Flu Shots, Mammograms, and the Perception of Probabilities

Katherine Grace Carman*
Peter Kooreman*

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Abstract

We study individuals' decisions to decline or accept preventive health care interventions such as flu shots and mammograms. In particular, we analyze the role of perceptions of the effectiveness of the intervention, by eliciting individuals' subjective probabilities of sickness and survival, with and without the interventions. Respondents appear to be aware of some of the qualitative relationships between risk factors and probabilities. However, on average they have very poor perceptions of the absolute probability levels as reported in the epidemiological literature. Perceptions are less accurate if a respondent is female and has no college degree. Perceived probabilities significantly affect the subsequent take-up rate of flu shots and mammograms.

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*k.g.carman@uvt.nl (corresponding author), p.kooreman@uvt.nl. Department of Economics Tilburg University, Tilburg, The Netherlands. We thank Joe Aldy, Orley Ashenfelter, Floriaan van Bemmelen, Wändi Bruine de Bruin, Wendy Carman, Eline van der Heijden, Arie Kapteyn, Emmett Keeler, Charles Manski, Miquelle Marchand, Angela Neijmeijer-Leloux, Johan Polder, David Ribar, Annette Scherpenzeel, Arthur van Soest, and Corrie Vis, as well as seminar and conference participants for helpful comments. This paper draws on data of the LISS panel of CentERdata. CentER and Netspar provided financial support for the data collection. Supporting materials, including a translation in English of the survey in Dutch, are available from the authors.

1. Introduction

Preventive health care is at the heart of many suggested reforms to control costs and improve the efficiency of health care. While preventive care obviously cannot eliminate death, it can help to extend life and avoid or delay the occurrence of diseases. Making decisions about using preventive care, however, can be very difficult. Individuals typically know little about the magnitude of the risk that they face and about the potential benefits of preventive care.

This paper examines the choices that people make about using preventive care, focusing on individuals' perceptions of probabilities of disease and death and of the effectiveness of interventions. The risk that an individual perceives can be broken down into two components: true risk and bias. While unobserved risk factors prevent separating these two components, our data permit us to address the following three questions. First we compare perceptions of risk to individually predicted risk based on epidemiological models. While the epidemiological models do not represent true risk for all individuals, they are an objective measure of risk and if averaged across individuals should be close proxies to the average true risk. Second we investigate whether individuals risk perceptions are influenced by their risk factors. Do individuals whose risk factors indicate higher risk, such as high blood pressure or diabetes, report higher subjective probabilities? Finally we consider the effect of risk perceptions on the use of preventive care. Individuals who perceive greater risk are expected to be more likely to use preventive care.

Careful consideration of risk factors and epidemiologically predicted risk is important to understanding behavior. While, economists have acknowledged the importance of risk perceptions, many continue to consider externally estimated probabilities rather than subjective probabilities. Our paper is unique in that we consider both. This allows us to address which are better predictors of behavior.

There are several key differences between the previous literature and the present paper. First, we measure individuals' perceptions of risk in the form of subjective, numerical probabilities. Numerical probabilities not only have more predictive power than more qualitative expectations data (Juster, 1966), but also allow better evaluation of the internal consistency and external validity of responses. Second, while the previous literature has primarily focused on a single intervention, we consider multiple preventive care measures for each individual. This allows us to analyze behavioral differences across preventive interventions. Third, we compare the effects of subjective and individually predicted epidemiological risks on behavior, for a general population sample that is not limited to the elderly population. Fourth, we explore several survey methods of eliciting subjective estimates of risk.

We find that a majority of respondents answer probability questions in a way consistent with basic probability concepts. Moreover, they appear to be aware of some of the qualitative relationships between risk factors and probabilities. However, on average, they have very poor perceptions of the absolute probability levels as reported in the epidemiological literature. Perceptions are less accurate if a respondent is female and has no college degree and the accuracy of perceptions deteriorates after age 50. Nevertheless, perceived probabilities strongly affect the subsequent take-up rate of flu shots, mammograms, Pap smears, sexually transmitted disease testing, and aspirin for the prevention of heart disease. Our results indicate that probability perceptions are key to understanding behavior regarding preventive care and designing effective preventive health care programs.

The paper proceeds as follows. Section 2 discusses literature on preventive health care and subjective probabilities. Section 3 describes the institutional details of preventive care programs in the Netherlands. Our survey and data collection are described in section 4. Section 5 considers the epidemiological literature on the relevant probabilities of disease and death. Section 6 presents our empirical results and section 7 concludes.

2. Preventive Health Care and Subjective Probabilities

From an economic perspective the decision to take up preventive care is an investment decision. Loosely speaking, such an investment is worthwhile if the expected present value of the reduction in illness and the probability of death is greater than the opportunity costs of the intervention; see, Grossman (1972), Cropper (1977), Hey and Patel (1983), Dardanoni and Wagstaff (1987 and 1990), Selden (1993), Chang (1996), and Byrne and Thompson (2001) for formalizations of these notions.

Whether people ultimately decide to invest in preventive care is largely an empirical matter. We mention a selection from the large empirical literature. Kenkel (1994) finds that the probability that women will have mammograms and Pap smears increases with schooling and insurance coverage and decreases with age. Mullahy (1999) finds that schooling and insurance coverage are important determinants of getting a flu shot. The interpretation of the effects of insurance coverage may reflect price effects, access to health care in general, or some 'adverse' selection (people with a high demand for health care are more likely to have insurance). Wu (2003) finds that self reported health, fear, and expectations for the future influence the use of preventive care. Belkar et al. (2006) suggest that awareness plays a key role in determining who uses preventive care and that failing to account for this awareness can influence the measurement of other effects. Trivedi et al. (2008) find that co-pays also play an important role. Insurance companies that introduce co-pays for mammograms see decreases in the percentage of women participating in these interventions.

Central in any analysis of preventive health care are the probabilities of illness and death and the effectiveness of prevention. Typically, these parameters are assumed to be known by the individual. However, individuals' perceptions of the risks they face may differ widely from the true underlying risks and thus perceptions are likely to be better predictors of individual behavior.

We measure perceptions using subjective probabilities. The measurement of subjective probabilities in economics was first proposed by Juster (1966). The standard question takes the form: "What is the percent chance that you will choose X" or that "X will happen". Juster shows the superior informational content of such probabilities over qualitative response scales (like "very likely", "probable", "rarely") when trying to predict consumer choice. Since the early 1990s, such subjective probabilities have become an integral part of major household surveys around the world. Their validity and predictive power has been shown in a wide range of contexts, including retirement behavior (Hurd and McGarry, 1995), bequests (Hurd and Smith, 2002), income expectations (Dominitz and Manski, 1997), contraceptive choice (Delavande, 2008), individual survival (Hurd and McGarry, 2002 and Gan, Hurd and McFadden, 2003), health risks of smoking (Khwaja, Silverman and Sloan, 2009), and life events of adolescents (Bruine de Bruin et al., 2007).

The existing literature that examines the relationship between risk perception and the use of preventive care has typically used qualitative risk perceptions and samples of limited size. Salant et al. (2006), for example, find that

33 women who are objectively assessed to be at high risk for breast cancer are unlikely to feel that they are at high risk and are skeptical of the effectiveness of prevention. Lipkus et al. (2000) find that information on both absolute risk and relative risks are necessary to encourage participation in prevention. Satterfield et al. (2000) consider the relationship between perceived risks and behaviors in the case of osteoporosis. They find that people who are more informed about recommendations regarding various preventive behaviors are more likely to follow those recommendations. They also asked about risk using categorical responses but did not relate that to behavior. Finally, Peters et al. (2006a) examine the relationship between worry, risk perceptions, and intentions to reduce medical errors in a small convenience sample. They find that worry matters more than risk perceptions, but focus on intentions to act (not on actual behavior) and use categorical representations of risk (not numerical subjective probabilities).

Our paper differs from these in several important ways. First, we use numerical subjective probabilities. Second, we relate these subjective probabilities to objective probabilities predicted by epidemiological models. Third, our sample size, 5,686, is significantly larger than previous studies. Fourth, each individual is asked about multiple preventive care interventions.

3. The Dutch Flu Shot and Mammogram Program

The Netherlands has mandatory health insurance for all residents. Each person is required to purchase a basic health insurance package from a private insurance company.[1] Individuals have the opportunity to change insurance companies at the beginning of each year, which discourages insurance companies from investing in prevention. While the minimum contents of the basic health insurance package are mandated by law, preventive care programs are currently not included. It is possible to buy supplementary insurance that covers additional services not covered by the basic insurance package.

Instead, the Dutch government funds some preventive care through the National Institute of Public Health and the Environment (RIVM). Preventive care, in the case of cancer screening can be expected to have benefits long after a one-year insurance contract ends and, in the case of influenza vaccines, has significant public health benefits. This paper considers three of the most important preventive care measures available through the RIVM to adults in the Netherlands: flu shots, mammograms and Pap smears.[2]

First, the RIVM provides influenza vaccines for everyone over the age of 60 (65 before 2008) and to certain high risk groups. In a typical year, roughly 5 to 20 percent of the population can be expected to catch influenza (or the flu).[3] For most people symptoms last 1 to 2 weeks. However for the elderly (ages 60 and up) and at risk populations, such as those with heart disease, pulmonary problems, or diabetes, influenza can lead to death. Mortality due to influenza for the elderly is approximately 130 per 100,000 people, 100 times mortality due to influenza for adults under the age of 50; see Thompson et al. (2003). Each year influenza vaccines are developed to

[1] Basic insurance is subsidized for low income households and insurance companies must accept all applicants.
[2] Other common preventive care measures, such as colonoscopies and Prostate-Specific Antigen (PSA) tests are not currently provided on a systematic basis either through the basic insurance packages or through the RIVM.
[3] By flu, we mean actual flu or influenza, not a cold or stomach flu. Symptoms of influenza include rapid onset, aching muscles all over the body, a high temperature and usually a pounding headache.

prevent the strains of influenza expected to be most likely in the coming year. Through the RIVM's program, general practitioners send letters in the fall to all of their patients who are eligible for these free flu shots inviting them to come in for their flu shot. Outside of this age range people can still receive a flu shot from their doctor. In this case the out-of-pocket price will depend on their specific health insurance package.

Second, to increase the chances of identifying breast cancer at an early stage, the RIVM provides mammograms to women between the ages 50 and 75. One in ten Dutch women will get breast cancer at some point in their life. Important risk factors for breast cancer include current age, age that menstruation began, age of first live birth, the number of relatives who had breast cancer, and the number of past breast biopsies. Annual mammograms can reduce the probability of death from breast cancer by 15 percent; see Gotzsche and Nielsen (2006). The RIVM funds mammograms every two years for women between the ages of 50 and 75, which leads to a slightly lower decrease in the probability of death. Women receive a letter from the RIVM directly inviting them to have a mammogram. Women outside of this age group may still receive mammograms, but the out-of-pocket price will depend on their specific insurance package.

We also consider Pap smears which are provided every five years to women between the ages of 30 and 60. According to a recent article in the New England Journal of Medicine,[4] Pap smears are one of the most effective preventive care interventions available. Annual Pap smears can reduce cervical cancer mortality by at least 94%. Early detection of benign abnormalities can even prevent cells from becoming cancerous. In the Netherlands, Pap smears are given once every five years. At this frequency, mortality can be reduced by 83%. As with mammograms, women receive a letter from the RIVM directly inviting them to schedule an appointment for a free Pap smear with their general practitioner. In the case of Pap smears, women may be able to receive Pap smears more often or before reaching age 30; the price will depend on their insurance.

In addition to these three publicly funded prevention programs, we consider two other preventive care measures. These provide an interesting contrast to the government funded programs because of the different incentives for individuals to use them, including the fact that they may not need to see a doctor.[5] The first is daily low dose aspirin for the prevention of cardiovascular disease. Low dose aspirin has been shown to promote both the primary and secondary prevention of cardiovascular disease, preventing both the development of cardiovascular disease and negative outcomes such as heart attacks and strokes. Second, we consider screening for sexually transmitted diseases (STD) among individuals under the age of 40. In some larger cities, young adults received invitations for STD screening, although receipt of these invitations is less systematic in the case of flu shots, mammograms and Pap smears. These preventive care interventions provide three intervention opportunities for men and five for women.

[4] Sawaya et al. (2001).

[5] It is recommended that people begin daily low dose aspirin after speaking with their doctor, however given the prominence of this intervention in the media; it is possible that some people would choose to begin such therapy on their own.

4. The Survey

Our primary data source is the LISS Panel, a random representative sample of Dutch individuals who participate in monthly Internet surveys.[6] It contains information on a large variety of domains including demographics, housing, work and time use, happiness and health, and financial decisions. The LISS Panel has two important advantages that make it particularly valuable for this research. First, it is possible to randomize the content and format of questions, for example to compare the effects of different wordings of questions. Second, it is possible to follow up with the same participants at a later date.

The largest part of the data used in this paper was collected in September 2008. Panel members were asked additional questions in January 2009. In the initial survey, respondents were asked a series of questions mainly on past take up of flu shots, mammograms, Pap smears, use of aspirin, and sexually transmitted disease screening, and various related perceived probabilities. The text of the subjective probability questions is available in Appendix Table 1. All respondents receive questions about influenza and heart disease. Only women receive questions about mammograms and Pap smears. Questions about sexually transmitted diseases are only asked to those under 40. Previous research on the elicitation of subjective probabilities shows that survey modes can affect responses; see e.g. Woloshin et al. (2000). We therefore use three different survey modes, randomly assigned to respondents: an open-ended probability question, (with a number between 0 and 100 to be typed in), a linear probability scale (with a number between 0 and 100 to be selected using the mouse) or the linear probability scale with magnifier (magnifying a part of the scale around the cursor location). The second two response modes use a visual scale on the screen allowing respondents to select their answer on a number line. With the magnifier, respondents see a number line similar to the linear scale, but when they click on the line with their mouse they see a magnified section allowing them to choose a number with more precision. These three response modes result in similar mean response across questions, however the visual scales reduce the use of focal responses such as 0, 50 and 100 and the use of multiples of 10 in general. These scales do not significantly change our results and are discussed in more detail in a companion paper: Bruine de Bruin and Carman (2010). Following the Survey of Economic Expectations, we introduce the subjective probability questions with a brief description of probabilities; see Manski (2004).[7]

In addition, individuals' numeracy and 'probability literacy' were assessed following Peters et al. (2006b). Individuals were randomly assigned to receive this numeracy assessment at the beginning or the end of the survey. In addition, we asked individuals who had had flu shots, mammograms or Pap smears about their monetary and time costs related to the use of prevention. For those who did not participate, we asked about their expected monetary and time costs. Monetary costs included both the cost of the intervention and any travel costs. We also asked a number of questions that might provide information about people's motivations for participating or not participating in preventive care. Individuals were asked whether someone they knew well had died of influenza or breast cancer. This question was intended to identify whether personal experience with a disease increases an individual's perception of their risk or their likelihood of participation. In January 2009 respondents were approached again, and

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[6] Those who do not have access to the internet are provided with a simple, easy to use computer (a SimPC) and internet access.

[7] The text of the subjective probability questions is included in Appendix Table 1. The full survey is available from lissdata.nl. The survey is labeled 33 Disease Prevention.

asked whether they had received a flu shot in October 2008 or thereafter. Both in September and January, individuals were asked to consider actual influenza, as defined in footnote 3.

Table 1 reports a number of descriptive statistics, including basic demographics, use of care, and expected costs and time to use care. Almost one quarter of respondents received a flu shot in the preceding year, nearly 40% of women have had a mammogram in the past two years, and 60% have had a Pap smear in the past 5 years. Participation rates are even higher among age groups that are targeted to receive these interventions.

5. **Epidemiological Measures of Health Risks**

Using epidemiological results we imputed each respondent's individual risk of developing various diseases and of dying from those diseases based on their own reported risk factors. For many diseases, including breast cancer and heart disease, there are risk prediction calculators based on epidemiological research available on the internet. Individuals can answer questions about their risk factors and receive predictions about their risk of developing various diseases; see http://www.yourdiseaserisk.com for an example. While these online calculators often only provide relative risk information in qualitative terms, such as "well below average", "below average", "average", "above average", "well above average" risk, there is a statistical model behind these calculators that can be used to calculate a numerical risk level.

Perhaps the most famous risk calculator is the Framingham Risk Assessment tool,[8] which can be used to calculate your risk of developing heart disease. This model was developed using the Framingham Heart Study data. This study empanelled much of the population of Framingham, Massachusetts and has followed this population and their offspring for over 50 years. Using this data, it was possible to identify risk factors that were correlated with the five year probability of developing heart disease.[9] The Framingham Risk Assessment tool calculates individual risk as a function of age, gender, blood pressure, total cholesterol, and whether the individual is a smoker.

Another famous risk calculator is the Gail Model (Gail et al., 1989), which can be used to calculate a woman's risk of developing breast cancer. This model used the Breast Cancer Detection Demonstration Project to identify risk factors that predict the probability of developing breast cancer in the next five years. Important risk factors for breast cancer include current age, age that menstruation began, age of first live birth, the number of relatives who had breast cancer, and the number of past breast biopsies. Given an individual's underlying risk for developing breast cancer, we can also calculate the individual's probability of dying from breast cancer in the next five, ten or twenty years, with and without annual mammograms. This is a function of the individual's risk of developing the disease and the age specific survival probabilities. Age specific survival rates from the Surveillance Epidemiology and End Results (SEER) database were used. The Gail Model was developed using a population who received annual mammograms. Annual mammograms have been found to cut the risk of death by 15 percent; see Gotzsche and Nielsen (2006). The Gail Model has been validated numerous times, both in the US and Europe, and has been shown to be a good predictor of risk; see, for example, Rockhill et al. (2001), Decarli et al. (2006), and Thomsen et al. (2002). We choose this model because of its prominence and because most risk factors could be

[8] Wilson et al. (1998)
[9] Ten year probabilities are roughly equivalent to two times the five year probability.

identified in our survey data. Other risk factors, such as breast density or genetic markers (such as BCR1 and BCR2), may be important predictors of risk but few women would be able to accurately report information on these factors in survey data.

For influenza, the epidemiological literature calculating the risk of influenza and death from influenza is less precise. The primary problem is that it is very difficult to measure influenza rates in the population. Many people who report having the flu, actually have a cold or a stomach virus and not influenza, and many people who have influenza never report it to doctors. Influenza can be detected with blood tests or using nasal specimens. We were unable to find a study that calculates influenza risk as a function of any risk factors. However, we were able to find the average mortality rate by age groups due to influenza for the 1990-1991 through 1998-1999 seasons. We use this measure as the probability of dying from the flu. Because of the difficulties associated with identifying influenza, and because many influenza related deaths can be reported to be due to other co-morbidities, there are three measures of the influenza death rate. The first and most conservative measure counts only laboratory confirmed influenza deaths. The second measure adds deaths attributed to respiratory and circulatory problems that are influenza related. The third and most liberal measure includes all causes of death that can be attributed to influenza. Table 2 shows the annual mortality rates by age used for our predicted risk of death as calculated by Thompson et al. (2003). Mortality rates increase dramatically with age, for both the liberal and the conservative estimates; individuals over the age of 65 are one hundred times more likely to die from influenza than individuals between the ages of 5 and 49. Of course, the actual risks associated with influenza evolve as a smooth function of age.

The most liberal estimates of the death rate from influenza have been used historically by many studies. However, these results are based on increases in all causes of death for people who have influenza. If a person who has influenza or has recently had influenza dies in a car accident this could be counted as an all-cause influenza related death. The most conservative estimates underestimate the mortality rate due to influenza, since influenza is more fatal for people who have co-morbidities such as respiratory or circulatory health problems and the cause of these deaths may be reported as respiratory. Therefore the moderate estimate of the death rate is our preferred estimate.

Similar epidemiological models for cervical cancer and STDs are not available. In particular, it is important that risk factors can be easily measured in a survey. Both cervical cancer risk and STD risks are highly dependent on detailed information about sexual behaviors, such as number of partners and use of condoms. These sensitive issues were considered, by the survey agency, to be inappropriate for our survey. Thus we are not able to compare subjective and epidemiological risks for these diseases. But we will look at the impact of risk perceptions on take up.

The epidemiological estimates come from a variety of sources, including population observations and randomized clinical trials. These probabilities may deviate from individual probabilities in the field, both because of heterogeneity in risk factors not accounted for in the epidemiological models, and behavioral responses to preventive interventions. In addition, these studies typically come from US data, while there could be some differences in the risk of disease in the Netherlands relative to the US, the epidemiological models will provide a good approximation of the level of risk and the relationship between risk factors and risk.

6. Empirical Results

6.1 Discrepancies between Epidemiologically Predicted and Perceived Probabilities

The data described in the previous two sections allow us to compare individuals' perception of risk to their risk as predicted by epidemiological models. As described in section 5, for each individual in our sample we calculate their individual-specific epidemiological risks using all available sample information on the respondent's risk factors. There are two possible reasons for discrepancies between the epidemiologically predicted risks and perceived risks. First, individuals might misperceive their true risk. Secondly, individuals may have information about additional risk factors unaccounted for in the epidemiological predictions. However, this would be unlikely to cause a difference between the mean (or medians) of the two *distributions* of probabilities.

Tables 3 and 4 present these comparisons of the distributions of perceived and predicted epidemiological risks. For influenza we see that people report a high likelihood of getting the flu without a flu shot, the mean subjective probability of getting the flu in the coming flu season is 31%; the median is lower at 21%. With a flu shot these numbers drop to 20% and 10% respectively. These numbers are higher than we might expect; in a typical flu season less 20% of the population gets influenza; see Hueston and Benich (2004) and Govaert et al. (1998). One possible explanation for this overestimate is that people often use the word flu to refer to other illnesses. While we do state at the beginning of the survey that we are interested in actual influenza and provide a definition, some people may not realize the distinction.

The mean subjective probability of getting breast cancer in 5 years is 19% and is 22% in ten years. Again these amounts are higher than the medians, at 10% and 14%, respectively. More striking is the difference between the subjective probabilities and those found using the Gail Model. The Gail Model implies that the average risk of being diagnosed with breast cancer in the next 5 years is approximately 1%, and 1.9% in ten years. Perhaps, some of this overestimation of risk is due to a prominent public service message in the Netherlands which stated that 1 in 10 women would get breast cancer in their lifetime.

The mean subjective probability of getting heart disease in 5 years is 16% and is 19% in ten years. Again these amounts are higher than the medians, both around 10%. As with influenza and breast cancer, individuals overestimate the risk of heart disease, however the overestimation is not as great. According to the Framingham model, the mean risk is 6.4% in 5 years, and doubles in 10 years. There may be less overestimation of the risk of heart disease because the epidemiological risks are not as small. As will be discussed below, individuals have a tendency to overestimate very small probabilities more, but this overestimation is less extreme with more moderate probabilities. We also present summary statistics for perception of risk of cervical cancer, and sexually transmitted diseases, although similar epidemiological models are not available.

Table 4 examines the subjective probability of dying from each of the various diseases. For influenza related deaths individuals were asked to report the probability of death if they were to get influenza; combining this with their subjective risk of getting the flu we can calculate the unconditional probability of dying from the flu. Table 4A reports the unconditional probabilities. Death from influenza, even for the elderly, is a very rare occurrence; the highest epidemiological predictions indicate that mean objective probability of death from influenza in a given year in our sample is 0.044% without a flu shot and 0.009% with a flu shot, more than 100 times less than the mean reported subjective probabilities (13.24% and 11.14% respectively). Similarly for breast cancer (Table

4B), the average subjective probabilities of death are about than 100 times those predicted by the epidemiological models. Again with heart disease (Table 4C), individual overestimate their risk of death less than with influenza and breast cancer.

The discrepancies between the two sets of probabilities are in line with previous research on probability perceptions in the health domain. Overestimation of health risks has been found for breast cancer (Skinner, 1998), and smoking-induced lung cancer (Viscusi, 1992). Bruine de Bruin et al. (2007) find that teenagers vastly overestimate the probability of death. As discussed above, these discrepancies in means are likely to be due to misperception rather than heterogeneity in individual risks.

For both influenza and breast cancer we also can compare the effectiveness of the prevention with the perceived effectiveness of the intervention. To do this we calculate the percentage reduction in risk of death due to using prevention: $(p_{wo}-p_w)/p_{wo}$, with p_{wo} and p_w the probabilities of death without and with the preventive intervention, respectively. Again individuals' perceptions deviate from the epidemiologically predicted risk reduction. Here there is more variation, partially due to the fact that some people report higher probabilities of death with preventive care than without it. While this may seem irrational, it would not be surprising if some individuals actually feel this way. One possible explanation might be significant media attention to the sudden death of several people in Israel immediately after receiving a flu shot in 2006, which led to a postponement of the vaccination program in the Netherlands. In addition, many people do not trust vaccinations and fear that the live virus in the vaccination will cause them to get influenza.

It is conceivable that the subjective probability distributions are different for respondents with high probability literacy. We therefore also inspected the distributions for the subsample of respondents who answered at least 10 out the 11 numeracy questions correctly. The average subjective probabilities for this subsample of highly numerate respondents are slightly lower than for the total sample, but not enough to change the conclusion that people dramatically overestimate the probabilities.[10]

6.2 Explaining Perceived Probabilities

In this section, we examine the factors that predict perceptions of risk. First, we compare the impact of epidemiological risk factors as predicted by those models to the impact of the same risk factors on perceptions of risk. Second, we present a regression illustrating which characteristics are most predictive of perceptions of risk. These first two methods will allow us to address whether known risk factors impact perceptions of risk or whether other factors that should not directly impact risk play a role. Finally, we consider whether there is a general tendency to overestimate risks, and whether some respondents are more likely to consistently overestimate risks.

As a first pass, we compare epidemiological risks broken down by risk factors to perceived risks broken down by the same risk factors. For influenza risk, we can only consider age as a risk factor. The last column of Table 2 presents the perception of risk of death from influenza by age. Here we can compare the epidemiologically predicted increase in risk as people age to the perceptions. We can see that perceptions of risk increase with age.

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[10] Using an alternative definition of numeracy based on consistency of probability answers – $P(T<t_1)$ should be smaller than $P(T<t_2)$ for $t_1 < t_2$ – gives similar results.

But in all age groups perceived risks are higher than the risks in even the most liberal model by several orders of magnitude. However, individuals underestimate the relative increase in risk that comes with age. The epidemiologically measured risk of death between the age of 50 and 64 is 8.3 times the risk of death under the age of 50, but perceived risks increase by only a factor of 1.3. Comparing the oldest to the middle aged, epidemiological risk increases by a factor of 10, but perceived risks increase only by a factor of 1.75.

For breast cancer and heart disease, we regress epidemiological and perceived risk only on the risk factors included in the epidemiological models. We compare regressions where the dependent variable is the subjective probability to regressions where the dependent variable is the epidemiologically predicted probability. This allows us to see whether the respondents are aware of the risk factors that are used to predict the epidemiological probabilities and whether their responses reflect the magnitudes of the risks associated with each risk factor.

Table 5A considers the natural log of breast cancer risk. In this case, the epidemiological model uses a multiplicative formula. The epidemiological model fits perfectly because it is the exact formula we use to predict risks. Each risk factor (or interaction in some cases) is assigned a different relative risk value. For some risk factors, such as age at first birth, different values are assigned for different ranges of ages. We include dummies for each possible value. The coefficients in the epidemiological model indicate the relative impact of each specific risk category. The only risk factor that even comes close to having a similar impact on perceived and epidemiological risks is a family history of breast cancer. In this model, age of first birth is interacted with family history. However, age of first birth has no significant impact among those with no family history and there is no significant difference between the coefficient for age at first birth among those with a family history of breast cancer. Previous biopsies do not influence risk perceptions. For some ages, age does influence risk perceptions, but the magnitudes of the effects are significantly different from those predicted in the epidemiological model. At the oldest ages, women actually perceive that the risk of getting breast cancer declines. This may be because the free program in the Netherlands only covers women up to age 75. This is primarily due to the fact that while the risk of cancer does not decline, the risk of death due to cancer does decline due to competing risks.

Tables 5B and 5C consider heart disease risk separately for men and women. In this case, the epidemiological model is predicted using a discrete table, which was originally based on a multiplicative formula. The epidemiological model does not fit perfectly in this case because we use the discrete table to predict risks, rather than the precise formula used by the original epidemiological model. We separate men and women in order to match the epidemiological models. These models are calculated by assigning each individual a number of points based on their risk factors. For example, diabetes adds 4 points for men and 2 points for women, while smoking adds 2 points for both men and women. We use the points assigned for each risk factor as the independent variables in our model. In the epidemiological model, we would expect the coefficients on the points for each risk factor to be the same, because the number of points added reflects the relative risk associated with that risk factor. An additional point raises the relative risk by approximately 23 percent for men and 14 percent for women in the epidemiological models.

Among women, in Table 5B, we see higher perceived relative risks associated with almost all risk factors: age, high blood pressure, cholesterol, and diabetes, but not smoking. But the marginal effect of additional risk points for some risk factors differs significantly from those predicted by the epidemiological model. Women underestimate the impact of aging and diabetes. They overestimate the effect of cholesterol and approximately correctly estimate the effect of high blood pressure. We find no significant effect due to smoking, perhaps because perceptions of risk also affect the decision to smoke. Men, as shown in Table 5C, perceive a higher level of risk as they age, and if they have high blood pressure, but we find no significant effect of cholesterol, diabetes or smoking. The coefficients on age and high blood pressure are not statistically significantly different than those in the epidemiological models.

These three tables suggest that individuals misperceive their risks, as their perceptions only very partially respond to risk factors. However, in all three tables, it is important to point out that these effects are averages. The fit of the models is poor, with R^2 ranging from .02 to .11. This suggests that there is quite a bit of variation that is unexplained by the risk factors from the epidemiological models. Therefore, we turn to a more complete model that allows us to investigate what other factors are correlated with risk perceptions. The epidemiological models that we use do not necessarily reflect all possible risk factors and certainly don't control for cognitive skills that may affect the assessment of risk. For example they don't control for education which may directly affect both true risks and risk perceptions.

Table 6 presents a broader model of risk perceptions. Column 1 considers the risk of death from influenza, column 2 the risk of heart disease in 5 years, and column 3 the risk of breast cancer in 5 years among women. Rather than focusing on the epidemiological models, here we include not only the epidemiological risk factors but also income, education, numeracy and dummies for the visual scales that were randomized across respondents. We again see that risk factors do in some cases play a role in forming perceptions of risk. Most of the results regarding risk factors mirror those in Table 5. Men perceive higher risk of heart disease, although only 1.1% higher than women. Age is perceived to increase the risk of heart disease and death from influenza, but not the risk of breast cancer. As in Table 5, we see that many risk factors that should influence risk do not. Diabetes, high blood pressure, high cholesterol and smoking do not affect the perceived risk of death from influenza. Similarly, diabetes does not affect the perceived risk of heart disease, although high blood pressure, high cholesterol and smoking do. For breast cancer, again only past family history of breast cancer influences perceived risks. Better self assessed health does decrease the perceived risk of all three diseases and BMI increases the perceived risk death from influenza and heart disease, suggesting that individuals respond to some private information that is not included in the epidemiological models.

These regressions also control for socio-economic characteristics including income and education. There may be direct relationship between actual risk and socio economic status (SES); those with better SES may actually enjoy better health. However there may also be an effect if SES is correlated with ability to answer subjective probability questions. We see that for heart disease, those with higher income report lower risks. Education does not exhibit the same relationship. The excluded category is those who have completed secondary education. We see that higher education does reduce the perceived risk of death from influenza, but lower education reduces the perceived risk of heart disease and breast cancer. We also control for numeracy, and find that numeracy reduces the perceived risk of death from influenza and heart disease. Those who are more able to answer standard numeracy questions report lower probabilities. While this may suggest a correlation between ability and health, it is more likely that those who are more numerate are less likely to dramatically overstate the probability of disease.

Two other pieces of these regressions strongly suggest that the differences between perceived probabilities and epidemiological probabilities are driven by misperceptions of risk not by unobserved differences in true risk. First, the randomized visual scale treatments actually increase reported probabilities; since these treatments are randomized this can not reflect an underlying health difference. Second, the constants in all three regressions are quite large, all around 18%, again highlighting the fact that the average values of the perceived risks are much too high to be a reflection only of additional information. Similarly the magnitudes of the coefficients on age in the regressions predicting death from influenza are simply too large to reflect reality. For example, individuals aged 75 to 79 perceive their risk of death from influenza to be 18 percentage points higher than those under 24; if perceived probabilities just reflect that individuals have more information than the epidemiological models, we would expect more than 18 percent of individuals between 75 and 79 to die of influenza each year. Taken all together, these results suggest that individuals tend to dramatically overestimate the risks that they face.

Thus we turn to a measure that will allow us to estimate the general tendency to overestimate risks. A useful tool to measure discrepancies between perceived and epidemiologically predicted risks is the probability weighting function described in Prelec (1998). Using this weighting function, it is possible to summarize an individual's general tendency to overestimate health risks in a single number. This function takes the following form:

$$(1)\quad w(p) = \exp[-(-\ln p)^{\alpha}]$$

Here $w(p)$ is the perceived probability and p is the actual probability. The parameter α is a summary measure of the degree of bias. If $\alpha=1$ there is no bias, $w(p)=p$; if $\alpha=0$ the function is similar to a step function with all underlying probabilities being reported at the same value. Given that we have multiple observations of perceived and epidemiological probabilities for each individual in our sample), we can estimate individual-specific values of α.[11] We estimate the α's as the coefficient on $\ln[-\ln(p)]$ in individual specific regressions (without a constant) where $\ln[-\ln(w(p))]$ is the dependent variable. Figure 1 shows the shape of the probability weighting function for various values of α's, including the median of our estimates ($\alpha=0.50$), the 25th percentile ($\alpha=0.21$), and the 75th percentile, ($\alpha=0.75$). Lower values of α indicate that small probabilities are overweighted more, higher values of α indicate that small probabilities are overweighted less.

Table 7 reports a regression that describes the relationship between these estimated individual values of α and a number of observed respondent characteristics. Higher values of α, indicating less over-estimation of small probabilities, are associated with higher income, numeracy, college education, and with being male. Being in excellent or good health is also associated with higher values of α. This may occur for two reasons. First, poor health may be associated with higher actual risk than predicted by the epidemiological models. Thus, individuals' assessments of their own risk may accurately be higher than the epidemiological prediction, leading to lower alphas

[11] Our estimates are based on the risk of dying from influenza, with and without a flu shot, the risk of getting breast cancer, the risk of dying of breast cancer, with and without mammograms over 10 and 20 years, the risk of developing heart disease, and the risk of dying of heart disease, with and without aspirin over 10 and 20 years.

for those in poor health. Second, good health may be a proxy for numeracy and literacy, leading to higher alphas for those in good health. Receiving an invitation for a flu shot, leads to lower levels of α, and thus more overestimation of risks. This may occur because the invitations alert people to the importance of receiving a flu shot and make the risks more salient. Risk factors either have no significant effect on alpha or increase overestimation of risks. Since epidemiological risks already adjust for these risk factors, this likely represents an overestimation of risks.

The results in this section point to an overwhelming tendency to overestimate risks above and beyond what can be explained by characteristics unobserved in epidemiological models. However overestimation of risks does not necessarily imply that risk perceptions affect behavior. In the next section we turn to the impact of risk perceptions on individual behavior.

6.3 The Take-Up of Preventive Care

This section examines the effect of risk perceptions on the use of preventive care. First we look at flu shots and aspirin, which can be measured for our whole sample. Then we turn to mammograms, Pap smears, and STD tests which can only be measured for subsets of our sample. Finally, we consider what happens if we jointly control for perceived and epidemiological risks. This allows us to measure whether risk perceptions influence behavior, holding risk factors or objective measures of risk constant.

The first two columns of Table 8A report regressions explaining flu shot take up in the fall of 2007 and after September 2008. It is important to note that in column 2, the information on the explanatory variables, notably the various perceived probabilities, come from the September 2008 survey, while the dependent variable, flu shot take-up, comes from the January 2009 survey. This makes it implausible that the results are driven by a justifications bias. While justification bias could play a role in the relationship between *past* flu shot take-up and current perceived probabilities (e.g. reporting low probabilities to justify not having a flu shot previously), it is highly unlikely to play a role in this case (e.g. having a flu shot in October 2008 to justify the high probabilities answered in September 2008). The results for 2007 and 2008 flu shots are very similar, suggesting that justification bias is not driving our results regarding previous use of preventive care.

The subjective probabilities p_{wo} and p_w jointly represent the perceived *level* of risk as well as the perceived *effectiveness* of the intervention. We choose to use p_{wo} as a measure of the level of risk and $(p_{wo}-p_w)/p_{wo}$ as a measure of the effectiveness of the intervention. This relative difference is often the form in which the results from epidemiological studies on intervention effectiveness are expressed. An additional benefit is that this measure is more comparable across individuals; an absolute change in risk of 5 percentage points has a very different implication when the perceived risk without intervention is 5% than when it is 95%.[12] Despite the fact that individuals overestimate their risk of disease, the effects of perceived probabilities are large and significant. For example, the coefficient on our measure of perceived effectiveness, $(p_{wo}-p_w)/p_{wo}$, implies that if the flu shot reduces risk by 10% (for example from 25% without a flu shot to 22.5% with a flu shot), take-up would increase by 1.6 percentage points. Individuals who perceive that flu shots increase the chance of influenza are 3.6 percentage points

[12] At the same time, regression results could be sensitive to the particular nonlinear transformation that is used. Robustness checks – including ones that use $(p_{wo}-p_w)$ as effectiveness measure – do not change our results, however.

less likely to receive a flu shot, although this effect is only significant in the regression that looks at future use of flu shots. The effectiveness of flu shots at preventing death and the risk of death without a flu shot also increase take up. Finally, a 10 percentage point increase in the level of the perceived risk of influenza without a flu shot, p_{wo}, increases take-up by 1.4 percentage points.

A very large effect is found for the invitation to receive a flu shot, which increases take-up by 32 percentage points. In addition to the effect of receiving the invitation (which partly depends on age), we find a strong separate positive age effect, although these results are suppressed in the table. Additional effects are also found for people with diabetes, heart disease, and high blood pressure, risk factors that increase the risk of severe complications. We find that having a college degree lowers the probability of flu shot take-up. One explanation is that the higher educated have higher opportunity costs of time.[13] Alternatively, they may be in better health which lowers the rationale for getting a flu shot.

Column 3 of Table 8A, considers the use of aspirin for the prevention of heart disease. The impact of perceived risks and effectiveness are smaller than those found with influenza. If aspirin reduces the risk of dying of heart disease by 10% (for example from 25% to 22.5%), take-up would increase by 0.6 percentage points. The risk of heart disease is associated with *lower* use of aspirin, perhaps due to the fact that those already taking aspirin perceive their risks to be lowered. Men are more likely to use aspirin, as are those with high cholesterol. Other coefficients are insignificant.

Table 8B considers preventive interventions offered only to subsets of the population. The first two columns consider mammograms and Pap smears. The third column considers tests for sexually transmitted diseases (STD). In all three cases, the perceived effectiveness of the intervention in reducing the risk of death increases the take-up of the intervention. If mammograms are perceived to change the probability of dying of breast cancer by 10%, take-up would increase by 0.3 percentage points. For Pap smears and STD tests the effect is 1 percentage points. The effect of invitations on mammogram and Pap smear take up is very large, increasing take-up by 75 and 71 percentage points, respectively. For STD tests, invitations increase take up by 47 percentage points. Numeracy and family history of breast cancer increase the take up of mammograms. For STD tests, men are 11 percentage points less likely to have undergone a test and those with a college degree are 11 percentage points more likely to have undergone a test.

It is also interesting to consider the effects of risk perceptions among subgroups of the population.[14] Because invitations play such an important role in the decision to use preventive care and because invitations are targeted based on underlying risk, it is possible that risk perceptions, invitations, and true risk are highly correlated. To address this possibility, we consider the effects of risk perceptions in four distinct population subgroups: those 65 and over who receive an invitation, those 65 and over who do not receive an invitation, those under 65 who receive

[13] Although higher opportunity costs of time would also increase the cost of illness, should it occur, these may be outweighed by the costs of time to receive a flu shot. This is especially true because flu shots are typically only available at the GPs office, or very occasionally at the place of employment.
[14] These results are available in Appendix Table 2.

an invitation and those under 65 who do not receive an invitation.[15] We find that for all age groups and invitation combinations, risk perceptions and perceptions of effectiveness affect take up of the flu shot.

Table 9, considers the effect of both subjective and epidemiological probabilities on take up of preventive care. Column 1 and 2 consider the use of flu shots; a 10 percentage point increase in the perceived probability of getting influenza increases take up by 2.2 or 2.3 percentage points, for 2007 and 2008 respectively. If we consider the perceived risk of death from influenza, the effects are 0.7 or 0.6 percentage points respectively. The epidemiological risk of death is significant in 2007 but not in 2008, due to changes in eligibility for flu shots, as discussed in section 2. The coefficients on the epidemiological risk are large, however this reflects the size of the underlying risk which is on average less than 0.03 percent and the huge success of the government influenza shot program.[16] For mammograms, after controlling for age and the government invitation, epidemiological probabilities have no effect on take up. Perceived risks of breast cancer do continue to have an effect on take up; cancer 10 percentage point increase in perceived risk increases take-up by 0.8 percentage points. For heart disease and the use of aspirin, only the epidemiological probabilities matter, perhaps because they are closely aligned with expert advice. An individual with a high risk of heart disease is more likely to have their doctor recommend the use of aspirin. The perceived risk has no additional effect on take up of aspirin. The difference between this result and others may be that controlling for the invitations for flu shots and mammograms may control for the underlying epidemiological risk. In the case of the use of aspirin for the prevention of heart disease, we have no similar control.

In standard economic models of decisions regarding preventive interventions, information on risk factors plays a role through the probabilities of getting the disease or dying from it with and without the intervention. Once these probabilities are known, the risk factors should not play an additional role in the take-up decision. Still, one might ask whether an exogenous change in perceived probabilities, leaving all observed and unobserved risk factors unchanged, will affect the take-up of preventive interventions. Such an exogenous change could result from the receipt of a letter with numerical probability information. Although we lack the ideal instrumental variables in our data set to answer this question, we have performed a number of IV estimations in the flu shot analysis. As instruments we used a) whether any individual in the respondent's household had received a flu shot invitation from an employer, and b) whether any individual in the respondent's household had received a flu shot invitation from a doctor. The second stage regressions shows diminished importance of perceived probabilities in explaining take-up; however, the first stage regressions indicate that the instruments are weak.

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[15] Everyone over the age of 65 should receive an invitation for a flu shot, however, some (12%) report not being invited. This may be due to clerical error, poor memory, or simply a failure to open their mail. For those under the age of 65: some receive invitations from their physician because they are at high risk, others receive invitations from their employer or other sources.

[16] Because influenza risk is determined by age only and because the flu shot invitations are also mostly determined by age groups, we include age and age squared rather than 5 year age groups. Thus the epidemiological risk captures the non-linearities in take up with respect to age.

7. Conclusion

This paper uses unique data measuring individuals' risk perceptions across multiple diseases to examine the relationship between individual risk perceptions, epidemiological measures of risk, and use of preventive care. We have three main findings. First, we find that on average individuals are aware of only some of the qualitative relationships between risk factors and their risk. Second, they vastly, and systematically, overestimate their risk of disease. Third, despite this overestimation and in some cases lack of awareness of risk factors, perceptions of risk play an important role in the decision to use preventive care. Those who perceive that they face more risk of disease and death are more likely to use preventive care, as are those who perceive prevention to be more effective. We tend to see no effect among those who think that the intervention will actually *increase* their risk of disease or death, except with the flu shot. For the flu, those who perceive the flu shot to increase their risk are less likely to take-up the intervention. This difference may stem from a misunderstanding of vaccines; a causal link between receiving a flu shot and an increased risk of influenza may be more plausible than a similar link between Pap smears and cancer. The perceived risk of death is only significant for flu shots and the use of aspirin, and the coefficients are remarkably similar.

Risk perceptions are significant predictors of the use of preventive care, even when we control for individually predicted epidemiological risks. There are several reasons why risk perceptions are likely to have an effect on behavior even after controlling for epidemiological risks. First, individuals may know more about their own situation than is captured in these epidemiological models, and thus risk perceptions would contain more information about true risks. Second, while epidemiological models may more closely estimate true risks, we would expect individuals to base their choices on their beliefs and not necessarily on potentially unknown true values. The dramatic overestimation of risk and the fact that individuals are not aware of many important risk factors, suggest that the former, on average is not the case. Instead the relationship between perceptions and behavior suggests that those who *perceive* greater risks are more likely to take action to reduce risks.

Individuals' perceptions of risk and effectiveness are often far from the epidemiologically predicted values, thus interventions to encourage use of preventive care should be designed carefully. If information focuses only on the underlying risk of disease, that could actually reduce the use of prevention since many perceive risks to be greater than they actually are. However, accurate information about the effectiveness of prevention could increase the use of preventive care. In particular, it is not uncommon for people to believe that preventive interventions will actually increase their risks. More accurate information about effectiveness could encourage especially those individuals to participate in preventive interventions.

In principle, the preventive health care choices considered here offer an opportunity to measure individual's willingness to pay for risk reductions on the basis of revealed preferences. Viscusi and Aldy (2003) provide a review of the literature on willingness to pay to reduce the risk of death. For example, suppose we observe a person who does not have a flu shot at age 59 (just below the free flu shot eligibility age) and does have a flu shot at age 60 (free flu shot). All else equal, this would allow us to estimate an upper and a lower bound for the person's willingness to pay for this particular risk reduction. Implementing such a procedure, however, is a road covered with pitfalls. First, the all else equal condition requires controlling for a large number of factors (like the amount of information available, spouse's health and behavior, the flu incidence in the population, and the opportunity costs of time).

Secondly, the lion's share of the personal costs of getting the flu are not the risk of death but the disutility from being ill and absent from work. Finally, deviations from rationality like hyperbolic discounting and other time-inconsistent preferences, prohibit a meaningful interpretation of the outcomes of such an exercise.

Our results indicate that written invitations for flu shots, mammograms, and Pap smears in the Netherlands strongly increased the likelihood of participation. One topic for future research is how information provision can be used more effectively through a careful design of information on risk and effectiveness, both in terms of (quantitative) content and in terms of framing.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.
Male	5687	0.460	0.498
Age	5687	47.281	15.451
Net household income	5686	3034	8289
Education level:	5686		
Did not finish 2ndary education	502	0.088	
2ndary education	2132	0.375	
MBO (similar to Associates degree)	1344	0.236	
HBO or WO (Bachelors degree or higher)	1708	0.300	
Received a flu shot in 2007	5687	0.226	0.418
Received a flu shot in 2008	4693	0.287	0.452
Had a mammogram in last 2 years	3072	0.394	0.489
Had a Pap smear in last 5 years	3072	0.605	0.489
Have used the kidney check	1404	0.237	0.426
Take daily low dose aspirin	5687	0.056	0.230

Table 2: Annual Influenza Associated Mortality Rates per 100,000 People by Age

Age	Conservative Measure: Underlying Pneumonia and Influenza Deaths	Moderate Measure: Underlying Respiratory and Circulatory Deaths	Liberal Measure: All-Cause Deaths	Perception of Risk of Mortality
5 to 49	0.2	0.5	1.5	10,032
50 to 64	1.3	7.5	12.5	13,845
65 plus	22.1	98.3	132.5	24,176

Note: Columns 1 through 3 from Table 5 of Thompson et al. (2003). Based on death due to influenza from the 1990-1991 through 1998-1999 seasons. Column 4 is from our own calculations.

Table 3: Subjective and Epidemiological Probabilities of Getting a Disease (percentages)

Disease	Time Period	Subj/Epid probability	Mean	Standard dev	Min	Median	Max
Influenza	1 year	Subj w/ flu shot	19.59%	21.49%	0	10.11%	100%
		Epid w/flu shot	-	-	-	-	-
		Subj w/o flu shot	30.95%	26.69%	0	20.64%	100%
		Epid w/o flu shot	-	-	-	-	-
		Subj Effectiveness $(p_{wo}-p_{w})/p_{wo}$	-303%	14042%	-999900%	33.33%	100%
		Epid					
Breast Cancer	5 year	Subj	19.131%	19.186%	0%	10.145%	100%
		Epid	0.865%	0.740%	0.003%	0.796%	3.642%
	10 year	Subj	21.626%	19.812%	0%	14.465%	100%
		Epid	1.918%	1.490%	0.009%	1.769%	7.137%
Cervical Cancer	5 year	Subj	13.71%	17.28%	0%	6.65%	100%
		Epid	<1%	-	-	-	-
	10 year	Subj	15.20%	17.69%	0%	9.86%	100%
		Epid	<1%	-	-	-	-
Sexually Transmitted Disease	5 year	Subj	7.40%	12.93%	0%	1.83%	99.3%
		Epid		-	-	-	-
	10 year	Subj	8.19%	13.56%	0%	2.44%	98.38%
		Epid		-	-	-	-
Aids	5 year	Subj	3.78%	9.34%	0%	0.93	99.99
		Epid		-	-	-	-
	10 year	Subj	4.03%	9.25%	0%	1	99.76
		Epid		-	-	-	-
Heart Disease	5 year	Subj	16.40%	18.42%	0%	10%	100%
		Epid	6.40%	5.91%	1%	4%	47%
	10 year	Subj	19.52%	19.83%	0%	10.32%	100%
		Epid	12.80%	11.81%	2%	8%	94%

Table 4: Subjective and Epidemiological Probabilities of Dying (percentages)

Table 4A: Subjective and Epidemiological Probabilities of Influenza Related Death

Time Period	Prevention	Subj/Epid probability	Mean	Stan. Dev	Min	Median	Max
1 year	With flu shot	Subj	11.14%	23.35%	0%	1.1500%	100%
		Epid- mod	0.006%	0.014%	0.0001%	0.0001%	0.0398%
	Without flu shot	Subj	13.24%	23.96%	0%	2%	100%
		Epid- mod	0.032%	0.068%	0.0006%	0.0006%	0.1988%
	Effectiveness of flu shot $(p_{wo}-p_w)/p_{wo}$	Subj	-105%	1942%	-75755%	1.393%	100%
		Epid	80%				

Table 4B: Subjective and Epidemiological Probabilities of Death from Breast Cancer

Time Period	Prevention	Subj/Epid probability	Mean	Stan. Dev	Min	Median	Max
10 year	With mammogram	Subj	15.80%	18.06%	0%	10%	100%
		Epid	0.195%	0.149%	0.001%	0.180%	0.792%
	Without mammogram	Subj	26.36%	23.66%	0%	20%	100%
		Epid	0.229%	0.176%	0.001%	0.211%	0.931%
	Effectiveness of mamm $(p_{wo}-p_w)/p_{wo}$	Subj	12.17%	459.%	-16485%	43.24%	100%
		Epid	15%				
20 year	With mammogram	Subj	17.34%	18.21%	0%	10.09%	100%
		Epid	0.279%	0.155%	0.015%	0.267%	0.903%
	Without mammogram	Subj	28.85%	24.56%	0%	20.41%	100%
		Epid	0.328%	0.183%	0.017%	0.314%	1.062%
	Effectiveness of mamm $(p_{wo}-p_w)/p_{wo}$	Subj	16.77%	439%	-19229%	38.71%	100%
		Epid	15%				

Table 4C: Subjective Probabilities of Death from Heart Disease

Time Period	Prevention	Subj/Epid probability	Mean	Stan. Dev	Min	Median	Max
10 year	With aspirin	Subj	16.61%	19.00%	0%	10%	100%
		Epid	0.493%	0.468%	0.068%	0.408%	3.196%
	Without aspirin	Subj	19.68%	21.52%	0%	10.09%	100%
		Epid	0.725%	0.688%	0.1%	0.6%	4.7%
	Effectiveness of aspirin $(p_{wo}-p_w)/p_{wo}$	Subj	-6%	341%	-13700%	1%%	100%
		Epid					
20 year	With aspirin	Subj	20.08%	21.14%	0%	10.32%	100%
		Epid	4.930%	4.679%	0.68%	4.08%	31.96%
	Without aspirin	Subj	23.78%	23.75%	0%	15%	100%
		Epid	7.250%	6.881%	1%	6%	47%
	Effectiveness of aspirin $(p_{wo}-p_w)/p_{wo}$	Subj	-18%	1388%	-99900%	2%	100%
		Epid					

Table 5: Relationship between Risk Factors and Perceived or Epidemiological Risks
Table 5A: 5 year Risk of Breast Cancer

	Ln of Epid. predicted risk	Ln of perceived risk
Biopsy required and age 50+	0.241	0.429
	.	(0.561)
Biopsy required and age less than 50	0.529	-0.143
	.	(0.535)
Age of first birth 20-24, no family history of cancer	0.218	0.438
	.	(0.360)
Age of first birth 25-29/ no children, no family history of cancer	0.437	0.498
	.	(0.351)
Age of first birth 30+, no family history of cancer	0.656	0.393
	.	(0.359)
Age of first birth 19 or less, family history of cancer	0.958	0.214
	.	(0.979)
Age of first birth 20-24, family history of cancer	0.986	0.612
	.	(0.453)
Age of first birth 25-29/ no children, family history of cancer	1.014	1.234***
	.	(0.394)
Age of first birth 30+, family history of cancer	1.042	1.156***
	.	(0.441)
Age 25-29	1.992	0.026
	.	(0.226)
Age 30-34	3.245	0.471**
	.	(0.210)
Age 35-39	4.154	0.471**
	.	(0.204)
Age 40-44	4.804	0.529***
	.	(0.203)
Age 45-49	5.193	0.563***
	.	(0.199)
Age 50-54	5.363	0.228
	.	(0.204)
Age 55-59	5.571	0.220
	.	(0.210)
Age 60-64	5.778	0.218
	.	(0.222)
Age 65-69	5.936	0.368
	.	(0.239)
Age 70-74	5.999	-0.213
	.	(0.302)
Age 75-79	6.056	-1.132**
	.	(0.501)
Age 80+	6.060	-0.123
	.	(0.336)
Constant	-10.414	1.071***
	.	(0.377)
Observations	3,072	2,976
R-squared	1.000	0.018

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5B: 5 year Risk of Heart Disease among Women

	Ln of Epid. predicted risk	Ln of perceived risk
Age Points	0.134***	0.062***
	(0.001)	(0.007)
Blood Pressure Points	0.155***	0.188***
	(0.005)	(0.055)
Cholesterol Points	0.178***	0.362***
	(0.011)	(0.131)
Diabetes Points	0.154***	0.099*
	(0.004)	(0.052)
Smoking Points	0.114***	0.083
	(0.005)	(0.060)
Constant	0.921***	1.317***
	(0.005)	(0.059)
Observations	3072	2853
R-squared	0.952	0.049

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5C: 5 year Risk of Heart Disease among Men

	Ln of Epid. predicted risk	Ln of perceived risk
Age Points	0.232***	0.241***
	(0.001)	(0.022)
Blood Pressure Points	0.230***	0.185***
	(0.002)	(0.063)
Cholesterol Points	0.221***	0.117
	(0.003)	(0.125)
Diabetes Points	0.218***	0.060
	(0.003)	(0.114)
Smoking Points	0.242***	0.068
	(0.002)	(0.062)
Constant	1.024***	0.951***
	(0.002)	(0.076)
Observations	2615	2288
R-squared	0.992	0.074

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6 OLS Regressions Predicting Perceived risk

VARIABLES	Perceived Risk of death from Influenza	Perceived Risk of Heart Disease in 5 yrs	Perceived Risk of Breast Cancer in 5 yrs
Dummy if Male	0.003	0.011**	
	(0.007)	(0.005)	
Age 25-29	-0.013	0.023	0.008
	(0.018)	(0.014)	(0.020)
Age 30-34	0.001	0.022*	0.062***
	(0.016)	(0.013)	(0.018)
Age 35-39	-0.019	0.036***	0.033*
	(0.016)	(0.012)	(0.017)
Age 40-44	0.005	0.070***	0.051***
	(0.015)	(0.012)	(0.017)
Age 45-49	-0.009	0.079***	0.048***
	(0.015)	(0.012)	(0.017)
Age 50-54	0.002	0.082***	0.031
	(0.016)	(0.012)	(0.021)
Age 55-59	0.018	0.091***	0.015
	(0.016)	(0.012)	(0.022)
Age 60-64	0.030*	0.113***	0.025
	(0.016)	(0.013)	(0.023)
Age 65-69	0.054***	0.106***	0.010
	(0.018)	(0.014)	(0.024)
Age 70-74	0.083***	0.132***	0.011
	(0.021)	(0.018)	(0.028)
Age 75-79	0.183***	0.140***	0.003
	(0.025)	(0.022)	(0.030)
Age 80-84	0.167***	0.095***	-0.002
	(0.035)	(0.030)	(0.047)
Age 85-92	0.143**	0.067	-0.078
	(0.065)	(0.062)	(0.078)
Received invitation	0.021**		0.019
	(0.008)		(0.014)
Self Assessed Health is Good or better	-0.016**	-0.046***	-0.031***
	(0.008)	(0.006)	(0.009)
Diagnosed with Heart Disease	0.024**		-0.004
	(0.012)		(0.015)
Diagnosed with Diabetes	0.012	0.016	0.018
	(0.014)	(0.012)	(0.016)
Diagnosed with High Blood Pressure	0.007	0.032***	0.013
	(0.009)	(0.007)	(0.010)
Diagnosed with High Cholesterol	-0.007	0.036***	-0.012
	(0.010)	(0.008)	(0.012)
Dummy if Smoker	-0.003	0.020***	-0.000
	(0.008)	(0.006)	(0.009)
BMI	0.0009**	0.0006*	0.0001
	(.0004)	(0.0003)	(0.0004)
Breast Cancer in Family			0.113***
			(0.025)

Previous Breast Biopsy			0.037
			(0.062)
Age of First Live Birth			-0.028
			(0.018)
ln(net household income)	0.000	-0.014***	-0.005
	(0.006)	(0.005)	(0.007)
Numeracy	-0.135***	-0.030**	-0.025
	(0.015)	(0.012)	(0.017)
Did not finish 2ndary education	0.010	-0.027***	-0.034**
	(0.013)	(0.010)	(0.014)
MBO (similar to Associates degree)	-0.020**	0.011	0.009
	(0.009)	(0.007)	(0.010)
HBO or WO (Bachelors degree or higher)	-0.020**	-0.008	-0.012
	(0.009)	(0.007)	(0.010)
Dummy if Magnifier scale	0.017**	0.032***	0.050***
	(0.008)	(0.006)	(0.009)
Dummy if Linear	0.021***	0.035***	0.048***
	(0.008)	(0.006)	(0.009)
Constant	0.182***	0.188***	0.183**
	(0.050)	(0.040)	(0.085)
Observations	4922	4448	2563
R-squared	0.084	0.115	0.058

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 7: OLS Regressions Predicting Alpha (overweighting of small probabilities) As Described by Prelec (1998)

	Whole Sample	Only those with Alpha between Zero and One	Women	Women with Alpha between Zero and One
Dummy if Male	0.042**	0.076***		
	(0.019)	(0.008)		
ln(net household income)	0.000	0.017**	-0.004	0.013
	(0.018)	(0.008)	(0.018)	(0.009)
Numeracy	0.205***	0.045**	0.199***	0.060**
	(0.044)	(0.019)	(0.047)	(0.024)
Did not finish 2ndary education	0.015	0.007	0.081**	0.021
	(0.036)	(0.015)	(0.039)	(0.020)
MBO (similar to Associates degree)	-0.002	-0.023**	-0.007	-0.023
	(0.026)	(0.011)	(0.029)	(0.014)
HBO or WO (Bachelors degree or higher)	0.036	0.007	0.036	0.012
	(0.025)	(0.010)	(0.028)	(0.014)
Self Assessed Health is Excellent or Good	0.087***	0.054***	0.096***	0.054***
	(0.023)	(0.009)	(0.026)	(0.012)
Dummy if Magnifier scale	-0.129***	-0.067***	-0.125***	-0.071***
	(0.023)	(0.010)	(0.026)	(0.013)
Dummy if Linear	-0.160***	-0.098***	-0.167***	-0.110***
	(0.023)	(0.010)	(0.026)	(0.012)
Flu Shot Invitation	-0.054**	-0.023**	0.003	-0.005
	(0.024)	(0.010)	(0.026)	(0.012)
Mammogram invitation			-0.029	-0.024
			(0.038)	(0.019)
Pap Smear invitation			-0.075**	-0.003
			(0.031)	(0.015)
Diagnosed with Diabetes	-0.047	-0.015	-0.088*	-0.038*
	(0.039)	(0.016)	(0.046)	(0.023)
Diagnosed with High Blood Pressure	-0.057**	-0.029***	-0.049*	-0.029**
	(0.025)	(0.010)	(0.028)	(0.014)
Diagnosed with High Cholesterol	-0.038	-0.024**	-0.022	-0.001
	(0.028)	(0.012)	(0.034)	(0.017)
Dummy if Smoker	-0.025	-0.006	-0.008	0.004
	(0.023)	(0.010)	(0.026)	(0.013)
BMI	-0.0010	-0.0002	-0.0003	-0.0002
	(0.0011)	(0.0005)	(0.0011)	(0.0005)
Breast Cancer in Family			-0.035	-0.021
			(0.034)	(0.017)
Constant	0.460***	0.399***	0.432***	0.389***
	(0.145)	(0.062)	(0.151)	(0.077)
Observations	4922	3737	2645	2104
R-squared	0.047	0.098	0.048	0.071

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions also control for 5 year age groups, and dummies for visual scales.

Table 8A: OLS Regressions Predicting Use of Preventive Care: Whole Sample

Dependent Variable	Flu Shot in 2007 (before survey)	Flu Shot in 2008 (after survey)	Use Aspirin for Prevention of Heart Disease
Subjective effectiveness at preventing disease: (pwo-pw)/pwo, if effectiveness is positive	0.1579***	0.1375***	
	(0.0121)	(0.0157)	
Dummy if subjective effectiveness of preventing disease is negative	-0.0126	-0.0365***	
	(0.0110)	(0.0142)	
Subjective probability of Getting Disease without intervention	0.1421***	0.1438***	
	(0.0144)	(0.0188)	
Subjective probability of Getting Disease			-0.0571***
			(0.0172)
Subjective effectiveness at preventing death: (pwo-pw)/pwo, if effectiveness is positive	0.0939***	0.1116***	0.0580***
	(0.0119)	(0.0155)	(0.0080)
Dummy if subjective effectives of preventing death is negative	-0.0237**	-0.0108	0.0026
	(0.0097)	(0.0126)	(0.0048)
Subjective probability of Dying (in 10 year for all but flu shot) without intervention	0.0718***	0.0679***	0.0829***
	(0.0155)	(0.0203)	(0.0172)
Received invitation for intervention	0.4349***	0.3170***	
	(0.0094)	(0.0123)	
Expected or Actual monetary cost of intervention	-0.0014***	-0.0010***	
	(0.0001)	(0.0002)	
Expected or Actual time cost of intervention	-0.0008***	-0.0008***	
	(0.0001)	(0.0002)	
Dummy if Male	0.0111	0.0021	0.0137***
	(0.0073)	(0.0095)	(0.0037)
ln(net household income)	0.0059	-0.0041	-0.0003
	(0.0066)	(0.0086)	(0.0033)
Numeracy	-0.0382**	-0.0209	-0.0018
	(0.0168)	(0.0219)	(0.0084)
Did not finish 2ndary education	-0.0010	0.0123	-0.0041
	(0.0135)	(0.0172)	(0.0070)
MBO (similar to Associates degree)	-0.0142	-0.0190	0.0002
	(0.0097)	(0.0126)	(0.0049)
HBO or WO (Bachelors degree or higher)	-0.0329***	-0.0153	0.0041
	(0.0093)	(0.0121)	(0.0047)
Dummy if has Diabetes	0.0983***	0.0949***	0.0029
	(0.0144)	(0.0185)	(0.0079)
Dummy if has Heart Disease	0.0876***	0.0534***	
	(0.0129)	(0.0162)	
Dummy if has High Blood Pressure	0.0230**	0.0253**	0.0047
	(0.0092)	(0.0118)	(0.0049)
Dummy if has High Cholesterol			0.0181***
			(0.0058)
Dummy if Smoker			0.0077*
			(0.0044)
BMI			0.0000
			(0.0002)

Self Assessed Health is Excellent or Good	-0.0249***	-0.0346***	0.0025
	(0.0084)	(0.0109)	(0.0042)
Dummy if friends have died of disease	0.0636***	0.0530*	0.0023
	(0.0244)	(0.0312)	(0.0037)
Constant	-0.0657	0.0037	-0.0197
	(0.0540)	(0.0700)	(0.0271)
Observations	4927	4313	4448
R-squared	0.658	0.570	0.061

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions also control for 5 year age groups.

Table 8B: OLS Regressions Predicting Use of Preventive Care: Sample to Relevant Demographic Groups

Dependent Variable	Mammogram in last 2 years	Pap Smear in Last 5 Year	Test for Sexually Transmitted Disease in Past
Sample	Women	Women	Younger than 40
Subjective probability of Getting Disease	0.0568	0.0822	0.1152
	(0.0370)	(0.0558)	(0.0959)
Subjective effectiveness at preventing death: (pwo-pw)/pwo, if effectiveness is positive	0.0337*	0.0969***	0.0984**
	(0.0176)	(0.0207)	(0.0405)
Dummy if subjective effectives of preventing death is negative	0.0169	-0.0058	0.0031
	(0.0172)	(0.0195)	(0.0334)
Subjective probability of Dying (in 10 year for all but flu shot) without intervention	0.0320	0.0488	-0.0054
	(0.0323)	(0.0473)	(0.0812)
Received invitation for intervention	0.7505***	0.7100***	0.4718***
	(0.0188)	(0.0174)	(0.0939)
Expected or Actual monetary cost of intervention	-0.0004***	-0.0017***	-0.0026***
	(0.0001)	(0.0001)	(0.0002)
Expected or Actual time cost of intervention	-0.0001	0.0002	0.0008***
	(0.0001)	(0.0002)	(0.0002)
Dummy if Male			-0.1118***
			(0.0240)
ln(net household income)	0.0091	0.0133	-0.0193
	(0.0088)	(0.0100)	(0.0193)
Numeracy	0.0711***	0.0258	-0.0590
	(0.0229)	(0.0259)	(0.0571)
Did not finish 2ndary education	0.0087	0.0038	-0.0203
	(0.0188)	(0.0214)	(0.0530)
MBO (similar to Associates degree)	0.0126	0.0056	0.0087
	(0.0136)	(0.0156)	(0.0307)
HBO or WO (Bachelors degree or higher)	0.0189	-0.0162	0.1149***
	(0.0132)	(0.0151)	(0.0320)
Dummy if has Diabetes	-0.0362*	-0.0464*	-0.0341
	(0.0215)	(0.0242)	(0.0859)
Dummy if has Heart Disease	0.0060	-0.0057	0.1463*
	(0.0199)	(0.0229)	(0.0841)
Self Assessed Health Excellent or Good	0.0062	0.0084	-0.0088
	(0.0119)	(0.0136)	(0.0243)
Dummy if Family Member had disease	0.0351**	-0.0358	
	(0.0165)	(0.0325)	
Dummy if friends have died of disease	0.0098	0.0135	0.0063
	(0.0107)	(0.0199)	(0.0931)
Constant	-0.1282*	-0.0494	0.3954**
	(0.0718)	(0.0812)	(0.1589)
Observations	2567	2578	1176
R-squared	0.742	0.662	0.194

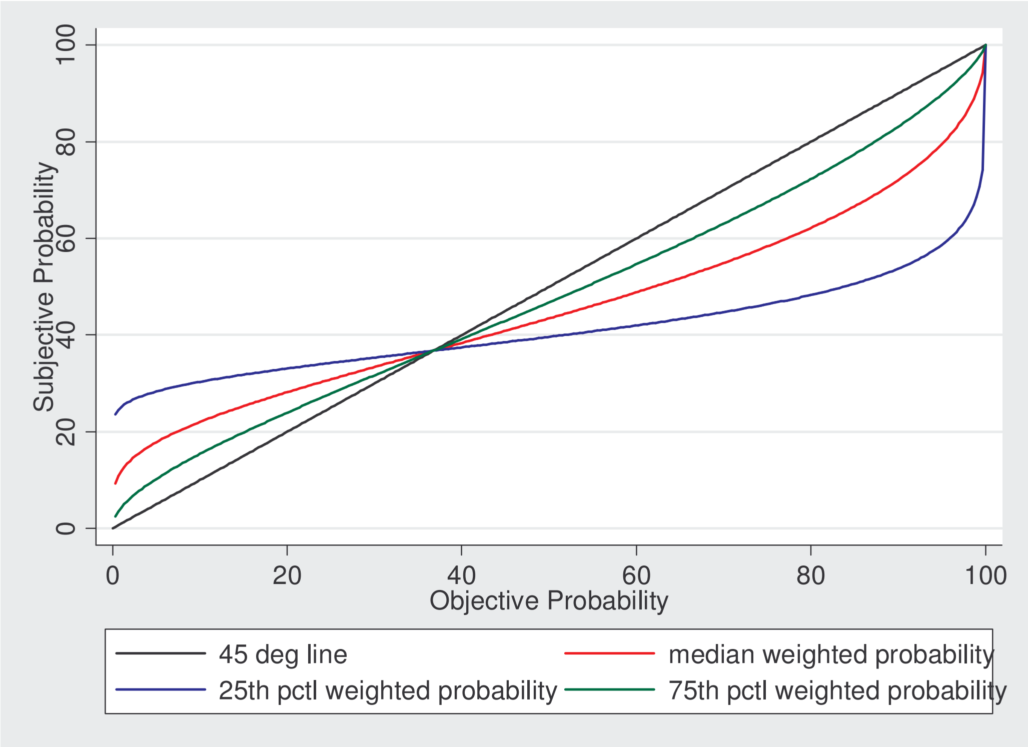
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions also control for 5 year age groups.

Table 9: OLS Regressions Predicting Use of Preventive Care: Comparing the Role of Subjective and Objective Probabilities

Dependent Variable	Flu Shot in 2007 (before survey)	Flu Shot in 2008 (after survey)	Mammogram	Use Aspirin for Prevention of Heart Disease
Sample	Whole Sample	Whole Sample	Women	Whole Sample
Subjective Probability of Flu without flu shot	0.2170***	0.2278***		
	(0.0143)	(0.0191)		
Epidemiological Probability of Death from Flu without flu shot	48.5852***	-17.5050		
	(10.0416)	(12.8396)		
Subjective Probability of Death from Flu without flu shot	0.0693***	0.0620***		
	(0.0160)	(0.0213)		
Subjective Probability of Disease in 10 years			0.0798***	0.0030
			(0.0255)	(0.0096)
Epidemiological Probability of Disease in 10 years			-0.9776	0.2146***
			(1.1401)	(0.0342)

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions also control for 5 year age groups (age and age squared for flu shots), invitations, expected or actual costs, male, household income, numeracy, education dummies, and health indicators.

Figure 1: The Relationship Between Subjective Risk and Epidemiological Risk



Appendix Table 1: Subjective Probability Questions

What is the percent chance that...
Flu
You will get the flu in the winter, if you get a flu shot this fall?
You will get the flu in the winter, if you don't get a flu shot this fall?
You will get the flu and (survive/die), if you get a flu shot this fall?
You will get the flu and (survive/die) if you don't get a flu shot this fall?
Breast cancer (if female)
You will get breast cancer in the next 5 years?
You will get breast cancer in the next 10 years?
You will get breast cancer and die from it in the next 10 years, if you get a mammogram every 2 years?
You will get breast cancer and die from it in the next 10 years, if you don't get any mammograms?
You will get breast cancer and die from it in the next 20 years, if you get a mammogram every 2 years?
You will get breast cancer and die from it in the next 20 years, if you don't get any mammograms?
Cervical cancer (if female)
You will get cervical cancer in the next 5 years?
You will get cervical cancer in the next 10 years?
You will get cervical cancer and die from it in the next 10 years, if you get a Pap smear every 5 years?
You will get cervical cancer and die from it in the next 10 years, if you don't get any Pap smears?
You will get cervical cancer and die from it in the next 20 years, if you get a Pap smear every 5 years?
You will get cervical cancer and die from it in the next 20 years, if you don't get any Pap smears?
Sexually transmitted infections (if under 40)
You will get an/another STD in the next 5 years?
You will get an/another STD in the next 10 years?
You will get AIDS and die from it in the next 10 years, if you get an STD test every year?
You will get AIDS and die from it in the next 10 years, if you don't get an STD test?
You will get AIDS and die from it in the next 20 years, if you get an STD test every year?
You will get AIDS and die from it in the next 20 years, if you don't get an STD test?
Heart disease
You will get heart disease in the next 5 years?
You will get heart disease in the next 10 years?
You will get heart disease and die from it in the next 10 years, if you take a low dose of aspirin every day (or every other day) to reduce your risk?
You will get heart disease and die from it in the next 10 years, if you don't take a low dose of aspirin every day (or every other day) to reduce your risk?
You will get heart disease and die from it in the next 20 years, if you take a low dose of aspirin every day (or every other day) to reduce your risk?
You will get heart disease and die from it in the next 20 years, if you don't take a low dose of aspirin every day (or every other day) to reduce your risk?

Appendix Table 2: OLS Regressions Predicting Use of Flu Shots by Subgroups

Dependent Variable	Full Sample	65 + & invited	65 + & not invited	<65 & invited	<65 & not invited
Subjective effectiveness at preventing disease: (pwo-pw)/pwo, if effectiveness is positive	0.1579***	0.3301***	0.4853***	0.3631***	0.0139***
	(0.0121)	(0.0461)	(0.1126)	(0.0417)	(0.0053)
Dummy if subjective effectiveness of preventing disease is negative	-0.0126	-0.0935**	0.0370	0.0260	0.0017
	(0.0110)	(0.0462)	(0.0908)	(0.0381)	(0.0047)
Subjective probability of Getting Disease without intervention	0.1421***	0.1107**	0.1333	0.3136***	0.0278***
	(0.0144)	(0.0522)	(0.1837)	(0.0473)	(0.0064)
Subjective effectiveness at preventing death: (pwo-pw)/pwo, if effectiveness is positive	0.0939***	0.1025***	-0.0670	0.1025***	0.0103*
	(0.0119)	(0.0389)	(0.1037)	(0.0364)	(0.0057)
Dummy if subjective effectives of preventing death is negative	-0.0237**	-0.0403	-0.0086	-0.0449	-0.0007
	(0.0097)	(0.0392)	(0.0960)	(0.0334)	(0.0042)
Subjective probability of Dying (in 10 year for all but flu shot) without intervention	0.0718***	0.0645	0.0307	0.1174**	-0.0002
	(0.0155)	(0.0478)	(0.1523)	(0.0513)	(0.0073)
Received invitation for intervention	0.4349***				
	(0.0094)				
Expected or Actual monetary cost of intervention	-0.0014***	-0.0038***	-0.0023	-0.0063***	-0.0001*
	(0.0001)	(0.0006)	(0.0020)	(0.0006)	(0.0001)
Expected or Actual time cost of intervention	-0.0008***	-0.0038***	-0.0017	-0.0027***	-0.0001
	(0.0001)	(0.0010)	(0.0017)	(0.0006)	(0.0001)
Dummy if Male	0.0111	0.0092	0.0225	0.0069	-0.0007
	(0.0073)	(0.0260)	(0.0691)	(0.0242)	(0.0033)
ln(net household income)	0.0059	0.0063	0.0934	0.0005	0.0036
	(0.0066)	(0.0268)	(0.0879)	(0.0217)	(0.0029)
Numeracy	-0.0382**	0.0083	-0.0648	-0.1692***	0.0012
	(0.0168)	(0.0541)	(0.1466)	(0.0528)	(0.0078)
Did not finish 2ndary education	-0.0010	0.0662**	-0.0403	-0.0769*	-0.0079
	(0.0135)	(0.0335)	(0.1083)	(0.0445)	(0.0068)
MBO (similar to Associates degree)	-0.0142	0.1006**	-0.1446	-0.0841***	0.0034
	(0.0097)	(0.0406)	(0.0962)	(0.0315)	(0.0042)
HBO or WO (Bachelors degree or higher)	-0.0329***	0.0268	-0.1105	-0.1178***	0.0064
	(0.0093)	(0.0327)	(0.0781)	(0.0314)	(0.0042)

Dummy if has Diabetes	0.0983***	0.0006	0.0299	0.1336***	-0.0002
	(0.0144)	(0.0330)	(0.1191)	(0.0341)	(0.0103)
Dummy if has Heart Disease	0.0876***	0.0768***	0.0589	0.0932***	-0.0056
	(0.0129)	(0.0284)	(0.0795)	(0.0337)	(0.0089)
Dummy if has High Blood Pressure	0.0230**	0.0581**	0.0998	0.0056	0.0075
	(0.0092)	(0.0255)	(0.0662)	(0.0276)	(0.0046)
Self Assessed Health is Excellent or Good	-0.0249***	-0.0544	-0.0883	-0.0764**	-0.0022
	(0.0084)	(0.0345)	(0.0755)	(0.0307)	(0.0036)
Dummy if friends have died of disease	0.0636***	-0.0160	0.1917	0.1822***	-0.0103
	(0.0244)	(0.0612)	(0.3636)	(0.0652)	(0.0134)
Constant	-0.0657	0.5552***	-0.9540	0.3925**	-0.0346
	(0.0540)	(0.2142)	(0.7157)	(0.1801)	(0.0236)
Percent Receiving flu shot	23%	82%	9%	55%	1%
Observations	4927	646	91	1010	3180
R-squared	0.658	0.373	0.420	0.480	0.027

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions also control for 5 year age groups.

References

Belkar, R, Fiebig D, Haas M, Viney R. (2006). “Why worry about awareness in choice problems? Econometric analysis of screening for cervical cancer,” *Health Economics*, vol. 15, pp. 33-47.

Bruine de Bruin, W., and Carman, K.G. (2010). “Measuring Risk Perceptions,” Working Paper.

Bruine de Bruin, W., Parker, A.M., & Fischhoff, B. (2007). “Can teens predict significant Life Events?” *Journal of Adolescent Health*, vol. 41, pp. 208-210.

Byrne, M.M. and P. Thompson (2001). “Screening and preventable illness,” *Journal of Health Economics*’, vol. 20, pp. 1077-1088.

Chang, F., (1996). “Uncertainty and investment in health,” *Journal of Health Economics*, vol. 15, pp. 369–376.

Cropper, M.L. (1977)."Health, Investment in Health, and Occupational Choice," *Journal of Political Economy*, vol. 85(6), pages 1273-94.

Dardanoni, V. and Wagstaff, A., (1987). “Uncertainty, inequalities in health and the demand for health,” *Journal of Health Economics*, vol. 6, pp. 283–290.

Dardanoni, V. and Wagstaff, A., (1990). “Uncertainty and the demand for medical care,” *Journal of Health Economics*, vol. 9, pp. 23–38.

Decarli, Adriano, Calza, Stefano, Masala, Giovanna, Specchia, Claudia, Palli, Domenico, and Gail,Mitchell H. (2006). “Gail Model for Prediction of Absolute Risk of Invasive Breast Cancer: Independent Evaluation in the Florence–European Prospective Investigation Into Cancer and Nutrition Cohort,” *Journal of the National Cancer Institute*, vol. 98, no. 23, pp.1686-1693.

Delavande, Adeline (2008). “Pill, Patch or Shot? Subjective Expectations and Birth Control Choice,” *International Economic Review*, 2008, vol. 49, pp. 999-1042.

Dominitz, Jeff and Charles F. Manski (1997). “Using Expectations Data to Study Subjective Income Expectations,” *Journal of the American Statistical Association*, vol. 92, pp. 855-867.

Gail, Mitchell H., Brinton, Louise A., Byar, David P., Corle, Donald K., Green, Sylvan B., Schairer, Catherine, and Mutvihill, John J., (1989). “Projecting Individualized Probabilities of Developing Breast Cancer for White Females Who Are Being Examined Annually,” *Journal of the National Cancer Institute*, vol. 81, pp.1879-1886, 1989.

Gan, Li, Michael Hurd and Daniel McFadden (2003). “Individual Subjective Survival Curves,” National Bureau of Economic Research Working Paper 9480.

Gotzsche, PC,and Nielsen, M (2006). “Screening for breast cancer with mammography,” *Cochrane Database of Systematic Reviews*, Issue 4. Art. No.:CD001877.

Govaert, T.M., Thijs, C.T., Masurel, N., Sprenger, M.J., Dinant, G.J., and Knottnerus, J.A., (1994). “The efficacy of influenza vaccination in elderly individuals. A randomized double-blind placebo-controlled trial,” *JAMA*, Dec 1994, vol. 272, pp. 1661 - 1665.

Grossman, M. (1972). “On the concept of health capital and the demand for health,” *Journal of Political Economy* 80, pp. 223-255.

Hey, John D. and Mahesh S. Patel (1983). “Prevention and cure? Or: Is an Ounce of Prevention Worth a Pound of Cure?” *Journal of Health Economics*, vol. 2, pp. 119-138.

Hueston, William J., and Benich, Joseph J., (2004). “A Cost-Benefit Analysis of Testing for Influenza A in High-Risk Adults,” *Annals of Family Medicine*, vol. 2, pp. 33-40.

Hurd, M. and K. McGarry (1995). “Evaluation of the Subjective Probabilities of Survival in the Health and Retirement Study,” Journal of Human Resources, 30, S268-S292.

Hurd, Michael D. and Kathleen McGarry (2002). “The Predictive Validity of Subjective Probabilities of Survival,” *Economic Journal*, vol. 112, pp. 966-985.

Hurd, M. and J. Smith (2002). Expected Bequests and Their Distribution,” National Bureau of Economic Research Working Paper 9142.

Juster, Thomas (1966). “Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design,” *Journal of the American Statistical Association*, vol. 61, pp. 658-696.

Kenkel, Donald S. (1994). “The Demand for Preventative Medical Care,” *Applied Economics*, vol. 26, pp. 313-25.

Khwaja, A, D. Silverman, F.A. Sloan, and Yang Wang (2009). “Are Smokers Misinformed*?*” *Journal of Health Economics*, vol. 28, pp. 385-397.

Lipkus, Isaac M., Maggie Kuchibhatla, Colleen M. McBride, Hayden B. Bosworth, Kathryn I. Pollak, Ilene C. Siegler, and Barbara K. Rimer (2000). “Relationships among Breast Cancer Perceived Absolute Risk, Comparative Risk, and Worries,” *Cancer Epidemiology, Biomarkers & Prevention*, vol. 9, pp. 973-975.

Manski, Charles (2004). “Measuring Expectations,” *Econometrica*, Vol. 72, No. 5 (Sept. 2004), pp1329-1376.

Mullahy, John (1999). “It’ll only hurt a second? Microeconomic determinants of who gets flu shots,” *Health Economics*, vol. 8, pp. 9-24.

Peters, E., Slovic, P., Hibbard, J. H., & Tusler, M. (2006a). “Why worry? Worry, risk perceptions, and willingness to act to reduce medical errors,” *Health Psychology*, vol. 25, 144-152.

Peters, E., Vastfjaal, D. Slovic, P., Mertz, C.K., Mazzacco, Ketti, & Dickert, S. (2006b). “Numeracy and Decision Making”, *Psychological Science*, vol. 17, no 5, 407-413.

Prelec, Drazaen (1998). “The Probability Weighting Function,” *Econometrica*, vol. 60, pp. 497–528.

Rockhill, Beverly, Spiegelman, Donna, Byrne, Celia, Hunter, David J., and Colditz, Graham A. (2001). “Validation of the Gail et al. Model of Breast Cancer Risk Prediction and Implications for Chemoprevention,” Journal of the National Cancer Institute, Vol. 93, No. 5, pp. 358-366.

Sawaya GF, Brown AD, Washington AE, Garber AM, (2001). “Current Approaches to Cervical-Cancer Screening,” *New England Journal of Medicine*, Volume 344: Number 21, pp. 1603-1607.

Salant Talya, Pamela S. Ganschow, Olufunmilayo I. Olopade, Diane S. Lauderdale (2006). “ ‘Why Take It If You Don’t Have Anything?’ Breast Cancer Risk Perceptions and Prevention Choices at a Public Hospital,” *Journal of General Internal Medicine*, vol. 21, pp. 779-785.

Satterfield T, Johnson SM, Slovic P, Neil N, Schein JR. (2000). “Perceived risks and reported behaviors associated with osteoporosis and its treatment,” *Women Health*, vol. 31, pp. 21-40.

Selden, T., (1993). “Uncertainty and health care spending by the poor: the health capital model revisited,” *Journal of Health Economics*, vol. 12, pp. 109–115.

Skinner, Celette Sugg, Matthew W. Kreuter, Sarah Kobrin, Victor J. Strecher (1998). “Perceived and Actual Breast Cancer Risk: Optimistic and Pessimistic Biases,” *Journal of Health Psychology*, vol. 3, pp. 181-193.

Thomsen, Troels F, McGee, Dan, Davidsen, Michael and Jørgensen, Torben (2002). "A cross-validation of risk-scores for coronary heart disease mortality based on data from the Glostrup Population Studies and Framingham Heart Study," *International Journal of Epidemiolog* , vol. 31, pp. 817-822.

Thompson, William W., Shay, David K., Weintraub, Eric, Brammer, Lynnette, Cox, Nancy, Anderson, Larry J. and Fukuda, Keiji (2003). "Mortality Associated With Influenza and Respiratory Syncytial Virus in the United States," *Journal of the American Statistical Association*, January 8, 2003, vol. 289, no. 2, pp. 179-186.

Trivedi, Amal N., William Rakowski, and John Z. Ayanian (2008). "Effect of Cost Sharing on Screening Mammography in Medicare Health Plans," *New England Journal of Medicine*, vol. 358, pp. 375-383.

Wilson, Peter W. F., D'Agostino, Ralph B., Levy, Daniel, Belanger, Albert M., Silbershatz, Halit and Kannel, William B. (1998). "Prediction of Coronary Heart Disease Using Risk Factor Categories," *Circulation*, vol. 97, pp. 1837-1847.

Woloshin, Steven, Lisa Schwartz, Stephanie Byram, Baruch Fischhoff, and Gilbert Welch (2000). "A New Scale foe Assessing Perceptions of Chance," *Medical Decision Making*, vol. 20, pp. 298-307.

Viscusi W. Kip (1992). *Smoking: Making the Risky Decision*, New York: Oxford University Press.

Viscusi, W. Kip, and Joseph E. Aldy. (2003). "The value of a statistical life: a critical review of market estimates throughout the world," *Journal of Risk and Uncertainty*. 27(1): 5–76.

Wu, S. (2003). "Sickness and preventive medical behavior," *Journal of Health Economics*, vol. 22, pp. 675-689.