Perceptions of Health Risks of Cigarette Smoking:
A New Measure Reveals Widespread Misunderstanding

ONLINE APPENDIX
Fig. 1 Proportions of Americans Who Failed to Assert That Smoking Is Dangerous to Human Health: Gallup Organization Surveys

Fig 2 Generalized Additive Models Predicting the Probability of Being a Current Smoker

SRBI Survey (n = 456)

Relative Risk vs. Attributable Risk:

Relative Risk vs. Absolute Risk:
Fig 3 Generalized Additive Models Predicting the Probability of Being a Current Smoker

Harris Interactive Survey \((n = 795)\)

Relative Risk vs. Attributable Risk:

Relative Risk vs. Absolute Risk:
Fig 4 Generalized Additive Models Predicting the Probability of Being a Current Smoker vs. Former Smoker

FFRISP ($n = 471$)

Relative Risk vs. Attributable Risk:

Relative Risk vs. Absolute Risk:
Fig 5  Generalized Additive Models Predicting the Probability of Being a Current Smoker vs. Never Smoker

FFRISP ($n = 714$)

Relative Risk vs. Attributable Risk:

Relative Risk vs. Absolute Risk:
Online Appendix 2

Difficulty of Mathematical Computations

The apparent use of relative risk by Americans to make decisions might seem surprising in light of past research suggesting that many people find even simple mathematical computations to be difficult to implement correctly (e.g., Batanero et al., 1994; Mokros & Russell, 1995; Reyna & Brainerd, 2007; Reyna, Nelson, Han, & Dieckmann, 2009), particularly people with less education (Galesic and Garcia-Retamero, 2010; Reyna & Brainerd, 2007) and the elderly (Galesic et al., 2009a; Reyna & Brainerd, 2007). The present findings might also seem to stand in contrast to evidence that people have more difficulty calculating ratios than they have performing addition (e.g., Anderson, 1974; Anderson & Butzin, 1974; Graesser & Anderson, 1974). Since children are typically taught addition and subtraction before multiplication and division, it might seem that subtraction (entailed in computing attributable risk) is easier than division (entailed in computing relative risk). Would not this discourage people from computing and using relative risk in their judgments and encourage them to use attributable risk instead?

In fact, once children realize that multiplication can be accomplished via repeated addition (4 x 3 = 4 + 4 + 4), they often solve multiplication problems via addition, which can entail many more computational steps but simplifies the reasoning process (see Fishbein et al., 1985, p. 3-4; see also Bell, Swan, & Taylor, 1981). Likewise, dividing 12 by 4 can be accomplished via subtraction (12 – 4 = 8, 8 – 4 = 4, 4 – 4 = 0). So in practice, multiplication and division may be no more difficult for adults than addition and subtraction. It may therefore not be so surprising that people use relative instead of attributable risk to plan their behavior, as both may be equally challenging to compute in practice.

Indeed, far simpler than computing attributable or relative risk would be to use absolute risk to make behavioral decisions. Of course, absolute risk levels alone are uninformative—without knowing the risk of lung cancer among nonsmokers, the risk among smokers does not reveal the dangers that may result from smoking. So although absolute risk is easier to conceive than are relative and attributable risk, it should come as no surprise that people do not seem to use the former to plan their behavior.

Of course, the present investigation provides no direct evidence that people naturally compute such ratios or
use them in their reasoning and behavior planning. But the present findings suggest that people behave as if they compute relative risk and use it when deciding whether to start or continue smoking. In addition to reading news about relative risk, people watch the lives of others unfold and can calculate how many smokers and nonsmokers experienced particular health problems. Some type of computation seems quite plausible. Moreover, research on numeracy has found that visual displays can be used to bridge the divide between people with high and low numeracy skills (Garcia-Retamero and Galesic 2009; Galesic et al. 2009b; Keller & Siegrist, 2009). Therefore, future research illuminating the cognitive processes people execute when generating estimates of relative risks will be useful. Such work might reveal that relative risk perceptions are indeed used more by people with better numeracy skills (see, e.g., Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006).

Measuring Perceived Probabilities

Since Savage (1954) asserted that perceived probabilities can only be observed indirectly (because they are revealed through the decisions people make in choice situations), many other scholars have endorsed this belief (e.g., di Finetti, 1990; Kadane & Winkler, 1988). And much literature has accumulated developing indirect methods for inferring people’s perceptions of probabilities (e.g., Gilboa, 1987; Gill & Walker, 2005; Gonedes & Ijiri, 1974). But other studies have explored a variety of techniques that ask people to report perceived probabilities directly. Some have asked people to report numbers between 0% and 100% (e.g., Galanter, 1962) or to mark a graduated line from 0% to 100% (e.g., Branthwaite, 1974), or more often to use elaborate visual aids, such as bowls filled with colored balls or “probability wheels” (for reviews, see Chesley, 1975; Garthwaite, Kadane, & O'Hagan, 2005). Some studies have asked what is the “percent chance” that particular events will occur (e.g., Dominitz, 1998; Dominitz & Manski, 2004). Some observers, however, have asserted that people cannot reliably generate such reports (see, e.g., Hogarth, 1975). The present evidence suggests that probabilities can be assessed with frequency questions, and these assessments sensibly predict actual behavior, suggesting that this assessment technique has some validity.
Ex-smokers most often say that they quit because they sought improved physical health and longevity (Ahluwalia, Resnicow, & Clark, 1998); Crowe, Torabe, & Nakornkhet, 1994; Dappen, Schwartz, & O'Donnel, 1996; Duncan et al., 1992; Haaga, Gillis, & McDermut, 1993; Halpern & Warner, 1993; Lichtenstein & Cohen, 1990; Schneider, 1984; Swenson & Dalton, 1983). Also, among people who participate in a smoking cessation program, those who initially believe more strongly that smoking causes health problems are most likely to quit successfully (Kaufert et al., 1986; Tipton, 1988; c.f., Klesges et al., 1988). People who try to quit for health reasons are more likely to succeed than those who try for other reasons (Borland, 1997; Curry, Grothaus, & Wagner, 1990; Duncan et al., 1992; Halpern & Warner, 1993; c.f. Rose, Chassin, Presson, & Sherman, 1996). Schnoll et al. (2003) found that among cancer patients, smoking cessation was predicted by smoking-related risk perceptions (c.f., Clark et al., 1998; Norman, Conner & Bell, 1999). Likewise, Kreuter and Strecher (1995) found that smokers who perceived greater personal risk of stroke were more likely to quit six months later.

Other studies also suggest that beliefs about health risks are important instigators of the desire to quit. For example, Dozois, Farrow, and Miser (1995) found that 72% of a sample of current smokers attempted to quit at least once before. The reason given most often was to avoid the undesirable health consequences. Likewise, Stone and Kristeller (1992) found that smoking’s deleterious health effects were the most commonly given reason by smokers for wanting to quit. Curry, Grothaus, and Wagner (1990) found that people who were motivated to quit for health reasons had a greater desire to quit than those motivated by other reasons. Several studies have found a positive correlation between personal health risk perceptions and intentions to quit (Clark et al., 1998; Norman, Conner & Bell, 1999; Weinstein, Marcus & Moser, 2005). Borland (1997) found that people who were more motivated by health concerns were more likely to intend to quit and were more likely to attempt to quit subsequently. And Rose et al. (1996) and Klesges et al. (1988) found that people who believed that smoking has deleterious health consequences were subsequently more likely to attempt to quit (c.f., Ahluwalia, Resnicow, & Clark, 1998; Chassin, Presson, & Sherman, 1984).
Online Appendix 4

Study One: Survey Methodology

The survey was conducted by Schulman, Ronca, and Bucuvalas, Inc. (hereafter SRBI). Random digit dialing (RDD) was conducted from a computer-assisted interviewing facility to a nationally representative sample of American adults. Interviews were conducted between August 24 and October 2, 2000. Up to 10 call-backs were made to “no answer” and “busy” telephone numbers in order to complete interviews. The adult resident of each household (age 18 or older) who either had the most recent birthday or would have a birthday next was selected to be interviewed. A total of 4,473 people were interviewed (AAPOR RR6 = 43.2%). Prior to the beginning of the interviewing, a quota of at least 2,000 interviews with current or former smokers was established.

Respondents were asked warm-up questions and then reported whether they had smoked 5 or more cigarettes during the past 7 days. Those who said “yes” were classified as current smokers. Those who said “no” were asked whether they had smoked 100 cigarettes or more during their entire lives; those who said “yes” were classified as former smokers. Forty-five percent of the 4,473 people interviewed identified themselves as current or former smokers and continued with the interview; non-smokers were asked no more questions.¹

Some of the respondents were randomly chosen to hear and evaluate various anti-smoking messages. Here, we report results generated using only data from the 477 respondents who heard no messages. As shown in the first and third columns of Online Appendix 4, the unweighted² SRBI sample of 477 current and former smokers corresponds closely with the sample of current and former smokers in the 2000 National Health Interview Survey.

¹ Different researchers have defined current and former smokers in different ways (for a review, see Delnevo & Bauer, 2009; http://www.cdc.gov/NCHS/datawh/nchdefs/cigarettesmoking.htm; accessed February 13, 2008). Since 1993, the National Health Interview Survey (NHIS) has defined former smokers as people who had smoked at least 100 cigarettes in his or her lifetimes but did not smoke now, and defined current smokers as people who smoked every day or some days at the time of an interview. Cummings et al. (2004) defined smokers as people who had smoked at least 100 cigarettes and smoked daily or on some days. Weinstein et al. (2004) defined smokers as people who had smoked at least once during the last 30 days and at least 100 cigarettes over the course of their lifetimes. Ayanian and Cleary (1999) defined a smoker as someone who smoked every day. Strecher, Kreuter, and Kobrin (1995) identified smokers as people who smoked at least one cigarette during the past 7 days. Thus, there is no single agreed-upon definition of current and former smokers. Our definition of former smokers matches that of the NHIS and those of Weinstein et al. (2004) and Cummings et al. (2004). Our definition of current smokers is narrower than those of the NHIS and Weinstein et al. (2004) but broader than those of Cummings et al. (2004), Ayanian and Cleary (1999), and Strecher, Kreuter, and Kobrin (1995).

² By “unweighted,” we mean that the data were weighted using the number of telephone lines that can reach the home and the number of adults living in the household to adjust for unequal probability of selection, but no post-stratification was done.
in terms of gender, age, ethnicity, and education, though low- and high-education individuals were under-represented, and moderately-educated individuals were over-represented. Applying post-stratification weights constructed using these demographic variables made the distributions conform more closely to the NHIS (see column 4, which shows the difference between columns 2 and 3).4

Study Two: Survey Methodology

To assess the robustness of the SRBI survey’s findings, we asked some of the same questions in a survey of a non-representative sample of current and former smokers who volunteered to complete Internet surveys in exchange for points that could be exchanged for gifts. Adult respondents were randomly selected from the Harris Interactive Internet panel (HPOL) within strata defined by sex, age, region of residence, and ethnicity. Probabilities of selection within strata were determined by probability of response (as determined by prior surveys of these groups), so the distributions of the demographics in the final sample of respondents would approximate those in the general U.S. adult population. Each panel member received an email invitation describing survey content and including a link to the survey questionnaire. Respondents received a unique password and could access the survey once. Between March 16 and April 17, 2006, 16,392 participants in the HPOL database were invited to participate, and 7,847 did so (completion rate = 48%).

Respondents were asked same questions as in the SRBI survey to ascertain smoking status, and 3,967 identified themselves as current or former smokers. Some respondents were randomly chosen to read and evaluate anti-smoking messages; our focus here is on the 801 respondents who read no messages. We again constructed

---

3 The NHIS is a multi-purpose health survey conducted by the National Center for Health Statistics (NCHS), a division of the Centers for Disease Control and Prevention (CDC), and serves as the principal source of information about health in the United States (see http://www.cdc.gov/nchs/nhis.htm for more information). The U.S. Census Bureau has been the data collection agent for the NHIS, and data has been collected continuously since 1957. The NHIS is a cross-sectional household interview survey, with data collection occurring through a personal household interview by Census interviewers, and the sampling plan follows a stratified multistage probability design that permits the representative sampling of households and non-institutional group quarters (e.g., college dormitories). Both the black and Hispanic populations are oversampled. Final weights were provided to be able to adjust estimates to be nationally representative. The total household response rate of the 2000 NHIS was 88.9 percent, resulting in 32,374 adult respondents. The total household response rate of the 2006 NHIS was 87.3 percent, resulting in 24,275 adults respondents.

4 All analyses described below weighted the data by probability of selection and implemented post-stratification. Post-stratification weights were constructed according to best practices outlined by the American National Election Studies (ANES) (DeBell & Krosnick 2009).
post-stratification weights based on sex, age, ethnicity, and education (see columns 5-8 in Online Appendix 4 for unweighted vs. weighted demographics of the survey sample and those of a representative sample of current and former smokers from the 2006 NHIS).\(^5\)

**Study Three: Survey Methodology**

Our last study explored these same issues by administering the same measures to a nationally representative sample of current and former smokers and people who had never smoked via the Face-to-Face Recruited Internet Survey Platform (FFRISP). All FFRISP respondents were recruited via face-to-face area probability sampling and were given a free laptop computer (or equivalent value in cash), high-speed Internet access at home (if they did not have it already), and regular cash payments in exchange for completing monthly questionnaires for a year.

The FFRISP began with 1,000 panelists who were recruited between June and October, 2008. The smoking measures were administered during the fourth wave of data collection, initiated in January, 2009. The response rate for panel enrollment was 46\% (AAPOR RR4); 973 individuals completed the fourth-wave questionnaire, yielding a 45\% cumulative response rate. Weights were computed to adjust for unequal probability of selection and to post-stratify with demographics. As the last four columns in Online Appendix 4 show, the FFRISP respondents closely resembled the American population before post-stratification and were even more similar after post-stratification.

Using the same questions as had been used in Studies 1 and 2, we found that 235 of the 973 respondents were current smokers, 222 were former smokers, and 516 had never smoked.

To test for question order effects, each respondent was randomly assigned to be asked the question about nonsmokers first or to be asked the question about smokers first. The two groups of respondents did not differ significantly from one another in terms of their answers to these questions (p=.69 and .62, respectively), indicating

---

\(^5\) Even after applying capped post-stratification weights, the Harris sample of current and former smokers substantially under-represented people who had not graduated from high school. Therefore, when conducting the GAMs, we estimated a set of models controlling for education and obtained results similar to those reported in the text (see Gelman, 2007, for an argument about why this method is suitable for controlling for sample discrepancies).
that question order had no impact on answers to these questions. Despite the lack of a significant difference, a dummy variable for question order was included in all regressions.
Online Appendix 5: Demographics of Current and Former Smokers in the SRBI Survey, Current and Former Smokers in the Harris Interactive Survey, all individuals in the FFRISP survey, and the Nation’s Population

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>47.4%</td>
<td>50.0%</td>
<td>50.1%</td>
<td>-0.1%</td>
<td>47.1%</td>
<td>52.7%</td>
<td>52.6%</td>
<td>0.1%</td>
<td>41.9%</td>
<td>47.9%</td>
<td>48.5%</td>
<td>-0.6%</td>
</tr>
<tr>
<td>Female</td>
<td>52.6%</td>
<td>50.0%</td>
<td>49.9%</td>
<td>1.1</td>
<td>52.9%</td>
<td>47.3%</td>
<td>47.4%</td>
<td>-0.1%</td>
<td>58.1%</td>
<td>52.1%</td>
<td>51.5%</td>
<td>0.6</td>
</tr>
<tr>
<td>Total 1%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
</tr>
<tr>
<td>Total N</td>
<td>477</td>
<td>477</td>
<td>54,466</td>
<td></td>
<td>801</td>
<td>801</td>
<td>10,020</td>
<td>968</td>
<td>966</td>
<td>207,921</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤25</td>
<td>12.5%</td>
<td>13.3%</td>
<td>13.3%</td>
<td>0.0%</td>
<td>3.8%</td>
<td>8.3%</td>
<td>10.0%</td>
<td>-1.7%</td>
<td>9.7%</td>
<td>10.4%</td>
<td>12.6%</td>
<td>-2.2%</td>
</tr>
<tr>
<td>26-35</td>
<td>18.2%</td>
<td>17.9%</td>
<td>17.9%</td>
<td>0.0%</td>
<td>12.5%</td>
<td>14.6%</td>
<td>14.3%</td>
<td>0.3%</td>
<td>20.2%</td>
<td>16.7%</td>
<td>17.9%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>36-45</td>
<td>19.3%</td>
<td>22.7%</td>
<td>22.7%</td>
<td>0.0%</td>
<td>15.1%</td>
<td>16.2%</td>
<td>17.3%</td>
<td>-1.1%</td>
<td>19.7%</td>
<td>16.5%</td>
<td>18.2%</td>
<td>-1.7%</td>
</tr>
<tr>
<td>46-55</td>
<td>22.2%</td>
<td>19.2%</td>
<td>19.2%</td>
<td>0.0%</td>
<td>27.8%</td>
<td>21.9%</td>
<td>21.3%</td>
<td>0.5%</td>
<td>19.2%</td>
<td>18.9%</td>
<td>19.5%</td>
<td>-0.6%</td>
</tr>
<tr>
<td>56-65</td>
<td>1.4%</td>
<td>12.6%</td>
<td>12.6%</td>
<td>0.0%</td>
<td>19.0%</td>
<td>18.6%</td>
<td>17.9%</td>
<td>0.6%</td>
<td>11.3%</td>
<td>14.3%</td>
<td>15.1%</td>
<td>-0.8%</td>
</tr>
<tr>
<td>66+</td>
<td>17.3%</td>
<td>14.3%</td>
<td>14.3%</td>
<td>0.0%</td>
<td>21.9%</td>
<td>20.5%</td>
<td>19.1%</td>
<td>1.4%</td>
<td>20.0%</td>
<td>23.2%</td>
<td>16.6%</td>
<td>6.6</td>
</tr>
<tr>
<td>Total 1%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
</tr>
<tr>
<td>Total N</td>
<td>477</td>
<td>477</td>
<td>54,466</td>
<td></td>
<td>801</td>
<td>801</td>
<td>10,020</td>
<td>966</td>
<td>966</td>
<td>207,921</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ethnicity a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White (incl. Hispanic)</td>
<td>82.9%</td>
<td>80.2%</td>
<td>81.4%</td>
<td>-1.2%</td>
<td>76.9%</td>
<td>79.1%</td>
<td>86.7%</td>
<td>-</td>
<td>79.3%</td>
<td>80.7%</td>
<td>82.4%</td>
<td>-1.7%</td>
</tr>
<tr>
<td>Non-white (incl. Hispanic)</td>
<td>17.5%</td>
<td>19.8%</td>
<td>18.6%</td>
<td>1.2</td>
<td>14.9</td>
<td>12.1</td>
<td>13.3</td>
<td>-</td>
<td>20.7</td>
<td>19.3</td>
<td>18.6</td>
<td>0.7</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td>8.2%</td>
<td>8.8%</td>
<td>-</td>
<td>-</td>
<td>13.3%</td>
<td>9.7%</td>
<td>13.7%</td>
<td>1</td>
</tr>
<tr>
<td>Total 1%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
</tr>
<tr>
<td>Total N</td>
<td>477</td>
<td>477</td>
<td>54,466</td>
<td></td>
<td>801</td>
<td>801</td>
<td>10,020</td>
<td>974</td>
<td>974</td>
<td>207,921</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Did not graduate from high school</td>
<td>8.2%</td>
<td>18.2%</td>
<td>18.4%</td>
<td>-0.3%</td>
<td>.3%</td>
<td>1.3%</td>
<td>18.6%</td>
<td>-17.3%</td>
<td>8.3%</td>
<td>11.9%</td>
<td>14.1%</td>
<td>-2.2%</td>
</tr>
<tr>
<td>High school graduate</td>
<td>33.5%</td>
<td>32.9%</td>
<td>32.8%</td>
<td>.1</td>
<td>22.4</td>
<td>40.1</td>
<td>32.8</td>
<td>7.3</td>
<td>24.6</td>
<td>30.9</td>
<td>30.9</td>
<td>0.0</td>
</tr>
<tr>
<td>Some college (incl. Assoc. deg.)</td>
<td>31.4%</td>
<td>24.7%</td>
<td>24.6%</td>
<td>.1</td>
<td>45.9</td>
<td>32.3</td>
<td>26.7</td>
<td>5.6</td>
<td>38.3</td>
<td>30.9</td>
<td>28.0</td>
<td>2.9</td>
</tr>
<tr>
<td>Bachelor's degree</td>
<td>16.3%</td>
<td>17.1%</td>
<td>17.1%</td>
<td>.1</td>
<td>19.3</td>
<td>18.7</td>
<td>15.5</td>
<td>3.1</td>
<td>17.2</td>
<td>15.3</td>
<td>17.7</td>
<td>-2.4</td>
</tr>
<tr>
<td>Graduate School</td>
<td>1.6%</td>
<td>7.1%</td>
<td>7.1%</td>
<td>.0</td>
<td>12.1</td>
<td>7.7</td>
<td>6.4</td>
<td>1.3</td>
<td>11.5</td>
<td>11.0</td>
<td>9.3</td>
<td>2.7</td>
</tr>
<tr>
<td>Total 1%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td></td>
</tr>
<tr>
<td>Total N</td>
<td>477</td>
<td>477</td>
<td>52,005</td>
<td></td>
<td>801</td>
<td>801</td>
<td>9,891</td>
<td>971</td>
<td>970</td>
<td>207,921</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1. Ethnicity was measured differently in the Harris and NHIS studies, precluding direct comparability. Nevertheless, even the unweighted percentages of non-whites closely approximated the NHIS sample.
Online Appendix 6

GAMs

A GAM is similar to a logistic regression, but the former does not assume a linear relation between risk perceptions and quitting. Instead, quitting is predicted by an additive model including several non-parametric functions (for technical details, see Hastie & Tibshirani, 1990). Estimating a logistic GAM is preferred to standard parametric regression techniques because relaxing the assumption of linearity prevents model misspecification. Inspection of the raw data revealed nonlinear relations of relative, attributable, and absolute risks with quitting. Because mis-specifying a model by imposing linearity can substantially distort inferences, especially when two variables are highly correlated, the flexibility and weak assumptions of the GAM are preferable. In the SRBI data, the distribution of relative risk was substantially skewed (skewness=6.40), whereas the distributions of attributable risk (skewness = .59) and absolute risk (skewness = .06) were not, so relative risk was logged for the analyses. The GAM results reported here were generated without including any demographic controls. When we re-estimated the GAM parameters controlling for demographics, the results obtained were comparable to those reported in the text.
There may be an illusion hidden in these results, as suggested by the work of Fischhoff and his colleagues (Bruine de Bruin, Fischhoff, Millstein, & Halpern-Felsher, 2000; Fischhoff & Bruine de Bruin, 1999), who argued that when people are asked to report a probability but do not know the answer, they sometimes answer “50,” meaning “fifty-fifty” or “unknown,” rather than meaning a 50% chance. To explore the impact of this potential source of measurement error on our conclusions, we re-estimated the logistic GAM after dropping the respondents who answered “500” to the question about nonsmokers or to the question about smokers. After sub-setting the data in this manner, the resulting parameter estimates supported the same conclusions even more strongly.

When comparing relative risk to attributable risk, the increase in the probability of quitting from moving across the interquartile range of relative risk was 16.2%. In contrast, moving across the interquartile range of attributable risk increased the probability of quitting by only 2.4%. Adding relative risk to a model predicting quitting with attributable risk significantly improved fit (p=.007). But adding attributable risk to a model predicting quitting with relative risk again failed to significantly improve fit (p=.45). Adding relative risk to a model with only absolute risk improved fit significantly (p=.001), whereas adding absolute risk to a model with only relative risk had no significant impact on fit (p=.17). Movement across the interquartile range of relative risk in this analysis produced an increase in the probability of quitting of 18.9%; movement across the same range for absolute risk decreased the probability of quitting by 8.8%.

Another way to handle the respondents who answered “500” to questions about nonsmokers or smokers would be to impute values for these respondents via multiple imputation generated using iterative predictive models (Rubin, 1987; Schafer, 1997; Schafer & Olsen, 1998). We did so using all available survey variables as predictors, including general perceptions of the quality of health care that most Americans received, how good a job President Clinton was doing to handle health care in the country, current smoking status, other measures of beliefs about smoking and lung cancer, the extent of regret and negative feelings due to smoking, race, age, and education. Data
augmentation was conducted with 50 iterations (k=50) to generate 5 imputations (m=5). Because the highest proportion of missing values was 23%, efficiency of estimates based on 5 imputations was 95.6% (Rubin, 1987). We averaged the values obtained by the imputations to yield a set of replacements for the 500s that respondents reported.

When we re-estimated the logistic GAMs with the imputed data, the results were similar to those reported above. Adding relative risk as a predictor to a model predicting quitting with attributable risk significantly improved fit (p=.008). Adding attributable risk as a predictor to a model predicting quitting with relative risk again did not improve fit significantly (p=.55). In a model predicting quitting with relative and attributable risk, movement across the interquartile range of relative risk was associated with a 12.7% increase in the probability of quitting. Movement across the interquartile range of attributable risk produced a 1.3% decrease in likelihood of quitting.

Adding relative risk to a model with only absolute risk again improved model fit significantly (p=.001). The addition of absolute risk to a model with relative risk did not significantly improve the fit (p=.32). As expected, movement across the interquartile range of relative risk was associated with a 14.5% increase in the probability of quitting, whereas movement across the interquartile range of absolute risk produced a 3.0% decrease in the likelihood of quitting.

Last, we dropped the respondents who gave a rating of 500, and used these respondents’ imputed values instead of their 500s (see columns 3 and 4 of each table). Dropping the 500s or imputing the values did not change the summary statistics substantially and did not support different conclusions about the prevalence of overestimation and underestimation of risk. Likewise, in Study Two, dropping respondents who answered “500” to either survey question produced comparable results.

In Study Three, the respondents who said that 500 of the 1000 smokers would get lung cancer (14.3%) or that 500 of the 1000 nonsmokers would get lung cancer (3.9%) were asked: “Did you type 500 because you don’t know, or because you think about half of the 1,000 people would get lung cancer?” People who said “don’t know” (5.4% for smokers and 1.9% for nonsmokers) were asked, “If you had to guess, about how many of those 1,000
people do you think would get lung cancer sometime during their lives?” When a person’s response to this follow-up differed from his or her original answer, the second response replaced the initial answer for our analyses. Because we asked these follow-up questions, there was no need to drop or impute people who selected “500” for Study 3.
References for Online Appendices


Klesges, R. C., Somes, G., Pascale, R. W., Klesges, L. M., Murphy, M., Brown, K., & Williams, E. (1988). Knowledge and beliefs regarding the consequences of cigarette smoking and their relationships to smoking status in a biracial sample. *Health Psychology, 7*, 387-401.


