EMPIRICAL PROBABILITY SCALES FOR VERBAL EXPECTATIONS DATA, with Application to Expectations of Job Loss

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Abstract

Survey researchers have long used verbal expressions of likelihood to elicit the expectations that respondents hold for future events. The General Social Survey (GSS) uses this question to elicit expectations of job loss: "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?" Recently, surveys have elicited expectations in the form of numerical probabilities. The Survey of Economic Expectations (SEE) asks: "What do you think is the percent chance that you will lose your job during the next 12 months?" Whereas verbal questions at most convey ordinal information on expectations, probabilistic questions measure expectations on a well-defined absolute scale. This paper shows that auxiliary data collection can enable probabilistic re-scaling of verbal expectations data and thereby enhance the value of such data. The idea is to pose corresponding verbal and probabilistic questions to a suitable sample of respondents. The responses may be used to learn the frequency distributions of subjective probabilities reported by persons who give different verbal answers. These frequency distributions may then be used to predict the probability responses of respondents to surveys that now collect only verbal expectations data. Applying the prediction process, we have administered the GSS and SEE questions on job loss to a national sample of Knowledge Networks (KN) panelists. The KN data enable us to impute the probabilistic job-loss expectations that GSS respondents would have reported had they been asked. We report the findings.

1. Introduction

Survey researchers have long used verbal expressions of likelihood to elicit the expectations that respondents hold for future events. Many questions in common use have a structure similar to this General Social Survey (GSS) question eliciting expectations of job loss (www.icpsr.umich.edu/GSS/):

GSS 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?"

Researchers analyzing verbal expectations data confront a manifest scaling problem. Responses to the GSS and similar questions at most convey ordinal information specific to the respondent and to the event under consideration. Consider a GSS respondent who answers "fairly likely" to the question about job loss. We learn that this respondent thinks job loss to be more likely than "not too likely" and less likely than "very likely," but we do not learn what this respondent means when he states that job loss is "fairly likely." Moreover, responses need not be commensurable across respondents and events. Indeed, findings reported in this paper show that persons vary substantially in their usage of "fairly likely" and the other GSS response phrases.

A direct solution to the scaling problem is to elicit expectations in the form of numerical probabilities. Probability measures the likelihood of an event with a well-defined absolute scale. Provided that respondents are able to formulate and express subjective probabilities with reasonable care, responses should be commensurable both across persons and across events.

In the past decade, elicitation of probabilistic expectations has developed into a useful tool of survey research. The longitudinal Health and Retirement Study (HRS) elicits probabilistic expectations of retirement, bequests, and mortality from older Americans (Juster and Suzman, 1995; Hurd and McGarry, 1995). The National Longitudinal Survey of Youth-1997 Cohort (NLSY97) elicits probabilistic expectations of school completion, parenthood, arrest and incarceration from American teenagers (Fischhoff *et al.*, 2000; Dominitz, Manski, and Fischhoff, 2001). The Survey of Economic Expectations (SEE) elicits probabilistic expectations of income, job loss, health insurance coverage and crime victimization from repeated cross-sections of Americans (Dominitz and Manski, 1997a, 1997b; Manski and Straub, 2000). In particular, SEE includes this probabilistic paraphrase of the GSS job-loss question:

<u>SEE Job-Loss Question</u>: “What do you think is the percent chance that you will lose your job during the next 12 months?”

Although there is much yet to be learned about effective elicitation of probabilistic expectations in survey settings, the recent experience has largely been positive. When respondents are adequately introduced to the “percent chance” scale employed in SEE and other recent surveys, it has been found that they have little difficulty using probabilities to express the likelihood they place on future events relevant to their lives.[1] Analysis of probabilistic

[1] The SEE module of expectations questions is prefaced by this set of instructions meant to familiarize respondents with the percent chance scale:

> Now I will ask you some questions about future, uncertain outcomes. In each case, try to think about the 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

expectations data has yielded a variety of substantive findings that could not be achieved through analysis of verbal data; see the articles cited above.

Perhaps elicitation of probabilistic expectations will eventually replace verbal questioning in future administrations of surveys such as the GSS. Whether or not this will happen, survey researchers will want to continue to use the existing body of verbal data, particularly where no analogous probabilistic data exists. Hence it is important to cope as well as possible with the scaling problem inherent in verbal data.

This paper shows that auxiliary data collection can enable probabilistic re-scaling of verbal expectations data and thereby enhance the value of such data. The idea, formalized in Section 2, is to pose corresponding verbal and probabilistic questions to a suitable sample of respondents. The responses may be used to learn the frequency distributions of subjective probabilities reported by persons who give different verbal answers. These frequency distributions, which empirically transform verbal expectations into probabilistic ones, may then be used to predict the probability responses of respondents to surveys that now collect only verbal expectations data. This prediction process is well-grounded if a particular form of *distributional invariance* holds across surveys: the frequency distribution of probabilistic responses conditional on verbal responses in the survey collecting probabilistic and verbal data

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> 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.

Following this preface, respondents are asked the percent chance that it will rain or snow in the next day, a prediction task familiar to them as consumers of weather forecasts.

should be the same as the corresponding distribution in the survey collecting only verbal data.

Applying the prediction process, we have administered the verbal GSS and probabilistic SEE questions on job loss to a national sample of Knowledge Networks (KN) panelists. Section 3 describes the frequency distributions of probabilistic responses by KN respondents with different verbal responses. We show how these distributions empirically transform the four GSS response options (very likely, fairly likely, not too likely, not at all likely) into predicted subjective probabilities of job loss. Thus, the KN data enable us to impute the probabilistic job-loss expectations that GSS respondents would have reported had they been asked.

This application yields various findings of interest. We learn that probabilistic responses by the KN respondents are positively associated with verbal ones in central tendency, but still exhibit considerable heterogeneity across respondents. This heterogeneity seems to be idiosyncratic; we find no evidence that persons with different demographic or schooling covariates systematically use verbal expressions of likelihood in different ways. Our imputations of probabilistic responses to GSS respondents indicates broad stability in job-loss expectations from 1977 through 1998. However, American workers appear to have experienced two relatively short periods of heightened job insecurity in the late twentieth century, one in the early 1980s and the other in the early 1990s.

The closest precedent to our development of empirical probability scales for verbal expectations data is the body of psychological research assessing how subjects transform verbal expressions of likelihood into probabilities and vice versa; Clarke *et al.* (1992) review studies conducted from the 1940s through the early 1990s. The psychological literature presents intriguing findings, but is distant from survey research in critical respects.

Whereas survey researchers draw probability samples from broad populations of interest, psychologists have studied the expectations of experts (e.g., weather forecasters' reported probabilities of precipitation) or convenience samples of certain types of non-experts (e.g., college students situated in a cognitive laboratory). To the best of our knowledge, there have been no psychological studies collecting verbal and probabilistic expectations data from probability samples of broad populations.

Whereas survey researchers query respondents about specific subjects of substantive interest, psychologists studying non-experts have asked subjects to transform abstract verbal expressions of likelihood into probabilities, without reference to a specific event. Thus, a psychologist might ask a subject to say what probability, or range of probabilities, comes to mind when he or she hears the phrase “fairly likely.” To the best of our knowledge, there have been no psychological studies comparing the responses of subjects to verbal and probabilistic questions such as the GSS and SEE job-loss questions.

Although this paper focuses solely on the problem of scaling verbal expectations data, it should be apparent that similar scaling problems arise in the analysis of various forms of attitudinal data. For example, survey researchers routinely use verbal questions to assess the health status, well-being, policy preferences, and ideologies of respondents. Commensurability of responses across respondents is a chronic concern when analyzing such data. It may sometimes be possible to formulate alternative questions seeking responses on a well-defined, interpersonally comparable scale. If so, then auxiliary data collection akin to that recommended here may enable constructive re-scaling of existing attitudinal data.

2. Methods

The Prediction Process

Some notation helps to show how auxiliary data collection can enable probabilistic re-scaling of verbal expectations data. Suppose that a survey researcher wants to learn the expectations that a population of interest holds for a specified event; for example, the population may be persons who are currently working and the event may be job loss in the next 12 months. Suppose that each member of this population could, if asked, report expectations in both probabilistic and verbal terms. Let p_i denote the subjective probability that person i would report if a probabilistic question were posed. Let v_i denote the response this person would give if the question were to call for choice among a set V of verbal expressions of likelihood; for example, V = (not at all likely, not too likely, fairly likely, very likely) in the GSS job-loss question. Let $F_0(p, v)$ denote the distribution of (p, v) values within the population.

Suppose that a survey posing verbal expectations questions has been performed. Leaving aside practical problems in survey research (e.g., interview and item nonresponse), this survey enables the researcher to learn the distribution $F_0(v)$ of verbal responses within the population. However, responses to verbal questions provide only ordinal information about the expectations that persons hold. A more informative portrait of expectations would emerge if it were possible to learn the distribution $F_0(p)$ of subjective probabilities within the population.

One can learn $F_0(p)$ by performing an auxiliary survey that poses both verbal and probabilistic questions to a suitable sample of respondents. The auxiliary sample need not be drawn from the population of interest. It suffices that the sample be drawn from a population which shares with the population of interest the distribution $F_0(p|v)$ of probability responses conditional on verbal responses. Thus, let $F_1(p, v)$ be the joint distribution of probabilistic and verbal expectations in the population generating the auxiliary sample. Assume that the *distributional invariance* condition

$$(1) \qquad F_0(p|v) = F_1(p|v)$$

holds. Then the researcher can use the original survey to learn $F_0(v)$, the auxiliary survey to learn $F_1(p|v)$, and apply the Law of Total Probability to learn $F_0(p)$. Thus,

$$(2) \qquad F_0(p) = \sum_{v \in V} F_1(p|v)F_0(v).$$

In this manner, the auxiliary sample enables the researcher to rescale the verbal responses into subjective probabilities.

The Distributional Invariance Assumption

The distributional invariance assumption underlying the prediction process is easy to describe and understand. Any effort to extrapolate from one population to another must assume that the two populations share some features in common. In the present case, distributional invariance enables extrapolation from the population generating the auxiliary sample to the population of interest.

It is important to recognize that the distributional invariance assumption is untestable; it can neither be validated nor rejected empirically. After all, respondents to the original survey were not asked to report their expectations in probabilistic terms. Hence we cannot determine empirically whether the distribution $F_0(p|v)$ is the same as, or close to, the analogous distribution $F_1(p|v)$ in the population generating the auxiliary sample.

In some settings, a researcher may not find it credible to assume distributional invariance across entire populations, but may find it credible to assume such invariance across sub-populations with common values of observable covariates. For example, one may believe that usage of verbal expressions of likelihood differs systematically across persons with different demographic and schooling attributes. Thus, one may believe that

$$(3) \qquad F_0(p|v, x) \quad = \quad F_1(p|v, x)$$

for each value of some observable covariates x. If so, then one may apply the Law of Total Probability within each sub-population to learn $F_0(p|x)$. Thus,

$$(4) \qquad F_0(p|x) \quad = \quad \sum_{v \in V} F_1(p|v, x)F_0(v|x).$$

In principle, analysis of the cognitive processes involved in formation and expression of expectations could shed light on the credibility of the distributional invariance assumption in varying circumstances. Unfortunately, research to date provides little guidance. Psychological work assessing how subjects transform verbal expressions of likelihood into probabilities has mainly been descriptive rather than interpretative; perhaps the closest approach to interpretation is the suggestion by some psychologists that persons use *membership functions* to transform abstract verbal expressions of likelihood into ranges of numerical probability values (see Wallsten *et al.*, 1986). Economists have conjectured that persons with well-formed probabilistic expectations respond to verbal expectations questions by breaking up the [0, 1] probability scale into sub-intervals, each of which they associate with one or another of the verbal expressions posed (see Manski, 1990). However, this work does not bear directly on the distributional invariance assumption.

3. Application to Expectations of Job Loss

3.1. Background

Expectations of job loss describe an important aspect of the economic uncertainties that persons face in their lives and presumably influence the behavior of workers in numerous ways. For these reasons, survey researchers have long queried respondents about job-loss expectations. The General Social Survey first posed its verbal job-loss question in 1977 and has repeated the question in all subsequent administrations of the survey except for 1980, 1984, and 1987. The question is asked of all respondents who state that they are working at the time of the survey.

Table 1 shows the distribution of responses in all years for which data are available. We learn, for example, that the percentage of working respondents who say that job loss is “not at all likely” rose from 63% in 1994 to 66% in 1998. This suggests that perceptions of job security improved from 1994 to 1998. However, not knowing how respondents interpret the phrase "not at all likely" and the other response options, we cannot learn much about time trends in expectations of job loss.

In the notation of Section 2, the GSS data only make it possible to estimate the distribution $F_0(v)$ of verbal job-loss expectations within the population of American workers in each year shown in Table 1. The GSS has not posed probabilistic questions, and so does not enable estimation of the corresponding distribution $F_0(p)$ of probabilistic job-loss expectations. To achieve this objective, we administered the GSS and SEE questions on job loss to a national sample of Knowledge Networks (KN) panelists. The events under consideration in the two questions differ somewhat. Whereas the GSS question asks about job loss or layoff, the SEE question asks about job loss alone. Nevertheless, the logic of the exercise remains intact. We can use the verbal and probabilistic responses of the KN respondents to estimate the distribution $F_1(p|v)$, invoke the distributional invariance assumption, and then apply the Law of Total Probability to learn $F_0(p)$.

3.2. Data

The KN panel comprises a random sample of 23,000 American households who have been given Web TV browsers and free internet access in return for their agreement to respond periodically to surveys on diverse topics, administered over the internet. The Knowledge Networks website provides a detailed description of the sampling process generating the panel and the manner in which surveys are administered.[2] Also see Clinton and Lapinski (2002) and Dennis (2001).

In May 2001, a random sub-sample of 6658 KN panelists were asked to complete a survey eliciting their expectations of various events. The GSS and SEE job-loss questions were posed to the 4325 respondents who reported that they were working. The item response rates for these two questions were 98.7% and 97.1% respectively. The analysis in this paper focuses on the 3943 respondents who reported that they were working, who responded to both job-loss questions, and who provided demographic and schooling data that we use as covariates in part of the analysis.

3.3. Empirical Findings

Marginal Distributions of Verbal and Probabilistic Responses

Table 2 reports the basic empirical findings. The top of the table shows the frequencies with which KN respondents give each of the four possible responses to the GSS verbal question. These frequencies imply this marginal distribution of verbal responses:

Not at all Likely = .41 Not too Likely = .48 Fairly Likely = .07 Very Likely = .04.

It is instructive to compare the KN distribution of responses with those of GSS respondents, shown in Table 1. We find that the KN and GSS respondents are very similar in their

[2] See www.knowledgenetworks.com/ganp/safe/surveymethod.html.

propensities to report “Fairly Likely” and “Very Likely.” However, the KN respondents report “Not at all Likely” much less often than do the GSS ones and, correspondingly, report “Not too Likely” much more often.[3]

The first column of Table 2 summarizes the marginal distribution of KN responses to the SEE probabilistic question. Manski and Straub (2000, Table 2) report the corresponding distribution of responses for SEE respondents interviewed from 1994 through early 1998. The two distributions are very similar, as shown below:

	Percent Chance							
	0	1 - 9	10 - 19	20 - 29	30 - 39	40 - 49	50	51-100
KN respondents	.30	.26	.17	.12	.03	.02	.04	.07
SEE respondents	.33	.27	.13	.09	.02	.01	.07	.07

Thus, in the spring of 2001 as in the mid-1990s, about 1/3 of working Americans foresaw no chance of job loss in the year ahead and about 3/4 perceived less than a twenty-percent chance of job loss. However, some working Americans were not so secure; 7/100 viewed themselves as facing more than a fifty-percent chance of job loss.

Distributions of Probabilistic Responses Conditional on Verbal Responses

[3] The percentages of KN and GSS respondents who report either “not at all likely” or “not too likely” are very much the same; that is, about 90%. The difference between the samples is only in the relative prevalence of the responses to these two adjacent categories. Whatever the reasons for this difference, it is important to understand that the distributional invariance assumption does not require that the two samples have the same distributions of verbal responses, only that they have the same distributions of probabilistic responses conditional on verbal ones.

The remaining four columns of Table 2 summarize the distributions of probabilistic responses made by KN panelists who responded in the same way to the verbal question. That is, these columns summarize our estimates of the conditional distributions $F_1(p|v)$ needed to rescale the GSS data.

The table shows that the central tendency of the distribution of probabilistic responses shifts strongly to the right with the verbal response. The median probabilistic responses associated with the four verbal responses are (1, 10, 50, 90) and the mean responses are (4.3, 15.3, 43.4, 72.1).[4] Thus, verbal and probabilistic expectations clearly tend to move together.

The table also shows substantial heterogeneity in the probabilistic responses of persons who make the same verbal response. The interquantile ranges of the probabilistic responses associated with the four verbal responses are (5, 20, 25, 50). The one verbal expression that yields a tight range of probabilistic responses is "not at all likely." Among KN respondents who choose this verbal expression, 85% give a probabilistic response in the range [0, 9] percent and 95% give a response in the range [0, 19] percent. The other verbal expressions yield much broader ranges of probabilistic responses. Among KN respondents who choose the verbal expression "very likely," 50% give a probabilistic response in the range [90, 100] percent and 81% give a response in the range [50, 100] percent.

Observe that the four GSS verbal response options do not partition the [0, 100] percent-chance scale into equal-sized intervals of probabilistic responses. One might hypothesize that

[4] The differences between median and mean responses reflect asymmetries in the response distributions shown in Table 2. Most respondents who state "not at all likely" or "not too likely" give low probabilistic response but some give high responses, implying that mean probabilistic responses are larger than the corresponding medians. Skewness in the opposite direction is evident for respondents who state "fairly likely" or "very likely."

persons responding (not at all likely, not too likely, fairly likely, very likely) would give percent chance responses in the ranges {[0, 25], [26, 50], [51, 75], [76, 100]} respectively. This is not what happens. For example, the median and mean probabilistic responses of those stating "not too likely" are 10 and 15.3, well below the range [26, 50].

Exploring the Heterogeneity in Probabilistic Responses

It is natural to ask whether some of the heterogeneity in probabilistic responses shown in Table 2 may be "explained" by observable covariates of the KN respondents. It could be that persons with different demographic and schooling attributes tend to use verbal expressions of likelihood in different ways. To explore this possibility, we estimated several best linear predictors (BLPs) of probabilistic job-loss expectations.

Table 3 presents the findings. The table presents the coefficients of linear least-squares and least-absolute-deviations fits of respondents' subjective probabilities of job loss to a constant and the variables (age, schooling, sex, race), with one value of each covariate omitted for normalization. The two BLPs are interpretable as mean and median regressions if these regressions are linear. We do not, however, impose this assumption in computing standard errors. The standard errors given under the coefficients assume only that the KN respondents form a random sample from a population of prospective respondents.

The findings are striking. The least-squares fit shows only negligible variation of probabilistic responses with demographic and schooling attributes; the least-absolute-deviations fit show no variation at all. The differences in the verbal response coefficients in the two fits reflects the differences in the mean and median responses to the probabilistic questions, already evident in Table 2. Thus, we find no evidence that persons with different demographic and schooling attributes tend to use verbal expressions of likelihood in different ways.[5] Of course it remains possible that a more thorough investigation would reveal that covariates other than (age, schooling, sex, race) have predictive power.

3.4. Predicted Trends in Probabilistic Job-Loss Expectations, 1977-1998

As shown in Table 1, the GSS provides data on trends in verbal job-loss expectations from 1977 on. Comparable data on trends in probabilistic expectations have been available only since 1994, when SEE was initiated. Our KN data enable prediction of trends in probabilistic job-loss expectations from 1977 on.

As summarized in Table 2, the KN data make it possible to estimate the distributions $F_1(p|v)$ of probabilistic responses conditional on verbal responses.[6] The GSS data reveal the distribution $F_0(v)$ of verbal responses in each year shown in Table 1. We may legitimately combine the KN and GSS data to infer the distribution $F_0(p)$ of probabilistic responses in each year if the distributional invariance assumption holds.

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[5] The fits shown in Table 3 examine how the central tendencies of probabilistic response vary with demographic and schooling attributes. It is also of interest to study how the dispersion of responses varies with these covariates. For example, some psychologists have found that dispersion falls with schooling (see Nakao and Axelrod, 1983; Clarke *et al.*, 1992). To explore this possibility, we performed asymmetric least-absolute-deviations fits that show how different quantiles of the response distribution vary with demographic and schooling attributes; see Koenker and Bassett (1978) for the relevant statistical theory. Here too we found only idiosyncratic variation in the way persons use verbal expressions of likelihood.

[6] We use $F_1(p|v)$ rather than $F_1(p|v, x)$ because, as reported in Section 3.3, we found no systematic variation of probabilistic responses with demographic and schooling covariates.

Table 4 summarizes the predicted distribution of probabilistic responses for each of the years in which the GSS job-loss question was administered. The first column gives our estimate of the mean probabilistic response in each year. The remaining columns report our estimates of three quantiles of $F_0(p)$; the 0.25-quantile, the 0.5-quantile (median), and the 0.75 quantile. Beneath each estimate in the table is a bootstrapped 95%-confidence interval, computed by re-sampling repeatedly from the empirical distributions of GSS and KN respondents.

The broad picture that emerges is one of stability over time in probabilistic job-loss expectations. Across the twenty-two year period 1977-1998, the estimates vary within relatively narrow bands. The mean subjective probability of job loss always lies between 10.5 percent and 14.3 percent; the median between 2 and 5 percent.

A closer look at the table reveals two periods in which working Americans perceived themselves as facing somewhat more job insecurity than at other times. The first such period was in the early 1980s, and the second in the early 1990s. The National Bureau of Economic Research dates the troughs of the two most recent business cycles at November 1982 and March 1991. Thus, our time series findings on probabilistic expectations of job loss correspond qualitatively with accepted macroeconomic evidence. Moreover, we are able to measure quantitatively the extent to which job insecurity has varied over the business cycle. We find that, on average, Americans perceived their chances of job loss to be two or three percentage points higher during the last two recessions than at other times in the late twentieth century.[7]

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[7] These findings on historical expectations of job loss among American workers would have been impossible to obtain using the GSS verbal data alone. In the absence of our KN data, one might conjecture that the four GSS verbal response options partition the [0, 100] percent-chance scale into the four equal-sized intervals [0, 25], [26, 50], [51, 75], [76, 100] and that the mean probabilistic response in each interval is its midpoint. Thus, one might conjecture that persons

4. Conclusion

The desire to maintain time-series consistency in data collection makes survey research a conservative enterprise. Implementation of improvements is often retarded by an understandable concern that historical data remain usable in the future. It is therefore important to develop ways to maintain the utility of historical data without stifling the implementation of improved procedures.

There is good reason to think that elicitation of probabilistic expectations significantly improves on traditional practices asking respondents to choose among verbal expressions of likelihood. In the past decade, several major new surveys (e.g., HRS, NLSY-97, SEE) have advantageously implemented modules of probabilistic questions. However, implementation has yet to take place in ongoing surveys such as the GSS, which have historically posed verbal questions.

This paper has shown how verbal expectations data can be re-scaled in probabilistic terms. The re-scaling method proposed and applied here does not come free; auxiliary data must be collected and a distributional invariance assumption must be maintained. Nevertheless, we think that the approach can enhance the value of existing verbal expectations data. We also hope that the availability of a procedure to maintain time-series consistency between verbal and

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who report (not at all likely, not too likely, fairly likely, very likely) would, if queried probabilistically, respond with (12.5, 37.5, 62.5, 87.5) on average. Applying this assumption to the GSS data for 1998 yields 23.5 as the predicted mean percent chance of job loss. This is much higher than the mean of 11.1 percent shown in Table 4.

probabilistic data will prompt ongoing surveys to implement probabilistic questions.

Table 1: Distribution of GSS Responses to the Verbal Job-Loss Question, by Year

Year	Not At All Likely	Not Too Likely	Fairly Likely	Very Likely
1977	.65	.24	.06	.04
1978	.72	.21	.03	.04
1982	.60	.26	.06	.07
1983	.61	.25	.08	.06
1985	.66	.23	.05	.06
1986	.68	.21	.07	.04
1988	.66	.26	.04	.04
1989	.70	.21	.03	.05
1990	.69	.23	.05	.03
1991	.62	.25	.07	.07
1993	.61	.27	.08	.04
1994	.63	.26	.05	.06
1996	.61	.29	.06	.04
1998	.66	.27	.04	.03

Table 2: Distribution of KN Responses to the Probabilistic Job-Loss Question, by Response to the Verbal Question

Percent Chance	All Responses (N = 3943)	Not At All Likely (N = 1622)	Not Too Likely (N = 1902)	Fairly Likely (N = 258)	Very Likely (N = 161)
0	0.300	0.573	0.124	0.027	0.075
1 - 9	0.256	0.281	0.282	0.054	0.031
10 - 19	0.166	0.091	0.258	0.050	0.025
20 - 29	0.117	0.029	0.199	0.128	0.031
30 - 39	0.034	0.007	0.046	0.116	0.019
40 - 49	0.020	0.001	0.026	0.101	0.006
50	0.042	0.005	0.034	0.291	0.112
51 - 59	0.003	0.001	0.002	0.023	0.012
60 - 69	0.006	0.000	0.003	0.054	0.025
70 - 79	0.015	0.003	0.008	0.097	0.081
80 - 89	0.009	0.002	0.008	0.019	0.075
90 - 99	0.013	0.003	0.008	0.027	0.137
100	0.019	0.005	0.002	0.012	0.373
Column Total	1.000	1.000	1.000	1.000	1.000
Mean	14.9	4.3	15.3	43.4	72.1
0.25-quantile	0.0	0.0	5.0	25.0	50.0
0.50-quantile	5.0	1.0	10.0	50.0	90.0
0.75-quantile	20.0	5.0	25.0	50.0	100.0

Table 3: Estimated Best Linear Predictors of KN Probabilistic Expectations of Job Loss
(standard errors in parentheses)

	Least Squares	Least Absolute Deviations
Constant	3.6 (1.8)	0 (2.5)
Age		
18-34	-0.8 (1.9)	0 (2.5)
35-49	-1.3(1.9)	0 (2.5)
50-64	-0.4 (1.9)	0 (2.5)
Schooling		
No Postsecondary	1.7 (0.6)	0 (1.1)
Some Postsecondary	1.2 (0.6)	0 (1.2)
Sex		
Female	0.4 (0.5)	0 (0.9)
Race		
Black	2.1 (0.9)	0 (1.4)
Other	2.3 (1.1)	0 (1.8)
Verbal Response		
Very Likely	67.5 (2.7)	90 (2.7)
Fairly Likely	38.7 (1.5)	50 (1.9)
Not Too Likely	11.0 (0.5)	10 (0.9)
Average Residual Variation		
from marginal	22.71	13.61
from BLP	16.79	9.35

Table 4: Predicted Distribution of GSS Responses to the Probabilistic Job-Loss Question, by Year
(bootstrapped confidence intervals in parentheses)

Year	Mean	Quantiles 0.25	0.50	0.75
1977	12 (10.7, 13.6)	0 (0, 0)	2 (2, 5)	10 (10, 13)
1978	10.5 (9.12, 11.8)	0 (0, 0)	2 (1, 2)	10 (10, 10)
1982	14.3 (12.8, 16.0)	0 (0, 0)	5 (2, 5)	15 (10, 20)
1983	14.3 (12.8, 15.9)	0 (0, 0)	5 (2, 5)	15 (10, 20)
1985	12.9 (11.5, 14.5)	0 0	2 (2, 5)	10 (10, 15)
1986	11.8 (10.4, 13.4)	0 (0, 0)	2 (1, 3)	10 (10, 10)
1988	11.7 (10.1, 13.5)	0 (0, 0)	2 (1, 5)	10 (10, 12)
1989	11.1 (9.5, 12.9)	0 (0, 0)	2 (1, 2)	10 (10, 10)
1990	11 (9.3, 12.6)	0 (0, 0)	2 (1, 3)	10 (10, 10)
1991	14 (12.2, 16.0)	0 (0, 0)	3 (2, 5)	12 (10, 20)
1993	13.2 (11.6, 15.0)	0 (0, 0)	4 (2, 5)	10 (10, 20)
1994	12.8 (11.6, 14.2)	0 (0, 0)	2 (2, 5)	10 (10, 15)
1996	12.7 (11.6, 13.9)	0 (0, 0)	3 (2, 5)	10 (10, 15)
1998	11.1 (10.0, 12.4)	0 (0, 0)	2 (2, 3)	10 (10, 10)

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