elicited expectations with a variety of historical sources, Fischhoff et al. (2000) conclude that these teens express largely sensible beliefs about a range of consequential events. Similar conclusions have been reached in other research eliciting probabilistic expectations from teenagers (Quadrel, Fischhoff, and Davis (1993), Dominitz and Manski (1996)).

6.4. *Using Probabilistic Expectations to Measure Knowledge of Facts*

Survey researchers routinely ask respondents to report facts about which they may have only partial knowledge. For example, persons may be asked to report their pension types, the length of a past spell of unemployment, or details of their medical histories. Respondents who are uncertain about these matters sometimes choose not to respond to the questions posed. When they do respond, their self reports may differ from actual values.

Empirical researchers often ignore missing data and misreporting problems, discarding respondents with missing data and assuming that all reported data are accurate. Researchers who are sensitive to these problems may impute missing data and use models of measurement errors to describe potential discrepancies between self reports and objective characteristics. On occasion, researchers perform validation studies to empirically learn the distribution of missing data and the accuracy of reported data.

Modifying survey research practices to permit respondents to express uncertainty about facts can potentially reduce nonresponse and misreporting. Constructive steps in this direction have been taken by the HRS, which has used *unfolding bracket* questions to enable respondents to flexibly provide interval data on their income and assets. Respondents who are willing to provide point responses can do so. Those who are unwilling to respond to questions eliciting point responses are asked whether the quantity of interest lies above or below a sequence of specified thresholds. See Juster and Suzman (1995) and Hurd (1999).

Probabilistic elicitation of facts offers another route for improvement of survey research practices. When the fact is categorical, respondents can be asked to report their subjective probabilities of membership in each category. For example, consider the reporting of pension type, which may be defined-benefit or defined-contribution. A respondent who knows that he holds a defined-benefit pension can report that his pension is of this type with probability one. Someone who is unsure can place positive probability on both types of pensions.

When the fact of interest is real-valued, such as income or assets, the method used by Dominitz, Manski, and Heinz (2003) to elicit expectations of the current maximum Social Security benefit may be applied (see Section 5.3). It would be of interest to compare responses obtained using probabilistic elicitation with those generated by the unfolding brackets approach used in the HRS. I conjecture that probabilistic elicitation would mitigate the anchoring problem encountered in applications of unfolding brackets, wherein the initial threshold specified by the survey researcher affects the data obtained at the end of the unfolding bracket sequence.[29]

[29]Psychologists have performed many randomized experiments showing that when subjects are told the value of some real variable (say A) and are then asked to provide a point estimate of another real variable (say B), estimates of B often vary monotonically with the specified value of A. Tversky and Kahneman (1974) named this phenomenon *anchoring*. In the experiments showing the most substantial anchoring, the variable B is a fact about which most respondents are not well informed. For example, Tversky and Kahneman (1974) report an experiment in which B is the percentage of African countries in the United Nations, Jacowitz and Kahneman (1995) report ones in which B is the length of the Amazon River or the height of the tallest redwood tree, and Wilson et al. (1996) report one in which B is the number of physicians and surgeons listed in the local phone book. Various researchers have reported that anchoring is less pronounced when

Although probabilistic elicitation of facts appears not to have previously been proposed as a tool of survey research, the idea has long had proponents in educational testing. Shuford, Albert, and Massengill (1966) argued that requiring a student to choose one answer to a true-false, multiple-choice, or fill-in-the-blank question reveals (p. 125) "only a very small fraction of the information potentially available from each query." They proposed that students instead be asked to state subjective probabilities for the correctness of alternative answers to a question. Moreover, they advocated use of *reproducing scoring systems* (i.e., proper scoring rules) to grade examinations. These scoring systems make it optimal for a student to honestly reveal his beliefs, provided that his objective is to maximize expected test score.

7. USING EXPECTATIONS DATA TO PREDICT CHOICE BEHAVIOR

A long term objective of economists engaged in research on expectations is to improve our ability to predict choice behavior. The research of the past decade, with its emphasis on measurement of expectations, has been a necessary prelude to realization of this objective.

Expectations data may be used to predict behavior in two rather different ways. Persons may be questioned about the choices that they would make in specified scenarios, and the responses used directly to predict their behavior. Or persons may be asked to report their expectations for unknown states of nature, and these data may be combined with choice data to estimate econometric decision models. These approaches are discussed below.

7.1. *Using Choice Expectations to Predict Choice Behavior*

A common practice in market research and psychology, and an occasional one in economics, has been to pose choice scenarios and ask respondents to state what actions they would choose if they were to face these scenarios.[30]

persons report themselves to be, or are conjectured to be, more knowledgeable about variable B. Wilson et al. (1996) asks subjects to classify themselves as less or more knowledgeable about variable B, and they find less anchoring among those who classify themselves as more knowledgeable. Hurd (1999) reports that HRS respondents answering unfolding bracket questions exhibit less anchoring when, in Hurd's judgement, they are more knowledgeable about variable B.

The apparent relationship between anchoring and respondent knowledge suggests that elicitation of probabilistic expectations for variable B may mitigate anchoring problems by permitting persons to express their uncertainty. Probabilistic questioning may be particularly effective when the method of elicitation enables respondents to self-anchor, as recommended by Morgan and Henrion (1990).

[30]See, for example, Beggs, Cardell, and Hausman (1981), Fischer and Nagin (1981), Louviere and Woodworth (1983), Tversky and Kahneman (1986), Manski and Salomon (1987), and Ben-Akiva and Morikawa (1990).

I have cautioned in Manski (1999) that stated choices may differ from actual ones if researchers provide respondents with different information than they would have when facing actual choice problems. The norm has been to pose *incomplete scenarios*, ones in which respondents are given only a subset of the information they would have in actual choice settings. When scenarios are incomplete, stated choices are point predictions of uncertain actual choices.

Elicitation of probabilistic choice expectations overcomes the inadequacy of stated-choice analysis by permitting respondents to express uncertainty about their choice behavior in incomplete scenarios. The original Juster (1966) proposal was to elicit consumer subjective probabilities for future purchases and uses the responses to predict actual purchases (see Section 4.3). Probabilistic polling elicits voting probabilities and uses the responses to predict actual voting behavior (see Section 5.5). Hurd and Smith (2002) use probabilistic expectations of bequests provided by HRS respondents to predict the bequests that these persons will actually make. One could also ask respondents to report choice expectations in scenarios that specify some conditioning event; for example, purchase probabilities supposing that some new product were available or voting probabilities supposing that some world event were to occur prior to the election.

Use of choice expectations to predict actual choice behavior has two noteworthy features, one disadvantageous and the other advantageous. The disadvantageous feature is that if this approach is to yield accurate predictions, persons should have rational (or at least unbiased) choice expectations and realized choices should be statistically independent (or at least not strongly dependent) across the population; see Manski (1999). The advantageous feature is that the approach does not require the researcher to know anything about the decision rules that persons use.

Both features are apparent in a set of exploratory questions on hypothetical changes in Medicare policy posed in two waves of SEE. Respondents of age 50 to 64 were asked to report choice expectations in two scenarios. The first scenario supposes that Medicare policy remains unchanged in the future:

> Politicians and the news media have been talking recently about changes in Medicare, the federal health insurance program for senior citizens. Currently, individuals 65 or older receive free insurance coverage, called Medicare Part A, which covers the cost of inpatient hospital care, home health care, hospice care, and some other services. In addition, these individuals may choose to purchase Medicare Part B, an insurance program which covers the costs of doctor's services, medical tests, and other health services not covered by Medicare Part A. The basic premium paid for Medicare Part B coverage is currently about $45 per month.
>
> Think ahead to when you are about to turn 66 years old. Suppose that Medicare premiums stay as they currently are (about $45 per month for Part B). In this scenario, what do you think is the percent chance (what are the chances out of 100) that you would choose to purchase Medicare Part B coverage when you turn 66? What do you think is the percent chance (what are the chances out of 100) that you would choose to work full-time when you turn 66?

The second scenario supposes that premiums double to $90 per month, and poses the same two questions about purchase of Medicare Part B coverage and about labor supply at age 66.

Responses to these questions provide empirical evidence on a policy question of some interest. It is enticing to think that one may be able to predict the impact of Medicare policy in such a straightforward manner, without knowledge of how persons make decisions about labor supply and insurance coverage. However, this presumes that the elicited choice expectations are accurate predictions of behavior.

7.2. *Using Expectations and Choice Data to Estimate Econometric Decision Models*

Researchers who employ econometric decision models to predict choice behavior envision using expectations data to relax assumptions about expectations for states of nature. Consider, for example, the situation of a labor economist studying schooling behavior. A researcher who observes only the choices that youth make confronts the identification problem illustrated in Section 2.1, but observation of youths' expectations of the returns to schooling solves this problem. As discussed in Section 5.6, elicitation of entire distributions of life-cycle earnings may be impractical. Nevertheless, a researcher may use whatever expectations data as are available to lessen the dependence of inference on assumptions about expectations.

The advantages and disadvantages of this use of expectations data reverse those of the approach discussed in Section 7.1. The advantageous feature is that persons need not have rational expectations; it is enough to assume that elicited expectations faithfully describe persons' perceptions of their environments. The disadvantageous feature is that, given expectations and choice data, econometric modeling still requires untestable assumptions about the distribution of preferences in the population of interest.

As far as I am aware, the only published research using probabilistic expectations data in econometric analysis of choice behavior is Nyarko and Schotter (2002), who used a proper scoring rule to elicit expectations of opponent behavior from experimental subjects playing a certain two-person game. Their analysis shows compellingly how probabilistic expectations data can enable experimental economists to overcome the identification problem illustrated in Section 2.2. Further evidence on the usefulness of expectations data in experimental economics is provided by Dominitz and Hung (2003), who study the dynamics of social learning in settings that theoretically yield information cascades.

Several recent unpublished studies use expectations data to analyze the actual decision making of respondents to sample surveys. Delavande (2003) surveyed a small sample of sexually active young women in Chicago regarding their contraceptive choices, and elicited their expectations for the effectiveness and side effects of alternative contraceptive methods. She combined the data on expectations and choices to estimate a random utility model of contraception behavior. Lochner (2003) combined NLSY97 data on arrest expectations and crime commission to estimate a random utility model of criminal behavior. Hurd, Smith, and Zissimopoulos (2002) investigated how the subjective survival probabilities elicited from HRS respondents affect the times when they choose to retire and to begin collecting Social Security benefits. Van der Klaauw and Wolpin (2002) used the HRS data on survival expectations and retirement expectations to help estimate a stochastic dynamic model of retirement behavior.[31] These studies are a start, but economists have hardly begun to use probabilistic expectations data in econometric analysis of decision making.

7.3. *Understanding Expectations Formation*

To perform the econometric analyses cited above, researchers did not need to understand how persons form expectations and revise them with receipt of new information. They needed only to measure the expectations that respondents held when they made their observed choices.

Suppose that one wants to use an econometric decision model to predict choice behavior in a new scenario. Measurement of the expectations associated with observed choices suffices if it is plausible to assume that the new scenario does not affect expectations or that it changes them in some obvious way. However, econometric decision models often are used to predict behavior following policy interventions or other events that may alter expectations in nonobvious ways. Then credible prediction requires an understanding of expectations formation, a large subject about which little is known.

Experimental psychologists and economists have studied how persons update objective probabilities following receipt of random sample data in highly structured settings similar to those presented in textbook statistics exercises. A particular concern has been to test adherence to and characterize departures from application of Bayes theorem; see, for example, Tversky and Kahneman (1974) and El-Gamal and Grether (1995). However, I find it difficult to draw lessons from this work for expectations formation in real life, where the information that persons receive rarely maps cleanly into a textbook exercise in probability updating. Bayesian updating, which expresses new information through the likelihood function, presumes that data are generated by a well-defined sampling process. Expectations formation in real life requires persons to assimilate government announcements, media reports, personal observations, and other forms of information that may be generated in obscure ways.

[31]The last study differs from the others cited here. The other studies use expectations data to relax assumptions about expectations. In contrast, van der Klaauw and Wolpin maintain a conventional rational expectations assumption that point-identifies their decision model. They use expectations data to improve the precision with which they are able to estimate this model. See also Dominitz (2001) for discussion of ways in which expectations data may be used in conjunction with rational-expectations assumptions.

One can learn something about updating in real life by eliciting expectations longitudinally or from repeated cross sections of the population. Dominitz (1998) elicited earning expectations at six-month intervals from a spring 1993 cohort of SEE respondents who were reinterviewed in fall 1993. He examined the association between revisions to expectations and the earnings that respondents realized between interviews. Dominitz and Manski (2003) examined time trends in the mutual-fund investment expectations elicited from successive monthly cohorts of respondents to the Michigan Survey of Consumers. They observed a positive time-series association between revisions to expectations and movements in the Standard and Poor stock index, but were not able to discern whether this index "leads" expectations or vice versa.

Research that measures revisions to expectations and associates them with observed event realizations can be informative. However, I think that understanding expectations formation will also require intensive probing of persons to learn how they perceive their environments and how they process such new information as they may receive. Large-scale population surveys such as the HRS or SEE are not amenable to investigations of this type—the time available to query respondents is too limited and the standardized question-response format of interviews is too confining. Economists may need to engage small samples of respondents in lengthy, semi-structured "conversations."

8. MEASURING AMBIGUITY

This paper has presented empirical evidence that survey respondents are willing and able to report expectations in probabilistic form. This does not, however, imply that persons actually think probabilistically and use subjective probability distributions to make decisions. After all, survey respondents also respond to questions seeking point predictions of uncertain events or verbal assessments of likelihood. Yet persons need not use point predictions or verbal assessments of likelihood to make decisions. What the empirical evidence does show is that, however they think and act, people are willing and able to report their beliefs in multiple forms—as point predictions, verbal assessments of likelihood, or probabilistic expectations.

Among economists and decision theorists, perhaps the most compelling alternatives to the hypothesis of probabilistic expectations have been put forward in research on decisions under *ambiguity*. Studies of ambiguity maintain that beliefs have some but not all the structure of a probability distribution.[32] A particularly common idea has been that a person may hold a set of subjective distributions for an unknown event, not a single distribution. This idea is

[32]The term *ambiguity* appears to originate in Ellsberg (1961). His famous thought experiment required subjects to draw a ball from either of two urns, one with a known objective distribution of colors and the other with an unknown objective distribution of colors. Ellsberg conjectured that many persons facing this problem would not behave as if they place any single subjective distribution on the composition of the second urn.

a primitive of research on *robust Bayes* analysis (e.g., Berger (1985)), which supposes that persons hold multiple subjective distributions prior to observing data, and it is a conclusion of some work in axiomatic decision theory (e.g., Gilboa and Schmeidler (1989)). It is also a conclusion of my research on partial identification of probability distributions, which shows that combining available data with credible assumptions may enable a decision maker to partially but not fully identify an objective probability distribution (Manski (2000a, 2003, 2004)). Walley (1991) and Camerer and Weber (1992) review parts of the literature.

Suppose that beliefs actually do take the form of sets of subjective distributions. Then the single distributions that we now elicit from survey respondents are probabilistic summaries of ambiguity, much as point predictions are deterministic summaries of uncertainty. To enable persons to express ambiguity, survey researchers could elicit ranges of probabilities rather than precise probabilities for events of interest. This should be straightforward in the case of binary events, for which one could pose questions such as:

> What do think is the percent chance that event A will occur? Please respond with a particular value or a range of values, as you see fit.

This format enables respondents to express whatever uncertainty or ambiguity they may feel. A respondent can express complete ignorance by reporting "0 to 100 percent," bounded ambiguity by reporting "30 to 70 percent," uncertainty by reporting "60 percent," or certainty by reporting "100 percent."

Elicitation of ranges of probabilities should resolve the unease that researchers eliciting probabilistic expectations have felt about the appropriate interpretation of the response "50 percent." Bruine de Bruin et al. (2000), and Fischhoff and Bruine de Bruin (1999) suggest that some respondents may report 50 as an expression of *epistemic uncertainty* (i.e., 'fifty–fifty'), rather than as a quantitative probability. Elicitation of ranges would enable respondents to express ambiguity directly, rather than indirectly by saying "fifty–fifty." Presumably, respondents who continue to report 50 when permitted to state a range of values really mean 50 as a precise probability.

9. LOOKING AHEAD

Economists have long been hostile to subjective data. Caution is prudent, but hostility is not warranted. The empirical evidence cited in this article shows that, by and large, persons respond informatively to questions eliciting probabilistic expectations for personally significant events. We have learned enough for me to recommend, with some confidence, that economists should abandon their antipathy to measurement of expectations. The unattractive alternative to measurement is to make unsubstantiated assumptions.

For all the progress that has been made in measurement, we may be able to improve the way we now elicit expectations. The wording used in the studies described in Section 5 has proved effective in eliciting expectations for binary events, but it may be possible to outdo the method used to elicit expectations for income and other real-valued variables. Little is known about how to elicit expectations for high-dimensional events, such as lifetime earnings streams.

Looking beyond measurement, I see a critical need for basic research on expectations formation. Understanding how persons revise their expectations with receipt of new information often is a prerequisite for credible use of econometric decision models to predict behavior.

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