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On the Measurement and Properties of Ambiguity in Probabilistic Expectations

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Abstract

Survey respondents' probabilistic expectations are now widely used in many fields to study risk perceptions, decision-making processes, and behavior. Researchers have developed several methods to account for the fact that the probability of an event may be more ambiguous for some respondents than others, but few prior studies have empirically compared the approaches. This article contrasts two of the most prominent methods using data from an experiment embedded in a recent Web survey of 926 volunteer panelists. Specifically, we comparatively evaluate the descriptive and relational properties of ambiguity scores obtained by placing follow-up questions after items eliciting expectations that ask either for (1) a range of probabilities that the respondent is confident to contain the true probability or for (2) a verbal response indicating assuredness. Our results show that these two methods produce measures that have more similarities than differences. Both methods yield ambiguity scores that (1) are not strongly associated with exposure to sources of relevant information, (2) are correlated across seemingly unrelated events, and (3) are consistently related to the level of reported risk.

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Probabilistic expectations are individuals' estimates of the probability or risk that an event will occur (Manski 2004). The quantification of probabilistic expectations is essential for several important lines of social research. For example, in recent years, survey researchers have used probabilistic expectations to examine such diverse issues as the relationship between voting intentions and voting behavior (Delavande and Manski 2010), the effect of racial context on perceived victimization risk (Quillian and Pager 2010), the accuracy of beliefs about infectious diseases and mortality risk (Bruine de Bruin et al. 2010; Fischhoff et al. 2010), the influence of perceived sanction risk on offending (Matsueda, Kreager, and Huizinga 2006), and cross-national variations in survival estimates (Delavande and Rohwedder 2011).

To elicit probabilistic expectations, researchers typically ask respondents to report the percent chance, or chances out of some set number (e.g., 10, 20, or 100), that an outcome of interest will occur (Hurd 2009; Manski 2004).[1] In most cases, the reported risk estimates are taken at face value and respondents reporting the same estimate of risk are treated identically in any resulting analyses.[2] This analytic strategy is problematic for several reasons (see, e.g., Fischhoff and Bruine de Bruin 1999; Manski and Molinari 2010). One significant concern is that individuals who report identical risk estimates may vary in their levels of confidence in those estimates (Bruine de Bruin and Carman 2012; Manski 2004). Put simply, the probability of a given outcome may be more *ambiguous* for some respondents than others.

High levels of ambiguity in risk perceptions may reduce the accuracy and reliability of resulting estimates (Bruine de Bruin et al. 2002; Hudomiet and Willis 2013; Manski and Molinari 2010). This will occur if ambiguity is positively associated with the likelihood of guessing at probabilities or answering off the top of the head, or if ambiguous risks are more difficult for respondents to quantify and express in precise probabilistic terms (Bruine de Bruin and Carman 2012; Fischhoff and Bruine de Bruin 1999; Lillard and Willis 2001). Ambiguity may also influence individuals' sensitivity to new information and thus may affect the stability of their risk perceptions over time. As Hudomiet and Willis (2013:154) explain, persons for whom the probability of an event is relatively unambiguous may "ignore any new information since they have already established a good understanding of the risks they face." Perhaps most importantly, ambiguity may have an impact on decision making and behavior, net of the effect of risk perceptions (Lillard and Willis 2001; Loughran et al. 2011). When faced with possible gains, individuals tend to be "ambiguity averse," preferring actions that have less ambiguous risks and rewards (Ellsberg 1961; Kahn and Sarin 1988).

For all of these reasons, there has been a wide recognition across academic disciplines of the need to quantify and assess ambiguity in subjective probabilities (Apel 2013; Bruine de Bruin and Carman 2012; Hurd 2009; Manski 2004). Importantly, a handful of recent studies have made initial advancements toward this end (Bruine de Bruin and Carman 2012; Hurd, Manski, and Willis 2007; Manski and Molinari 2010). However, the methods used in prior research to measure ambiguity have differed because they have corresponded to alternative theoretical conceptualizations of the phenomenon. Additionally, these methods have not been comparatively evaluated. Thus, it is not yet clear how best to quantify ambiguity in probabilistic expectations, or whether existing methods measure the same underlying construct.

The current study addresses this issue by contrasting the two leading methods that have been developed by scholars for measuring ambiguity. Using experimental data from a national sample of 926 respondents, we examine both the descriptive and relational properties of the ambiguity scores produced by the different methods. Before describing our methodology and findings, we first discuss the different theoretical conceptualizations of ambiguity that have given rise to alternative approaches to measuring the phenomenon, and we review the relevant prior research.

Conceptualizing and Operationalizing Ambiguity: Two Theoretical Perspectives

As a theoretical construct, economists and Bayesian decision theorists present a clear, if somewhat complicated, definition of ambiguity in risk perceptions. Under the notion that when faced with an unknown (or unknowable) quantity, such as one's true risk for victimization, individuals form a subjective belief distribution of which the mean (or first moment) can be interpreted as a point estimate of risk. The spread of this distribution can then be interpreted as ambiguity or degree of uncertainty in this belief (Camerer and Weber 1992).[3] According to this perspective, then, respondents form subjective probability distributions—or conceptual ranges of possible probabilities—for different events, which they consider when answering probabilistic questions (Manski 2004). The belief is that in most cases respondents report a measure of central tendency (mean, median, or mode) from their relative subjective distribution as their point estimate for the percentage chance of a given outcome occurring (Hurd 2009; Lillard and Willis 2001). However, it is emphasized that two respondents providing identical point estimates may have two very different ranges of possible probabilities in their minds that both yield the same point estimate of risk. A key assumption is that respondents with less variability (or spread) in their subjective probability distributions for a given event will be more confident (or have less ambiguity) in their risk estimates (Manski 2004).

This Bayesian conceptualization of ambiguity has given rise to a probabilistic method for measuring the phenomenon. It involves asking respondents to report a range of probabilities that they are certain to contain the actual probability of the event. Manski (2004:1370) first proposed this approach, suggesting that the width of the reported range should correspond to the spread of one's subjective probability distribution, and thus it should indicate his or her level of ambiguity. Manski and Molinari (2010) tested a version of this method with survival expectations and found that many respondents (45 percent) had a range in mind when providing a point estimate of risk, and these ranges were often quite wide (mean [M] = 17.6).

In contrast to a strict Bayesian interpretation of ambiguity, a second line of theoretical and empirical work collectively suggests that a proportion of ambiguity in risk perceptions may result not from the variation in one's subjective probability distribution for a given event but rather from stable individual differences in cognitive abilities or styles or dispositional traits (Brim 1955; Bruine de Bruin and Carman 2012; Bruine de Bruin et al. 2000; Fischhoff and Bruine de Bruin 1999; Gouret and Hollard 2011; Kézdi and Willis 2003; Kleitman and Stankov 2007). For instance, the ability or willingness to develop a well-formed subjective probability distribution, a requirement for formulating precise probabilistic expectations, may vary across persons in accordance with their numeracy skills or capacity for cognitive reflection (Bruine de Bruin and Carman 2012; Bruine de Bruin et al. 2000; Hurd 2009; Liberali et al. 2012). Similarly, individual differences in traits such as general self-confidence or intolerance of ambiguity may influence assuredness in risk estimates, irrespective of personal subjective probability distributions (Brim 1955; Kleitman and Stankov 2007, see also Stankov 1998).

In prior studies, different dimensions of dispositional ambiguity have been variously discussed as "epistemic uncertainty" (Bruine de Bruin and Carman 2012; Fischhoff and Bruine de Bruin 1999), a lack of "coherence" (Gouret and Hollard 2011), the propensity to have imprecise probabilistic beliefs (Kézdi and Willis 2003; Lillard and Willis 2001), or the absence of "sureness" (Kleitman and Stankov 2007). The direct survey measures of ambiguity that have evolved from this work involve follow-up questions with verbal responses that measure individuals' assuredness in their risk estimates. This has been done by asking respondents to report (1) how "confident" they are in their risk estimate (1 = *very confident*, 7 = *not confident at all*; Fischhoff and Bruine de Bruin 1999), (2) how "sure" they are about their answer (1 = *very sure*, 5 = *not very sure*; Brim 1955; Kleitman and Stankov 2007), or (3) whether their answer is a good estimate or if they actually don't know the probability (Bruine de Bruin and Carman 2012; Hurd 2009; Hurd, Manski, and Willis 2007). Of these three approaches, the last is arguably the most limited because it measures only the presence and not the amount of ambiguity in risk estimates (Bruine de Bruin and Carman 2012).

Relevant Prior Research on Ambiguity in Probabilistic Expectations

Researchers have yet to examine whether the range and verbal response methods produce similar estimates of the extent of ambiguity in risk estimates. Additionally, studies have not examined whether ambiguity scores produced by the two methods are related in similar ways to risk estimates and to other theoretically relevant factors. This is important because the different theoretical conceptualizations of ambiguity associated with the range and verbal response methods suggest that the two approaches may tap different constructs.

Specifically, the Bayesian conceptualization of ambiguity, which is associated most closely with the range method, predicts individuals' levels of ambiguity should be directly determined by the nature of the information they have about the probability of a *specific* event. To be clear, the variance of a respondent's subjective probability distribution for any given outcome is theoretically presumed to shape the width of the range of plausible probabilities that he or she reports (Manski 2004). This variance should necessarily decline as he or she gains more information about that *particular* risk. In Ellsberg's (1961:657) words, ambiguity depends "on the amount, type, reliability, and 'unanimity' of information" and gives "rise to one's degree of 'confidence' in an estimate of relative likelihoods." Likewise, Camerer and Weber (1992:330) argue that "ambiguity is . . . created by missing information that is relevant and could be known." In this interpretation, then, only information signals which are informative *about a specific event* should influence ambiguity regarding the risk of that event, and ambiguity levels should be unrelated across disparate events.

By contrast, scholarship on dispositional ambiguity, which is associated most closely with the verbal response method, suggests that trait-based assuredness in risk estimates should be largely unrelated to event-specific information and should be highly correlated across dissimilar events (Kézdi and Willis 2003; Kleitman and Stankov 2007). It also suggests the possibility that ambiguity levels and point estimates of risk might be linked, if the individual differences influencing ambiguity also shape risk estimates (Brim 1955; Brim and Hoff 1957).

While not comparing the range and verbal response methods on the basis of the aforementioned issues, prior studies have used the latter to investigate whether risk estimates of "50 percent" tend to be especially ambiguous (Bruine de Bruin and Carman 2012; Fischhoff and Bruine de Bruin 1999; Hurd, Manski, and Willis 2007). The general conclusion has been that ambiguity increases the likelihood of answering "50 percent" to probabilistic questions and that this is an important explanation for the high frequency of such responses in surveys. This was in fact documented more than 50 years ago in a seminal study by Brim (1955:71) who characterized the finding as "equiprobability through ignorance." His research also suggested that ambiguity may be positively associated with the propensity to report other middle-range estimates of risk as well, and thus its distribution across risk estimates may take on an inverted U shape. To our knowledge, Brim's (1955) study, which drew on data from a small sample of college students, has been the only one to date to evaluate the distribution of self-reported ambiguity across the full range of risk estimates.[4]

A few prior studies have also used the verbal response method to examine the sources or correlates of ambiguity in risk estimates. This work has yielded mixed evidence about the extent to which confidence in risk estimates is driven by event-specific information and experiences or stable individual differences. Hurd's (2009) findings, for instance, suggested that event-specific knowledge may reduce ambiguity. He found that respondents who follow the stock market closely were less likely to use 50 percent as way to say they are unsure about the probability of stock market gain. By contrast, Bruine de Bruin and Carman's (2012) study of survival expectations indicated that general cognitive abilities may play a significant role in shaping ambiguity levels. They demonstrated that after providing risk estimates, individuals with less educational attainment and lower numeracy skills were more likely to report that they "actually have no idea about the chances" or that "no one can know the chances" (pp. 233-34). Kleitman and Stankov's (2007) research has provided perhaps the strongest evidence that ambiguity is a function of stable individual differences. Drawing on data from 296 college students, they examined the internal consistency of an index composed of sureness ratings for responses to 23 different probabilistic expectations. They found that the index had high internal consistency ($\alpha = .89$) and loaded on a broader self-confidence factor.

It bears emphasizing, though, that the small existing body of research that has examined the correlates of ambiguity has failed to consider how different measurement methods might affect findings. This study extends this work by comparatively evaluating the properties of the ambiguity scores produced by both the range and verbal response methods. Specifically, we contrast these two methods on the basis of the following criteria: (1) the rank ordering of average ambiguity levels in different perceived risks, (2) the distribution of ambiguity scores across risk estimates, and (3) the correlation of those scores to other theoretically relevant factors.[5]

Method

The data for this study come from a Web-based experiment conducted in March 2013 with a national sample of 926 adults (18 years and older) who were randomly selected from SurveyMonkey's large online Audience panel. This panel includes more than 400,000 volunteer panelists who are provided two incentives—a donation in their name to charity and entry into a weekly drawing for US$100—to participate in surveys. The respondents in our study represent a probability sample of the Audience panel, and thus the results are generalizable to its members. Although only panel members were sampled for this study, these data are appropriate for our purposes because we focus on experimentally testing different methods, and we do not attempt to generate prevalence estimates of population values.[6] The American Association of Public Opinion Research's recent report on online panels emphasizes that "nonprobability online panels . . . have proven to be a valuable resource for methodological research of all kinds" (Baker et al. 2010:759). This is in part because Web surveys permit participants to respond at their convenience and pace and minimize interviewer-induced measurement error. Relative to other modes of data collection, such surveys may also elicit more valid self-reports of attitudes and behaviors (Chang and Krosnick 2009; Kreuter, Presser, and Tourangeau 2008). Additionally, there is growing evidence that relational inferences obtained from volunteer Internet surveys generally correspond to those observed with representative samples of the general population (Ansolabehere and Schaffner 2014; Berrens et al. 2003; Bhutta 2012; Sanders et al. 2007).

For the current project, the sampling frame was limited to panelists who were U.S. residents and who were over the age of 18. Generic e-mail invitations were sent to a total of 3,761 sampled respondents, of which 970 began the survey and 926 completed the questionnaire. Thus, the overall participation rate was 25 percent.[7]

Measuring Probabilistic Expectations

Respondents' risk perceptions were elicited with questions that asked them to estimate the percent chance that different events would occur in the future. We chose to ask about six events—catching the flu, living 10 additional years, burglary arrest, murder arrest, assault victimization, and robbery victimization—that have been the focus of prior research and that also correspond to two seemingly unrelated domains—health and crime. The exact wording of these questions is provided in Appendix A, and the descriptive statistics for the resultant measures are provided in Table 1. The probabilistic questions began with this introduction:

> To begin, we would like to ask your opinion about how likely you think it is that various events will happen. Some of the questions will ask you about the PERCENT CHANCE of something happening. The percent chance must be a number from 0 to 100. Here numbers like 2 or 5 percent would mean "almost no chance," and numbers like 95 or 98 percent would mean "almost certain." The percent chance can also be thought of as a number of chances out of 100.

Respondents were then asked to estimate the "percent chance (or chances out of 100)" that each of the following events would occur:

Catch Flu: If you didn't get a flu shot, you would get sick with the flu at some point during the next 12 months?
Live 10 Years: You will still be alive 10 years from today?
Burglary Arrest: The police in your local county would be able to catch and arrest a person who broke into a stranger's home and stole something?
Murder Arrest: The police in your local county would be able to catch and arrest a person who attacked and killed a stranger on the street?
Assault Victimization: You will be the VICTIM of an AGGRAVATED ASSAULT during the next 12 months?
Robbery Victimization: You will be the VICTIM of a ROBBERY during the next 12 months?

The legal definitions for the offenses of aggravated assault and robbery were provided to respondents before they were asked the respective

Table 1. Descriptive Statistics.

	Group 1		Group 2	
Variables	Mean	*SD*	Mean	*SD*
Measures of ambiguity				
Range flu	16.54	14.20	—	—
Range live	16.53	19.10	—	—
Range burglary arrest	19.40	17.14	—	—
Range murder arrest	19.40	17.35	—	—
Range assault victimization	11.21	14.90	—	—
Range robbery victimization	12.31	16.12	—	—
Unsure flu	—	—	2.77	1.27
Unsure live	—	—	2.41	1.14
Unsure burglary arrest	—	—	2.71	1.06
Unsure murder arrest	—	—	2.67	1.03
Unsure assault victimization	—	—	2.64	1.15
Unsure robbery victimization	—	—	2.75	1.16
Probabilistic expectations				
Catch flu	39.40	27.73	39.91	27.24
Live 10 years	81.39	22.23	78.68	23.39
Burglary arrest	45.65	27.96	46.86	28.07
Murder arrest	61.83	25.43	62.83	26.25
Assault victimization	16.07	20.17	15.90	20.40
Robbery victimization	18.88	21.20	18.58	21.17
Information sources				
General sources				
Local TV news (days)	3.20	2.67	3.06	2.64
Newspaper (days)	2.70	2.78	2.59	2.73
Health-specific sources				
Overall health	3.93	.73	3.93	.71
Smoker	.09	.28	.09	.29
Binge drinker	.24	.43	.20	.40
Work exposure	.52	.50	.51	.50
Frequency of PT	1.94	1.14	1.76	.99
Had flu	.20	.40	.20	.40
Crime-specific sources				
TV crime dramas (Days)	1.87	2.18	1.79	2.09
Neighborhood disorder	1.50	.59	1.46	.54
Neighborhood social change	3.08	.63	3.11	.70
LE employment	.05	.22	.04	.21
Family LE employment	.37	.48	.36	.48
Arrested	.14	.35	.15	.35
Family arrest	.50	.50	.48	.50

(continued)

Table 1. (continued)

	Group 1		Group 2	
Variables	Mean	*SD*	Mean	*SD*
Victim	.20	.40	.16	.37
Family victim	.31	.46	.26	.44
Control variables				
White	.84	.37	.87	.34
Age	49.04	16.18	50.02	15.45
Female	.55	.50	.52	.50
Education	2.79	.98	2.82	.99
Income	2.96	1.30	2.89	1.29
N	434		492	

Note: LE = law enforcement; PT = public transportation; SD = standard deviation; TV = television.

questions. Because of the potential for question order effects, we randomized whether respondents were asked the questions about arrest risk before or after those about victimization risk.[8]

Measuring Ambiguity

After answering each probabilistic question, respondents were asked a follow-up question to measure their assuredness in that specific risk estimate. One randomly selected group of respondents received follow-up questions that asked for a range of probabilities that they were confident contained the actual probability of the event (see Manski 2004; Manski and Molinari 2010). The exact wording of these questions is provided in Appendix A. Note that in Manski and Molinari's (2010) study, only those respondents who first indicated that they had a range in mind were asked to report a range. However, we were concerned that allowing respondents to avoid additional questions by initially reporting that they had an exact number in mind may lead to an underestimate of ambiguity levels. Thus, all respondents in this group were asked the follow-up range questions, and those who were confident in their original risk estimate were asked simply to reenter that answer twice (i.e., range width = 0).[9]

Before proceeding, it is important to highlight two potential limitations of the range method. First, respondents may tend to report ranges that are symmetrical around their risk estimates, which, in turn, would constrain range width at low and high levels of perceived risk. To illustrate, of the respondents who reported a probability range with a width greater than 0, roughly 25 percent to 35 percent, depending on the event, reported one that was perfectly symmetrical around their point estimate of risk. Second, the range questions may be cognitively burdensome for some respondents. For example, individuals with low numeracy skills may find it difficult to estimate the numerical ranges that accurately reflect their level of confidence in their risk perceptions (see, e.g., van Santen, Alessie, and Kalwij 2012). For instance, on each of the six events, 3 percent to 5 percent of respondents reported a range that did not include their risk perception, which may reflect response errors due to question difficulty.[10]

A second randomly selected group of respondents received a follow-up question after each probabilistic question that asked, "How sure are you about this answer?" The response categories for this item ranged from 1 = *very unsure* to 6 = *very sure*. We reversed these categories in the analyses. These "sureness" questions are consistent with scholars' suggestions for measuring ambiguity (Apel 2013; Loughran et al. 2011) and are nearly identical to those used by Brim (1955) and Kleitman and Stankov (2007). One potential limitation of this method, however, is that different respondents may interpret the provided response options (e.g., very unsure vs. unsure) as corresponding to different levels of ambiguity (see Manski 2004). As a result, two people who respond "unsure" may not have identical amounts of ambiguity. In contrast, the range method provides a quantitative scale that may increase comparability of responses, provided respondents share a similar understanding of the quantitative scale. The Likert-style sureness questions may also be more susceptible to stylistic responding (e.g., response acquiescence) than the range items (see, e.g., Pickett and Baker 2014; Revilla, Saris, and Krosnick 2014).

Measuring Exposure to Information Sources and Respondent Demographics

The analyses include several measures of respondents' exposure to potential sources of information about health and crime risks, which should be correlated with ambiguity levels to the extent that the latter are responsive to information. These include media consumption, social context, and prior personal and vicarious experiences. The measures are described in Appendix B. We also control for the standard demographic measures. These include respondents' race, age in years, gender, education, and annual household income. Education is measured ordinally, where 1 = *high school degree or less*; 2 = *some college*; 3 = *college degree*; and 4 = *graduate degree*. Income is measured as follows: 1 = *up to US$24.9k*; 2 = *US$25–49.9k*; 3 = *US$50–99.9k*; 4 = *US$100–149.9k*; and 5 = *US$150k or more*.[11]

Results

Table 1 reports the means for the ambiguity measures for both groups of respondents.[12] A clear pattern emerges for the range measures, but it does not replicate with the sureness items. Ambiguity as measured with the width of the reported range is highest for estimates of arrest risk and lowest for estimates of victimization risk. By contrast, as measured with the sureness questions, ambiguity is highest for estimates of flu and robbery victimization risk and lowest for estimates of the probability of living for an additional 10 years.

To further examine the descriptive properties of ambiguity as measured with the two methods, we conduct a series of nonparametric rank-sum tests (not shown). First, we test for the equality of distributions between each of the 15 pairwise combinations of sureness questions. For 10 of these tests, we cannot reject a null hypothesis that the distributions of the two sureness scores are equivalent at any conventional level. Only the five tests involving the living question have significantly different distributions from the other questions. In other words, with the exception of one specific question, the distributions of the sureness responses are statistically identical. We conduct similar rank-sum tests to check for equality in the range distributions. In 13 of the 15 pairwise tests, we can safely reject the null hypothesis of equality (all p values $< .02$). We are unable to reject the null in only two cases involving the two pairs of similar crime-related questions (i.e., arrest for murder vs. arrest for burglary; assault victimization vs. robbery victimization). In other words, we are able to detect important question-specific variability in the distribution of reported ambiguity in nearly all cases using the range method, while in only one case using the sureness method. These results demonstrate that the descriptive properties of ambiguity differ depending on whether it is operationalized using range width or sureness score. They also suggest that the quantitative scale of the range method may increase comparability of responses by allowing respondents to specify more precisely their level of ambiguity.

Next, we explore whether ambiguity as measured with both the range and sureness methods is higher for 50 percent responses to probabilistic expectations than for other answers. Recall that prior research using the verbal response method suggests that risk estimates of 50 percent tend, on average, to be relatively more ambiguous than other reported probabilities (Bruine de Bruin and Carman 2012; Hurd 2009). Table 2 presents the mean ambiguity levels, as measured with both the range and sureness methods, for 50 percent

Table 2. Comparison of Mean Levels of Ambiguity in "50 Percent" Responses Versus Other Probabilities for Health- and Crime-Related Probabilistic Expectations.

	Group 1		Group 2	
Measure of Ambiguity	50% Responses	Other Responses	50% Responses	Other Responses
Range flu	18.95	15.85*	—	—
Range live	20.76	16.18	—	—
Range burglary arrest	25.61	18.19*	—	—
Range murder arrest	22.38	18.88	—	—
Range assault victimization	19.62	10.78*	—	—
Range robbery victimization	21.59	11.52*	—	—
Unsure flu	—	—	3.02	2.68*
Unsure live	—	—	3.15	2.28*
Unsure burglary arrest	—	—	2.89	2.68
Unsure murder arrest	—	—	2.98	2.62*
Unsure assault victimization	—	—	3.16	2.60*
Unsure robbery victimization	—	—	3.14	2.71*

*Difference is significant at the $p < .05$ (one-tailed) level.

responses versus all other responses. In every case, ambiguity is higher for 50 percent responses. The differences are statistically significant in 9 of the 12 comparisons. Thus, the two methods converge in showing that ambiguity is higher among respondents who report 50 percent than among those who give other responses.

The focus of the analyses now turns to the relationships between ambiguity levels and theoretically hypothesized predictors. As an initial step, we investigate the bivariate correlations between ambiguity levels for expectations about health-related (flu and survival) and crime-related (arrest and victimization) events. These correlations are reported in Table 3. For comparison, the table also provides the bivariate correlations between the point estimates of risk for these different events. If event-specific information is the primary driver of ambiguity levels, then one would expect to find at most weak correlations between ambiguity levels for health- and crime-related expectations.[13] For example, there is little reason to expect that persons who are highly informed about influenza should also be highly informed about arrest or victimization.[14] The findings in Table 3, however,

Table 3. Bivariate Correlations Between Health- and Crime-Related Probabilistic Expectations and Ambiguity Levels.

	Group 1		Group 2	
	Health-Related Probabilistic Expectations			
Crime-Related Expectations	Catch Flu	Live 10 Years	Catch Flu	Live 10 Years
Burglary arrest	.123*	.075	.168*	.101*
Murder arrest	.079	.114*	.142*	.145*
Assault victimization	.255*	–.015	.219*	–.150*
Robbery victimization	.245*	–.004	.241*	–.093*
	Health-Related Ambiguity			
Crime-related ambiguity	Range Flu	Range Live	Unsure Flu	Unsure Live
Range burglary arrest	.377*	.449*	—	—
Range murder arrest	.400*	.454*	—	—
Range assault victimization	.318*	.443*	—	—
Range robbery victimization	.394*	.315*	—	—
Unsure burglary arrest	—	—	.443*	.458*
Unsure murder arrest	—	—	.446*	.460*
Unsure assault victimization	—	—	.410*	.471*
Unsure robbery victimization	—	—	.409*	.473*

*$p < .05$ (two-tailed).

show that for both the range and sureness measures, there are sizable correlations (r ranges from .32 to .47) between ambiguity levels for the four crime-related and two health-related expectations. And in all 16 cases, the correlations are positive and significant. By contrast, the correlations between point estimates of risk are much smaller in magnitude (none exceeds .26), and vary in both direction and significance.

The results here thus reveal that the range and sureness methods converge in showing that ambiguity is highly correlated across different types of expectations. This similarity in relational properties is to be expected if range width and sureness scores are both manifestations of the same underlying construct. In addition, we observe that there are far stronger correlations between ambiguity levels for health-related and crime-related expectations, regardless of whether operationalized as range width or sureness score, than between the respective point estimates of risk. This would be anticipated if ambiguity levels are a function of stable individual differences rather than event-specific information (Kleitman and Stankov 2007). We further examine this issue with multivariate models that include measures of exposure to sources of relevant information.

Tables 4 to 6 report the results of a series of ordinary least squares (OLS) regression models predicting levels of ambiguity, as measured with the range and sureness methods, for each of the probabilistic expectations. Standardized regression coefficients are shown. Multicollinearity is not a problem in any of the models; the variance inflation factors are all below 1.90, with the exception of those for the power polynomials entered in the final models. It bears noting that neither the range nor the sureness measures of ambiguity are normally distributed continuous variables. Both are skewed, and the latter are ordinal with six response categories. We present OLS results for ease of interpretation. However, the results are robust to alternative operationalizations of the dependent variables.[15] The results are also robust to alternative operationalizations of the explanatory variables; for example, the results do not change if dichotomous variables are used for each of the specific values of the ordinal predictors (e.g., education and income).

Models 1 and 4 in Table 4, and models 1, 4, 7, and 10 in Table 5 show the associations between exposure to different information sources and ambiguity levels, when ambiguity is measured as the width of the reported range. The comparable results for the sureness measures are shown in models 7 and 10 in Table 4 and models 1, 4, 7, and 10 in Table 6. The methods converge in showing that exposure to information sources has little relation to ambiguity. None of the information sources are consistently related to ambiguity levels, regardless of how ambiguity is measured. Additionally, the largest adjusted R^2 in any of these 12 models is .039 (model 10, Table 4), which indicates that very little of the variation in ambiguity can be explained by exposure to the included information sources.

Next, we examine whether ambiguity levels for the two health-related expectations can be explained by ambiguity levels in the four crime-related expectations and vice versa. Models 2, 5, 8, and 11 in Table 4 include a variable, *Crime Ambiguity*, which is equal to a respondent's mean ambiguity level across the four crime-related expectations. Models 2, 5, 8, and 11 in Tables 5 and 6 include a variable, *Health Ambiguity*, equal to a respondent's mean ambiguity level across the two health-related expectations. In every case, for both the range and sureness methods, the *Crime Ambiguity* index predicts ambiguity levels for health expectations, and the *Health Ambiguity* index predicts ambiguity levels for crime expectations. In all 12 models, the

Table 4. Regression Models Predicting Health-Related Ambiguity.

	Group 1						Group 2					
	DV = Range Flu			DV = Range Live			DV = Unsure Flu			DV = Unsure Live		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Respective probabilistic expectation												
Probabilistic expectation	—	—	.939***	—	—	.912***	—	—	.849***	—	—	.976***
Probabilistic expectation^2	—	—	–.739***	—	—	–1.063***	—	—	–.896***	—	—	–1.318***
Individual differences												
Crime ambiguity	—	.461***	.412***	—	.509***	.496***	—	.486***	.450***	—	.561***	.503***
Information sources												
Local TV news	–.008	.006	–.025	–.087	–.072	–.059	–.095	–.056	–.063	–.093	–.048	–.002
Newspaper	–.003	–.002	.006	.029	.030	.012	.001	.003	.009	.045	.047	.013
Overall health	–.034	–.015	.009	–.016	.005	.038	–.106*	–.038	–.044	–.160**	–.082	–.010
Smoker	.006	–.035	.001	–.010	–.055	–.046	–.045	–.031	–.033	.035	.051	.020
Binge drinker	.052	.073	.055	–.069	–.046	–.033	–.016	.009	.019	–.022	.007	.016
Work exposure	–.030	–.006	–.022	–.050	–.023	–.001	–.025	–.016	–.005	.068	.078*	.071*
Frequency of PT	.028	.023	.012	.010	.005	–.005	.054	.028	.017	.041	.011	.017
Had flu	.147**	.130**	.064	.050	.031	.048	.038	.027	.009	–.015	–.027	–.016

(continued)

Table 4. (continued)

	Group 1						Group 2					
	DV = Range Flu			DV = Range Live			DV = Unsure Flu			DV = Unsure Live		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Control variables												
White	–.020	–.044	–.048	.036	.009	.030	–.047	–.025	–.069	–.032	–.007	.014
Age	–.084	–.005	–.045	–.135*	–.049	–.069	.045	.019	.031	.185**	.155**	.044
Female	–.006	.048	.012	–.171**	–.111*	–.100*	–.039	–.063	–.035	.071	.043	–.002
Education	.006	.004	–.008	–.062	–.064	–.053	.019	–.007	–.015	–.092	–.122**	–.059
Income	.090	.076	.064	.035	.019	.024	.138**	.101*	.073	–.006	–.049	–.040
Adjusted R^2	.011	.216	.309	.029	.281	.353	.025	.255	.322	.039	.346	.506

Notes: DV = dependent variable; PT = public transportation; TV = television. Standardized regression coefficients are shown. For group 1, the crime ambiguity measure is equal to the average across a respondent's scores on the range burglary arrest, range murder arrest, range assault victimization, and range robbery victimization variables. For group 2, the crime ambiguity measure is equal to the average across a respondent's scores on the unsure burglary arrest, unsure murder arrest, unsure assault victimization, and unsure robbery victimization variables.
*p < .05; **p < .01; ***p < .001 (two-tailed).

Table 5. Regression Models Predicting Crime-Related Ambiguity (Group 1—Range Measures).

	DV = Range Burglary Arrest			DV = Range Murder Arrest			DV = Range Assault Victimization			DV = Range Robbery Victimization		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Respective prob. exp.												
Prob. exp.	—	—	.969***	—	—	1.102***	—	—	.646***	—	—	.725***
Prob. exp.^{2}	—	—	–.870***	—	—	–1.099***	—	—	–.410**	—	—	–.480***
Individual differences												
Health ambiguity	—	.503***	.480***	—	.502***	.503***	—	.472***	.436***	—	.424***	.379***
Information sources												
Local TV news	–.048	–.011	–.045	–.057	–.020	–.039	–.009	.026	.007	–.040	–.009	–.039
TV crime dramas	.085	.038	.028	.033	–.014	–.024	.058	.014	–.006	.083	.044	.016
Newspaper	.007	.002	.014	.007	.002	.015	–.034	–.039	–.039	–.034	–.039	–.052
Neigh disorder	.025	.024	.039	–.044	–.044	–.044	–.054	–.054	–.065	–.012	–.012	–.036
Neigh. social change	–.028	–.073	–.081	.078	.033	.030	.039	–.004	–.038	.067	.028	–.017
LE employment	.030	.034	.032	.008	.011	.010	.054	.057	.040	–.055	–.052	–.034
Family LE employ	–.155**	–.106*	–.097*	–.103*	–.054	–.045	.019	.065	.043	.063	.105*	.079
Prior arrest	.000	–.018	–.015	–.001	–.019	–.023	–.052	–.069	–.043	–.011	–.027	–.000
Prior family arrest	–.024	.004	.014	.021	.049	.052	.030	.057	.083*	–.033	–.009	.040
Victim	–.041	–.009	.027	.078	.109	.081	–.002	.027	.032	–.079	–.052	–.028
Family victim	.076	–.015	–.025	–.004	–.095	–.084	.069	–.017	–.055	.202*	.125	.049

(continued)

Table 5. (continued)

Variables	DV = Range Burglary Arrest			DV = Range Murder Arrest			DV = Range Assault Victimization			DV = Range Robbery Victimization		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Control variables												
White	.068	.049	.043	.096*	.077*	.062	.024	.006	.020	.050	.034	.035
Age	–.119	–.062	–.064	–.101	–.044	–.037	–.103	–.049	–.034	–.092	–.044	–.017
Female	–.040	.007	–.038	–.099	–.052	–.078	–.096	–.052	–.073	–.068	–.028	–.056
Education	–.041	–.023	–.055	–.032	–.015	–.042	.017	.033	.034	.044	.058	.029
Income	.016	–.016	.009	.045	.013	.007	–.006	–.035	–.002	.006	–.021	.011
Adjusted R^2	.017	.256	.316	.018	.256	.325	–.003	.208	.291	.023	.192	.276

Notes: DV = dependent variable; LE = law enforcement; Neigh. = neighborhood; Prob. exp. = probabilistic expectation. Standardized regression coefficients are shown. The Health Ambiguity measure is equal to the average across a respondent's scores on the range Flu and range live variables.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed).

Table 6. Regression Models Predicting Crime-Related Ambiguity (Group 2—Sureness Measures).

	DV = Unsure Burglary Arrest			DV = Unsure Murder Arrest			DV = Unsure Assault Victimization			DV = Unsure Robbery Victimization		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Respective prob. exp.												
Prob. exp.	—	—	1.088***	—	—	1.288***	—	—	.772***	—	—	.727***
Prob. exp.^{2}	—	—	–1.142***	—	—	–1.427***	—	—	–.632***	—	—	–.667***
Individual differences												
Health ambiguity	—	.545***	.530***	—	.512***	.479***	—	.536***	.527***	—	.550***	.542***
Information sources												
Local TV news	–.090	–.032	–.049	–.076	–.022	–.020	–.040	.017	–.012	–.048	.010	–.012
TV crime dramas	–.020	–.003	–.006	–.032	–.017	–.021	–.042	–.026	–.056	.001	.017	–.014
Newspaper	–.073	–.064	–.055	–.083	–.075	–.065	.020	.029	.022	–.015	–.006	.001
Neigh. disorder	–.004	–.009	.008	.051	.046	.021	.062	.057	.026	.069	.063	.051
Neigh. social change	–.033	–.005	–.006	–.036	–.009	–.036	–.012	.015	.003	.042	.070	.052
L.E. employment	.025	.043	.027	–.015	.002	–.002	–.030	–.013	–.013	–.020	–.002	.004
Family LE employ.	–.061	–.027	–.021	–.097*	–.064	–.044	.051	.084*	.075	.026	.060	.063
Prior arrest	–.038	–.022	–.034	–.043	–.027	–.042	–.015	.002	–.010	–.051	–.034	–.039
Prior family arrest	–.028	–.004	.008	–.053	–.030	.006	–.004	.020	.019	.006	.030	.030
Victim	–.032	–.055	–.037	–.096*	–.117*	–.087*	.090	.067	.041	.039	.016	–.011
Family victim	–.001	.013	.001	.044	.058	.042	.000	.015	–.007	.002	.016	–.001

(continued)

Table 6. (continued)

	DV = Unsure Burglary Arrest			DV = Unsure Murder Arrest			DV = Unsure Assault Victimization			DV = Unsure Robbery Victimization		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Control variables												
White	–.051	–.017	–.002	–.055	–.024	–.018	–.048	–.015	.008	–.060	–.026	–.017
Age	.059	–.020	–.017	.128*	.054	.038	.046	–.031	–.026	.082	.002	.017
Female	.000	–.002	.013	–.007	–.010	–.006	.105*	.102*	.069	.053	.051	.039
Education	–.032	.014	.007	.044	.087*	.040	.023	.068	.070	.048	.095*	.094*
Income	.081	.035	.030	.090	.047	.031	.057	.012	–.000	.094	.048	.029
Adjusted R^2	–.004	.289	.375	.026	.284	.409	–.003	.281	.350	–.000	.298	.350

Notes: DV = dependent variable; LE = law enforcement; Neigh. = neighborhood; Prob. exp. = probabilistic expectation. Standardized regression coefficients are shown. The health ambiguity measure is equal to the average across a respondent's scores on the unsure flu and unsure live variables.
*p < .05; **p < .01; ***p < .001 (two-tailed).

effects are large and highly significant ($p < .001$). Further the adjusted R^2s in these models range from .192 to .346, demonstrating that the inclusion of these indices greatly increases the explanatory power of the models over those including only the information and control variables.

Finally, we comparatively evaluate one additional dimension of ambiguity as measured with the range and sureness methods. Recall that prior research suggests that 50 percent responses specifically (Bruine de Bruin and Carman 2012; Hurd 2009), and perhaps middle-range responses more broadly (Brim 1955), may be associated with greater ambiguity levels. It is important to examine this possibility in the current study both to compare the two methods for measuring ambiguity and because the existence of a relationship between point estimates of risk and ambiguity may account for why ambiguity levels are correlated across events.

To assess the relationship between point estimates of risk and ambiguity, we incorporate the respective probabilistic expectation in the model predicting ambiguity for that specific expectation (models 3, 6, 9, and 12 in Tables 4 to 6). Consistent with Brim's (1955) expectations, we find that the relationship between point estimates of risk and ambiguity is nonlinear, with a quadratic form. Specifically, in all 12 models, the coefficients for the linear and quadratic terms for the *Probabilistic Expectation* variable are both significant. The former is always positive and the latter is always negative, which provides consistent evidence that the relationship between risk estimates and ambiguity is positive with a decelerating slope. The curvilinear relationship persists in every instance, even if 50 percent responses are deleted (not shown). To illustrate this relationship, Figures 1 and 2 display the predicted values of ambiguity at different levels of estimated risk, with other variables set at their means. In every case, the relationship conforms exactly to the inverse U shape suggested by Brim (1955).

It is also notable that regardless of whether ambiguity is operationalized as range width or sureness score, the effects of the *Crime Ambiguity* and *Health Ambiguity* indices persist even after accounting for the relationship between point estimates of risk and ambiguity. Indeed, the coefficients for these indices change very little in the full models. In short, both the range and sureness methods converge in showing that (1) two strong predictors of ambiguity for any given probabilistic expectation are ambiguity in other expectations and the respective point estimate of risk and (2) these effects are largely independent.

Discussion

The analysis of risk perceptions is important for several current avenues of social research, and thus the use of survey questions eliciting probabilistic

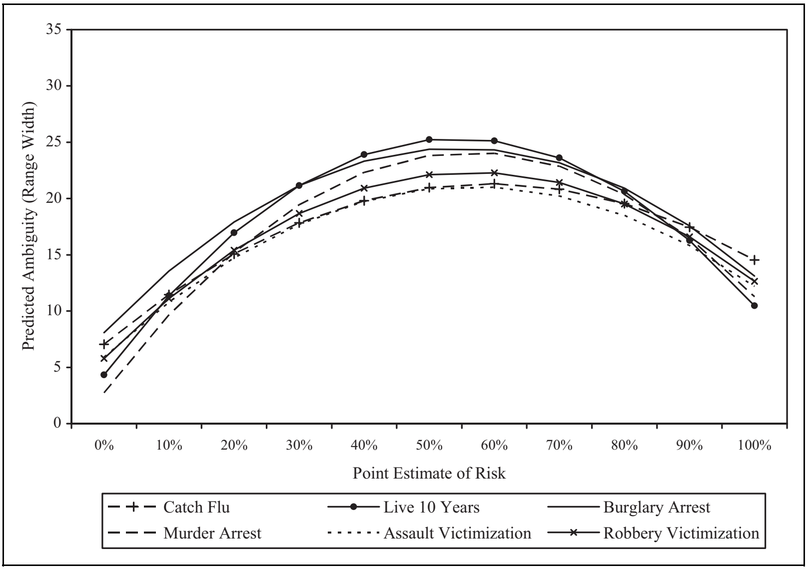

Figure 1. Predicted ambiguity levels across point estimates of risk for health- and crime-related events (group 1—range measures).

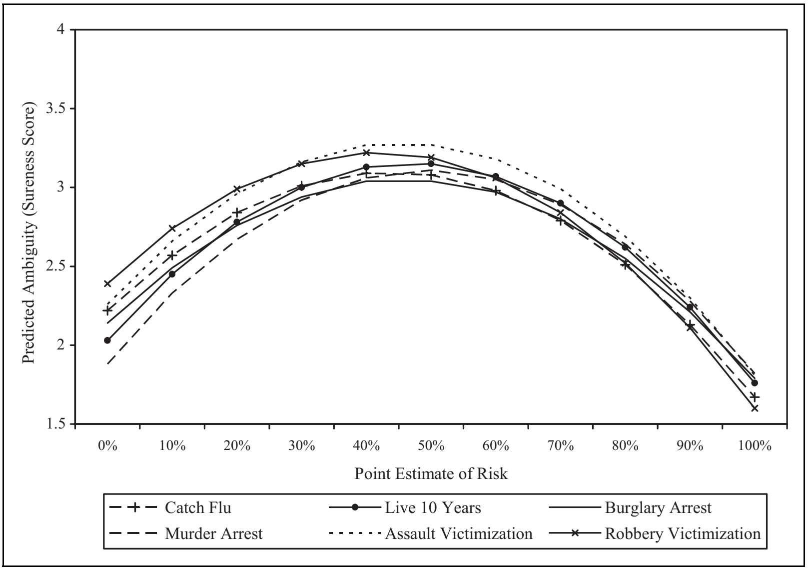

Figure 2. Predicted ambiguity levels across point estimates of risk for health- and crime-related related events (group 2—sureness measures).

expectations is widespread in many academic fields (Hurd 2009; Manski 2004). This interdisciplinary focus on probabilistic expectations is indicative of the "broad social significance" of studying perceived risks (Apel 2013:95). As Fischhoff and Bruine de Bruin (1999:161) explain, "understanding individuals' risk perceptions is essential to predicting their behavior and to providing them with needed information." Risk perceptions, however, provide only partial information about probability beliefs and decision-making processes. Obtaining more complete information requires quantifying ambiguity in risk perceptions (Bruine de Bruin and Carman 2012; Manski 2004). But this is rarely done because there exists no standard method for doing so. No doubt, this reflects the inherent difficulty of operationalizing a phenomenon for which there are multiple theoretical conceptualizations.

To advance the study of risk perceptions in social research, we comparatively evaluated two potential methods—follow-up questions asking for a probability range versus follow-up questions asking about sureness—for measuring ambiguity. These methods have been recommended by scholars but, surprisingly, have not previously been compared. Our findings revealed that the two methods yielded dissimilar rank orderings of mean ambiguity across risk perceptions. These differences may be the result of interpersonal variability in the interpreted meaning of the response options (e.g., very sure vs. sure) for the sureness method. Alternatively, it may be that relative to the sureness method, the level of ambiguity as measured with the range method is more sensitive to the level of estimated risk, because of the tendency among some respondents to report symmetrical ranges around their risk estimates.[16] Regardless of the explanation, however, pending further research, we suggest caution when using either method to estimate the prevalence of ambiguity in different perceived risks.

By contrast, we found that both methods produced ambiguity scores that had similar relational properties. Regardless of the measurement strategy used, ambiguity was generally unrelated to exposure to sources of relevant information. Rather, the two strongest predictors of ambiguity, whether operationalized as range width or sureness score, were a respondent's ambiguity levels in other risks and his or her respective point estimate of risk. The methodological implication is that the two measurement approaches appear to be tapping the same construct and have similar construct validity. It follows that both may have comparable utility for the purposes of studying the sources and effects of ambiguity in risk perceptions.

Our results also have notable theoretical implications regarding the nature of ambiguity in risk perceptions, assuming of course that they generalize beyond the sample of Internet panelists analyzed herein. We find little evidence that ambiguity levels correlate meaningfully with individuals' exposure to information sources. This correlation is central to the theoretical understanding of ambiguity as the amount of variability in an individual's subjective probability distribution (Camerer and Weber 1992). Thus, our findings generally suggest that the measures of ambiguity obtained with the two types of follow-up questions used herein do not correspond well to the Bayesian conceptualization of the ambiguity as a lack of confidence in risk estimates resulting from inadequate or inconsistent information. Instead, the results reveal that ambiguity levels are correlated across seemingly unrelated events and relate consistently to reported risk estimates. This is consistent with theoretical scholarship on dispositional ambiguity (Brim 1955; Kleitman and Stankov 2007) but suggests that there may be at least two different underlying mechanisms explaining variation in levels of trait-based ambiguity.

First, the positive correlations observed between ambiguity levels for different probabilistic expectations, which persist even after controlling for risk estimates, may be suggestive of the effects of the general self-confidence trait identified in studies by Stankov and associates (Kleitman and Stankov 2007; Pallier et al. 2002; Stankov 1998, 2000; Stankov and Crawford 1996, 1997). This metacognitive trait structures self-monitoring and thus disposes individuals "to be consistent, relative to each other, in attaching a particular level of confidence to a great variety of cognitive tasks" (Stankov 1998:48).

Second, the consistent curvilinear relationship observed between ambiguity levels and risk estimates, which remain even if 50 percent responses are excluded from the analyses, is perhaps indicative of the impact of some third variable on responses both to probabilistic questions and to follow-up items measuring assuredness in answers.[17] Theoretically, intolerance of ambiguity (Budner 1962; Frenkel-Brunswik 1949), which involves the inclination to view ambiguous situations "as a threat or a source of discomfort" (Grenier, Barrette, and Ladouceur 2005:594), would constitute a likely factor affecting these responding behaviors (see, e.g., Brim and Hoff 1957; Naemi, Beal, and Payne 2009; Soueif 1958). Brim (1955:74-75), for example, argues that individuals who are intolerant of ambiguity may tend to adopt survey response styles that minimize felt uncertainty, namely reporting both extreme probabilities and high levels of assuredness. Stated differently, intolerance of ambiguity may discourage both the reporting of middle-range risk estimates and admissions that the probability of an event is ambiguous, because both types of responses indicate that life events are more difficult to predict (see Naemi et al. 2009). If this is the case, it would suggest that ambiguity levels and risk estimates may both be influenced by factors other than probability beliefs.

Alternatively, the curvilinear relationship between ambiguity and point estimates of risk may be explained by a Bayesian updating process whereby, on average, the act of acquiring information both increases individuals' confidence in their risk estimates—by reducing the variance of their subjective probability distributions—and adjusts those estimates away from 50 percent (see Camerer and Weber 1992).[18] We doubt this explanation for two reasons. First, as noted previously, we find no evidence that ambiguity, regardless of how it is measured, is strongly correlated with exposure to sources of relevant information. Second, in another analysis with a third randomized group of respondents ($N = 428$), we evaluated the relationship between the amount of information respondents reported having about a specific event and their risk estimates for that event.[19] Whereas a curvilinear relationship was consistently observed between ambiguity levels and risk estimates, no such relationship was observed between information levels and risk estimates (results available upon request).[20]

It is also possible, of course, that two theorized sources of ambiguity—information versus dispositional factors—commonly have an interactive effect on one's overall ambiguity levels. Stated differently, individual differences may condition the influence of domain-specific information on ambiguity in probabilistic expectations (Kézdi and Willis 2003). Accordingly, in supplementary models we created product terms between each of the potential information sources (e.g., self-reported health, prior arrest) and the two individual-difference components (i.e., the two ambiguity indices [*Crime Ambiguity*, and *Health Ambiguity*]). We entered the product terms into the full models for each of the six events (models 3, 6, 9, and 12 in Tables 4 to 6). In total, then, we estimated 180 separate models with 29 different product terms. Twenty significant interaction effects emerged, but these effects were not consistent across both the range and sureness measures of ambiguity (results available upon request). In our view, this provides little evidence that two different sources of ambiguity primarily have an interactive effect on ambiguity levels. Nonetheless, additional investigations are needed that further explore this issue with a broader array of information sources and dispositional factors. The supplementary results do indicate that one difference between the range and sureness measures may the way in which they moderate the effects of domain-specific information on ambiguity.

Before closing, it is important to note that one limitation of our study is that the opt-in Internet panelists in our sample differ demographically from the U.S. population and are also experienced survey takers. Accordingly, there is a possibility that our results will not generalize to the broader population. We believe this is unlikely, however, for two reasons. First, to our knowledge, there is no existing theory or research that suggests that either the validity of different measures of ambiguity or the nature of the relationship between ambiguity and risk estimates should vary in a systematic way across different population groups. Second, two prior studies using the sureness measures have reported similar findings regarding the properties of ambiguity. Specifically, our multivariate results for the relationship between ambiguity and risk estimates are similar to the descriptive findings for sureness measures obtained by Brim (1955) more than 50 years ago. Likewise, our finding that ambiguity levels are correlated across seemingly unrelated events is corroborated by the evidence from Kleitman and Stankov's (2007) analysis of sureness measures. Even still, our study is the first to experimentally compare the sureness and range measures, and it is also the first to examine the properties of these different measures of ambiguity using multivariate methods. For this reason, future studies are needed to replicate our results with a representative sample of Americans.

Taken together, our findings outline several important avenues for additional inquiry. First, further research is warranted that explores whether a similar relationship between ambiguity and risk perceptions is observed when probabilistic expectations are measured on other scales, besides the 0 percent to 100 percent scale (see, e.g., Delavande, Giné, and McKenzie 2011; Pickett et al. 2012). Relatedly, investigators seeking to build on our research might consider whether the relationship between risk estimates and ambiguity is similar if probabilistic expectations are treated as estimates of relative risk rather than absolute risk. For example, researchers might construct measures of relative probabilistic expectations equal to the percentage difference from the average level of subjective risk in a sample and then examine the distribution of ambiguity across these estimates of relative risk.[21]

Second, subsequent studies should examine how ambiguity in risk perceptions may affect individuals' decision making and behavior. Such research has the potential to illuminate the nuanced influences on behavioral choices. There is also potential value to investigations evaluating whether using the range and verbal response methods to account for ambiguity in risk perceptions improves resultant parameter estimates and relational inferences. This relates to Hurd's (2009:51) recent observation that "to use subjective probabilities effectively . . . we need indicators of the quality of the reported probability by each individual." One approach may be to weight individuals' risk perceptions on the basis of their levels of ambiguity. However, we avoided such an analysis in our study because it seemed premature without first developing an accurate understanding of the nature of ambiguity in probabilistic expectations. For example, the meaning of ambiguity-based weights would vary considerably depending on whether ambiguity results from a lack of risk-specific information or stable individual traits. Accordingly, an important next step is for studies to adjudicate between the different theorized sources of ambiguity, such as information levels, trait self-confidence, and intolerance of ambiguity.

Appendix A

Question Wording for Probabilistic Expectations and Range Ambiguity

Catch Flu: "Using this scale from 0 to 100, what do you think is the percent CHANCE (or CHANCES OUT OF 100) that, if you didn't get a flu shot, you would get sick with the flu at some point during the next 12 months? Please enter a number between 0 and 100: ____."

Range Flu: "When answering the question above, some people are more confident giving a RANGE of numbers instead of an exact number. For example, if you put 50 percent above, you might be very confident that your chance of getting sick is between 49 percent and 51 percent, between 40 percent and 60 percent, or is in some other range. Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains your percent chance of getting sick with the flu during the next 12 months? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Live 10 years: "What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that you will still be alive 10 years from today? Please enter a number between 0 and 100: ____."

Range Live: "Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains your percent chance of still being alive 10 years from today? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Burglary Arrest: "What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that the police in your local county would be able to catch and arrest a person who broke into a stranger's home and stole something? Please enter a number between 0 and 100: ____."

Range Burglary Arrest: "Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains the percent chance that the police in your local county would be able to catch and arrest a person who broke into a stranger's home and stole something? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Murder Arrest: "What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that the police in your local county would be able to catch and arrest a person who attacked and killed a stranger on the street? Please enter a number between 0 and 100: ____."

Range Murder Arrest: "Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains the percent chance that the police in your local county would be able to catch and arrest a person who attacked and killed a stranger on the street? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Assault Victimization: "An AGGRAVATED ASSAULT occurs when someone unlawfully attacks another person and either causes serious bodily harm or is armed with a dangerous weapon. What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that you will be the VICTIM of an AGGRAVATED ASSAULT during the next 12 months? Please enter a number between 0 and 100: ____."

Range Assault Victimization: "Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains the percent chance that you will be the VICTIM of an AGGRAVATED ASSAULT during the next 12 months? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Robbery Victimization: "A ROBBERY occurs when an individual uses force or the threat of force to take money or property directly from another person. What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that you will be the VICTIM of a ROBBERY during the next 12 months? Please enter a number between 0 and 100: ____."

Range Robbery Victimization: "Thinking about the number you reported above, what is the RANGE of numbers around that number that you are very confident contains the percent chance that you will be the VICTIM of a ROBBERY during the next 12 months? Please enter the RANGE below. It can be as small or as large as you need it to be. If you are very confident in the answer you gave above, just put that same number in both of the boxes below. Lowest number in the range: ____. Highest number in the range: ____."

Appendix B

Question Wording for Items Measuring Exposure to Information Sources

General information sources.

Local TV News and *Newspaper*: "In a typical WEEK, on how many days do you do each of the following: . . . Watch local television news? . . . Read a newspaper?" The response options ranged from 0 = 0 days to 7 = 7 days. We focus on local TV news because it should be most informative about personal risks, which are most responsive to the local environment.

Health-specific information sources.

Overall Health: "In general, how would you rate your overall health?" 1 = *very poor*; 2 = *poor*; 3 = *fair*; 4 = *good*; and 5 = *excellent*.

Smoker: "During a normal DAY, how many cigarettes do you smoke?" 1 = *none*; 2 = *1 to 2 cigarettes*; 3 = *3 to 5 cigarettes*; 4 = *6 cigarettes to 1 pack*; and 5 = *more than 1 pack*. We recoded the responses to generate a binary measure where 0 = *none* and 1 = *1 or more cigarettes*.

Binge Drinker: "Think back over the LAST TWO WEEKS, how many times have you had five or more alcoholic drinks (beer, wine, liquor) in a row? 1 = *none*; 2 = *once*; 3 = *twice*; 4 = *3 to 5 times*; 5 = *6 to 9 times*; and 6 = 10 or more times." We recoded the responses to generate a binary measure where 0 = *none* and 1 = *1 or more times*.

Work Exposure: "Are you currently in a job or other position—perhaps as a teacher, student, public greeter, waiter/waitress, flight attendant—where you come into close contact with more than 20 people each day?" 0 = *no* and 1 = *yes*. We include this variable because daily exposure to a large number of people should increase both the risk of catching infectious diseases and exposure to information about the number of people who get sick in a given time period.

Frequency of Public Transportation: "How often do you take public transportation—bus, train, subway, plane—to get somewhere?" 1 = *every day*; 2 = *a few times each week*; 3 = *a few times each month*; 4 = *a few times each year*; and 5 = *less than once a year*. We reversed these response categories in the analyses so that higher values indicate greater use of public transportation. We include this variable because use of public transportation should increase both the risk of catching infectious diseases and exposure to information about the number of people who get sick in a given time period.

Had Flu: "Over the past 12 months, have you gotten sick with the flu?" 0 = *no* and 1 = *yes*.

Crime-specific information sources.

TV Crime Dramas: "In a typical WEEK, on how many days do you do each of the following: . . . Watch crime programs like COPS, CSI, and Law and Order?" The response options ranged from 0 = *0 days* to 7 = *7 days*.

Neighborhood Disorder: This variable is a 5-item index (α = .83 for group 1, and .79 for group 2) derived from the following question: "How much of a problem is each of the following in your neighborhood: Litter and trash? . . . Graffiti? . . . Run-down houses? . . . Noisy neighbors? . . . Teenagers hanging out on corners? 1 = *not a problem*; 2 = *a small problem*; 3 = *a problem*; 4 = *a big problem*; and 5 = *a very big problem*. Because few respondents reported these issues were very big problems, we combined the last two response categories. We then averaged across respondents' responses to the 5 items. We include this variable in the analyses because research shows that neighborhood disorder conveys salient information about both police performance and criminal risk (Bursik and Grasmick 1993; Farrall, Jackson, and Gray 2009). Specifically, graffiti, litter, unmonitored teens, and other physical and social incivilities are visible "signs of crime" (Skogan and Maxfield 1981:107) that are informative about criminal risks and also point to officials' inability to address social issues, suggesting that when crimes occur "nobody will intervene and thus the risk of apprehension is low" (Apel 2013:80).

Neighborhood Social Change: This variable is a 4-item index (α = .87 for group 1, and .89 for group 2) derived from the following question: "In your community, how much has each of the following decreased or increased in the past five years: . . . The sense of belonging among residents? . . . The sense of trust among residents? . . . The sense of right and wrong among residents? . . . The sense of shared responsibility for the community among residents?" 1 = *decreased greatly*; 2 = *decreased some*; 3 = *stayed about the same*; 4 = *increased some*; and 5 = *increased greatly*. We reversed these response categories so that higher values indicated social deterioration and then averaged across responses to the 4 items. We include this variable in these analyses because studies find that perceptions about both police effectiveness and criminal risk are informed by judgments about changes in community cohesion, social trust, and shared moral values (Jackson and Bradford 2009; Jackson and Sunshine 2007).

Law Enforcement Employment: "Have you ever been employed as a police officer or in law enforcement?" 0 = *no* and 1 = *yes*.

Family Law Enforcement Employment: "Have any of your family members or close friends ever been employed as a police officer or in law enforcement?" 0 = *no* and 1 = *yes*.

Arrested: "Have you ever been arrested?" 0 = *no* and 1 = *yes*.

Family Arrest: "To the best of your knowledge, have any of your family members or close friends ever been arrested?" 0 = *no* and 1 = yes.

Victim: "Over the past 5 years, have you personally been the victim of a crime?" 0 = *no*; 1 = yes.

Family Victim: "Over the past 5 years, has anyone in your household been the victim of a crime?" 0 = *no* and 1 = yes.

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Notes

1. Prior work documents the advantages of probabilistic questions over attitudinal survey items with verbal response options and demonstrates that respondents are willing and able to provide meaningful estimates of numerical probabilities (Dominitz and Manski 1997).
2. We use the terms "probabilistic expectation" and "risk estimate" interchangeably to refer to an individual's subjective estimate of the absolute (rather than relative) likelihood that an event will occur.
3. This definition would correspond closely to Camerer and Weber's (1992) description of ambiguity as a *second-order probability*.
4. Manski and Molinari (2010) evaluated range usage and range width at focal point responses but did not explore the distribution of ambiguity across the full range of risk estimates.
5. We do not investigate whether adjusting for ambiguity influences the accuracy of individuals' risk perceptions, because the meaning of such adjustments would be difficult to interpret without first developing a precise understanding of the nature and sources of ambiguity.
6. Studies that test alternative methods commonly draw on data from nonprobability samples, including samples of college students (see, e.g., Barrera and Simpson 2012; Fischhoff and Bruine de Bruin 1999; Jann, Jerke, and Krumpal 2012). In addition, recent research supports the use of opt-in Internet respondents in experimental studies and demonstrates that they have advantages over the more common approach of relying on in-person convenience samples (Berinsky, Huber, and Lenz 2012; Buhrmester, Kwang, and Gosling 2011; Gosling et al. 2004).
7. The current best practice in research using volunteer Web surveys is to report a participation rate (completions/total invitations) in lieu of a response rate (Baker et al. 2010:760). A substantial literature documents that across modes of data collection, the level of nonresponse in a survey is a poor predictor of nonresponse bias because the propensity to respond is commonly a function of factors unrelated to survey variables (Curtin, Presser, and Singer 2000; Groves 2006; Groves and Peytcheva 2008; Keeter et al. 2000, 2006). For example, Tourangeau et al. (2009) found that neither the topic of a Web survey nor its sponsor influenced online panelists' response propensity.
8. To ensure that the ordering of questions did not influence the findings, we disaggregated the two experimental groups into four groups, based on the measure of ambiguity (i.e., range vs. sureness) and whether the respondents first received the questions about crime risk or arrest risk. We then separately estimated the

regression models shown in Tables 4 to 6 for each of the four subsamples. Similar results emerged across all four subsamples.

9. Consistent with our concerns, 79 percent to 88 percent of respondents, depending on the event, indicated that the risk in question was somewhat ambiguous to them by providing a range of values. In Manski and Molinari's (2010) study, only 45 percent of respondents provided a range. Based on the suggestion of a helpful reviewer, we studied the distributions of the widths of each reported range to compare how our findings differed from those of Manski and Molinari. In our sample, the median widths of the reported ranges, even including all respondents (i.e., those who reported a width of zero), were 14 (flu), 10 (living 10 years), 15 (burglary arrest), 15 (murder arrest), 9 (assault victimization), and 10 (robbery victimization), suggesting a good deal of ambiguity on average. In Manski and Molinari's study, the median reported width would be zero. Furthermore, conditioning on only those who report a nonzero range (i.e., the 79 percent to 88 percent), these median values increase to 15, 15, 20, 20, 10, and 10, respectively. This indicates a large amount of variability in range width in our sample that is quite different from what was observed in Manski and Molinari's study where respondents were only asked for a range if they first admitted their risk estimate was an approximation.
10. We include these respondents in the analyses because it is theoretically plausible that such responses have substantive meaning if the respondents' reported the mode of their subjective probability distribution as their point estimate of risk, but then reported a range around the mean of the distribution (see Hudomiet and Willis 2013). However, substantively identical findings are obtained when the models are reestimated after dropping these individuals.
11. To avoid losing respondents (25 in group 1 and 35 in group 2) solely due to nonresponse on the income question, we imputed missing values for this measure using scores on the other explanatory variables. This did not appreciably alter the results.
12. Both groups of respondents differ demographically from the U.S. population. For example, in both groups, minorities, persons without a college degree, and individuals with household incomes under US$100,000 are underrepresented. This is common in Internet surveys (Baker et al. 2010). What is most important for our purposes, however, is that the demographic and attitudinal characteristics of respondents in groups 1 and 2 generally parallel each other.
13. For some individuals, there may be an information-driven correlation between ambiguity levels for expectations about victimization and survival because knowledge about victimization risk may also be informative about the probability of survival (see Fischhoff et al. 2000, 2010).
14. As one reviewer noted, it is of course possible that some individuals are simply more knowledgeable about most things than others. If this is the case, then there

may be relationship between ambiguity levels across seemingly unrelated events, but this relationship should disappear once controls are introduced for measures of general knowledge (e.g., educational attainment).

15. Substantively identical results are obtained after logging the measures to address the skew, when ordinal logistic regression is used to estimate scores on the sureness measures, and when binary logistic regression is used with binary versions of both the range and sureness measures.
16. For example, consider two respondents whose response styles entail providing symmetrical ranges. If the first individual has a point estimate belief of 10 percent, symmetry would imply that the maximum range this person could provide would be a width of 20, since zero is a necessary boundary. Comparatively, a second individual with a point estimate of 50 percent could conceivably report a range with a width as large as 100.
17. At the request of a reviewer, we reestimated the full models after including a binary indicator for "50 percent" responses. The results were substantively identical. We also examined whether the functional form of the relationship between risk estimates and ambiguity might be either cubic or quartic. As suggested by the reviewer, these models also included a binary indicator for 50 percent responses. The coefficient for the cubic term was not significant in 10 of the 12 respective models, and the coefficient for the quartic term was not significant in 11 of the 12 respective models. In our view, this suggests that, as Brim (1955) has suggested, the functional form of the relationship between ambiguity and risk estimates is quadratic.
18. The assumption is that a completely uninformed individual has a subjective probability distribution with two values—0 percent and 100 percent—that yields a maximally ambiguous risk estimate of 50 percent. Each piece of new information will add a value to that subjective distribution. In most cases, this will reduce its variance and push the risk estimate upward or downward from 50 percent, depending on the direction of the information.
19. The information questions took the following general format but were tailored to each event, "How much information do you have about the risk of getting the flu?" (1 = *a great deal*; 2 = *a good bit*; 3 = *some*; 4 = *very little*; 5 = *none*).
20. With one exception (murder arrest risk), there were no significant differences in perceived information levels between respondents who provided 50 percent responses to the probabilistic questions and those who gave other answers. This finding contrasts the results for ambiguity levels, where ambiguity was correlated with the level of probability. In addition, and contrasting the results for ambiguity levels, there was not a consistent curvilinear relationship between information levels and risk estimates. However, a strong bivariate and multivariate relationship did emerge between perceived information levels for seemingly unrelated

events. These results, in our view, suggest a Bayesian updating process whereby information acquisition affects risk estimates by altering subjective probability distributions likely cannot account for the clustering of high ambiguity values in middle-range risk estimates. They also point to the possibility that individuals' perceptions of how informed they are about different risks may themselves be influenced by some underlying trait, such as self-confidence.

21. We are thankful to an anonymous reviewer for suggesting this interesting line of inquiry for future studies.

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