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VALUE OF RISKY LIFESTYLE CHOICES

Abstract

Using data from the Panel Study of Income Dynamics on breast cancer diagnosis and lifestyle choices, we estimate how being diagnosed influences smoking, drinking, and exercising habits for more than 9,000 women over the period 1999 to 2011. These data allow us to learn more about the trade-offs women are willing to make between participating in unhealthy (but enjoyable) habits and increasing one's life expectancy. Our parameter estimates indicate that the impact of diagnosis has a different effect on smoking, drinking, and exercising behavior, and the impact also depends upon the recency of the diagnosis. We find that recently diagnosed women exercise and smoke less but do not change their drinking habits relative to healthy women. These changes are not always consistent with public information on cancer risk factors, but are rationalized after considering that lifestyle choices increase the utility of living. For a woman diagnosed with breast cancer, our results indicate that a woman will smoke only if the value placed on smoking is greater than 6% of the total utility from being alive. We find the threshold is lower for drinking where drinking has a positive impact on the value of life if the value placed on drinking is greater than 3% of the total utility from being alive. Finally, a woman with breast cancer will find it valuable to engage in exercise even when it brings disutility of 3% of the value of living. Using conventional estimates for the value of a year of life, we find that these choices imply that, per year, women value smoking at about $49,000 for smokers, drinking at about $29,500 for drinkers, and exercising at about $28,200 for exercisers.

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Value of Risky Lifestyle Choices

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February 13, 2019

Abstract: Using rich data from the Panel Study of Income Dynamics on breast cancer diagnosis and lifestyle choices, we estimate how being diagnosed influences smoking, drinking, and exercising habits for more than 9,000 women over the period from 1999 to 2011. These data allow us to learn more about the trade-offs women are willing to make between participating in unhealthy (but enjoyable) habits and increasing one's life expectancy. Our parameter estimates indicate that breast cancer diagnosis (and recency of diagnosis) impacts lifestyle choices. However, the impact of diagnosis has a different effect on smoking, drinking, and exercising behavior, and the impact also depends upon the recency of the diagnosis. We find that women who had a diagnosis recently in their lives (within the last five years) exercise less and smoke less but do not change their drinking habits relative to healthy women. These changes in behavior are not always consistent with information provided to the public on breast cancer risk factors. However, we find that these choices are rationalized when one considers the overall value of life where lifestyle choices increase the utility of living. For a woman diagnosed with breast cancer, our results indicate that a woman will smoke only if the value placed on smoking is greater than 6% of the total utility from being alive. We find the threshold is lower for drinking where drinking has a positive impact on the value of life if the value placed on drinking is greater than 3% of the total utility from being alive. Finally, a woman with breast cancer will find it valuable to engage in exercise even when it brings disutility of 3% of the value of living. Using conventional estimates for the value of a year of life, we find that these choices imply smoking is valued at about $49,000 per year for smokers, drinking is valued at about $29,500 per year for drinkers, and exercising is valued at about $28,200 for exercisers.

1 Introduction

About 13% of US women will develop breast cancer at some point during their life, and worldwide incidence is rising.[2] The impact is high in terms of mortality, costs of treatment, and emotional effects (Parkin et al., 2005).[3] There are a number of factors linked to breast cancer risk such as family history, older age, use of estrogen replacement therapy, and a later

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[2] Surveillance Epidemiology and End Results survey (Gloeckler Ries et al., 2007)

[3] For the United States, Campbell and Ramsey (2009) report an estimate of lifetime per-patient cost of breast cancer going from $20,000 to $100,000. Similarly, Mariotto et al. (2011) report that annual costs of care for breast cancer for women younger than 65 is $27,693 in the initial phase of care and $94,284 during the last year of life.

start to childbearing (Berry et al., 2005). In addition, the medical literature reports that several lifestyle habits are associated with breast cancer incidence including weight gain, fat intake, and level of physical activity, while others have been inconsistently linked with the disease including alcohol consumption and cigarette smoking.[4]

Whether to engage in physical activity, drink alcohol, or smoke are choices associated with how to live.[5] Therefore, understanding lifestyle decisions made by diagnosed women and the value they derive from these choices can provide useful information in the fight against breast cancer. The goal of this paper is to quantify how women with breast cancer value unhealthy (but enjoyable) habits relative to life expectancy.

We develop a model that allows us to examine the impact a breast cancer diagnosis has on engaging in (potentially addictive) risky behaviors over time. The Panel Study of Income Dynamics contains rich longitudinal information on the timing of breast cancer diagnosis and lifestyle choices that we use to estimate the parameters of the model. These estimates, combined with national statistics on the impact of the risky behaviors for life expectancy, allow us to determine the implied value of risky lifestyle behaviors.

This approach provides valuable information along many dimensions. First, it illustrates to what extent women who are faced with negative information about life expectancy take this into consideration when deciding to engage in risky behaviors. Second, it allows us to quantify the cost of engaging in (potentially addictive) risky behaviors when the chance of survival is negatively impacted and hence the value of life is most salient. Finally, using conventional estimates on the value of life, our results provide insight into the monetary value women place on enjoyable but harmful lifestyle choices.

Our parameter estimates indicate that breast cancer diagnosis impacts lifestyle choices. However, the impact of diagnosis has a different effect on smoking, drinking, and exercising behavior, and the impact also depends upon the recency of the diagnosis. We find that women who had a diagnosis within the last five years exercise less and smoke less but do not change their drinking habits relative to healthy women. These changes in behavior are not always consistent with information provided to the public on breast cancer risk factors.[6]

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[4] For example, see Demark-Wahnefried et al. (2000), Singletary and Gapstur (2001), Pinto et al. (2002), and Blanchard et al. (2004).

[5] There are numerous papers that examine risky behaviors such as smoking, drinking, and exercise/obesity. See for example, Perreira and Sloan (2001), Khwaja et al. (2006), and Klijs et al. (2011).

[6] There is a related literature on how publicly available information and guidelines impact behavior. See

However, we find that these choices are rationalized when one considers the overall value of life where lifestyle choices increase the utility from living.

Not surprisingly, we find that the value of the loss of life associated with risky behaviors regardless of breast cancer diagnosis depends critically on the woman's discount rate. With respect to smoking, we find that 1/3 of the "cost" associated with smoking for a woman who has been diagnosed with breast cancer is due to the harmful effects of smoking that all individuals have regardless of diagnosis. However, 2/3 of the cost are due to the interaction effect of smoking and breast cancer diagnosis. Therefore, on average, a woman who smokes will find it worthwhile to stop this behavior after being diagnosed with cancer. Our findings also explain why women do not change their drinking habits. The main reason is that women enjoy drinking and that it does not have a meaningful effect on death probabilities. We also note that this behavior is in line with medical literature that suggests that, in some situations, drinking can improve health. For a woman diagnosed with breast cancer, our results indicate that a woman will smoke only if the value placed on smoking is greater than 6% of the total utility from being alive. We find the threshold is lower for drinking, where drinking has a positive impact on the value of life if the value placed on drinking is greater than 3% of the total utility from being alive. Using conventional estimates for the value of a year of life (Cutler, 2004; Murphy and Topel, 2006), we find that these choices imply smoking is valued at about $49,000 per year for smokers, drinking is valued at about $29,500 per year for drinkers, and exercising is valued at about $28,200 for exercisers.

There are numerous studies in the economics and medical literatures that examine issues associated with breast cancer.[7] However, there are relatively few that consider the relationship with lifestyle choices,[8] and, to the best of our knowledge, ours is the first paper to examine changes in behavior while controlling for persistence in lifestyle choices. Among those papers that examine lifestyle choices among breast cancer survivors, Bellizi et al. (2005) conduct a descriptive analysis of the prevalence of health behaviors (smoking, alcohol use, physical activity, and cancer screening) of cancer survivors by age, time since

for example, Hu et al. (1995), Ippolito and Mathios (1995), and Jacobson and Kadiyala (2017).

[7] These include studies on cancer mortality (e.g., Cutler, 2008), investment in research (e.g., Budish, Roin, and Williams, 2015), mammography screening (e.g., Bitler and Carpenter, 2016; Jacobson and Kadiyala, 2017), costs of treatment (e.g., Einav, Finkelstein, and Williams, 2016), and insurance coverage (e.g., Decker, 2005). We do not provide a comprehensive review of this vast literature.

[8] These include Blanchard et al. (2004), Demark-Wahnefried et al. (2000), Pinto et al. (2002), Braithwaite et al. (2012) who focus on smoking, Ibrahim and Al-Homaidh (2011) who focus on physical activity, and Singletary and Gapstur (2001) who focus on alcohol consumption.

diagnosis, and cancer site using data from the National Health Interview Survey. They find that cancer survivors are more likely to meet the recommendations for physical activity and cancer screening compared with noncancer controls. However, they do not find any evidence of different behavior among survivors with respect to smoking and alcohol consumption. We complement and add to the previous studies in a number of ways. First, we use a large, nationally representative sample that includes women diagnosed with breast cancer. Second, we examine changes in lifestyle behaviors over time where we allow for persistence in behavior. Finally, we develop a framework to quantify the value of risky lifestyle choices among women with cancer.

We proceed as follows in the rest of the paper. In the next section, we provide an overview of the related literature. In section 2, we discuss the data. In section 3, we present a framework that links breast cancer diagnosis and risky lifestyle choices. We discuss the estimation methodology in section 3.2 and the estimation results in section 3.3. In section 4, we quantify the trade-off women make when choosing to undertake risky behavior and how it depends on a recent breast cancer diagnosis. We conclude in section 5.

2 Data

Our research uses data from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal study that started in 1968 with over $18,000$ individuals from $5,000$ households in the United States and now includes more than $22,000$ individuals from over $9,000$ households. One person per family, designated as the "head," is interviewed regularly and answers questions about himself, his spouse (or his long-term female cohabitator) and his family members.[9] Families from the core sample are interviewed biennially. Every wave contains information about employment, income, education, wealth, marriage, childbearing, and various other topics. We choose to use the PSID data set because of its longitudinal structure which allows us to follow the same individuals and their corresponding behaviors across time. Further, these data are collected not only for breast cancer patients but also for persons without a history of cancer. This allows us to make comparisons between breast

[9] The head can be a man or a woman. Because it is more often the husband, we use the masculine form to refer to it. The head of the household provides answers for questions related to his spouse. The literature has shown that spouses have very precise perceptions of the time spent by the other spouse on different activities (Stern, 2003). Similarly, it has been shown (see, for example, Kolonel et al., 1977; Mejia et al., 2017) that spouses provide complete information for various lifestyle behaviors of their spouse such as smoking and drinking behaviors.

cancer patients and healthy individuals.

We use data from seven waves from 1999, when cancer outcomes were first recorded, until 2011. We retain the data from respondents who are aged 15 and older and are female, because breast cancer almost exclusively affects women. Our starting sample consists of $9,447$ women for a total of $46,061$ person-years. Table 1 provides an overview of how we obtain our final estimation sample. First, we drop individuals who have missing information on demographics,[10] cancer condition, and breast cancer condition. We lose a total of 310 persons and are left with a sample of $9,137$ persons and $42,875$ person-years. Secondly, we use this sample as a new starting point and drop missing values for that choice. For example, for our analysis on "smoking behaviors," we drop only those observations with missing values for questions related to smoking habits. This is shown in the bottom panel of Table 1.[11]

Variables of Interest	Starting # Person-Years	Starting # Persons	# Person-Years Dropped	#Persons Dropped
Explanatory Variables	46061	9447		
Demographics[1]			2999	238
Cancer Condition			37	6
Breast Cancer Condition			150	66
Dependent Variables	42875	9137		
Smoking Habits			39	1
Drinking Habits			55	0
Exercising Habits			251	10

[1] Demographics include age, race, education level, and income.

Table 1: Sample Selection Analysis

Table 2 reports demographic summary statistics, and Table 3 reports health behaviors summary statistics for our sample. The PSID was initially designed to study the dynamics of income and poverty. The oversampling of families who were poor in the late 1960s resulted in a substantial subsample of blacks (PSID, 2013). In our sample, we also have a large proportion of black respondents (30%). One of our main interests is the health status of our respondents and, in particular, their cancer status. As can be seen in Table 2, 8.4% of the sample have been diagnosed with cancer and 2.1% with breast cancer, which matches the proportion of cancers that are breast cancers reported in the national breast cancer statistics of the American Cancer Society (2007). As can be seen in Table 3, approximately 53% of our respondents ever drink alcoholic beverages, which is slightly below the national average

[10] This corresponds to missing values for age, race, education level, or income.

[11] For example, our analysis of "exercising behaviors" is based on a sample of $9,137 - 10 = 9,127$ persons and $42,875 - 251 = 42,624$ persons-years.

Variable	Mean	Std. Dev.
Age	44.577	15.993
White	0.579	0.494
Black	0.307	0.461
Married	0.638	0.481
Employed	0.637	0.481
Has Children	0.810	0.392
Highest Education Degree:		
No Degree	0.172	0.377
High School	0.415	0.493
University	0.325	0.469
Post Graduate	0.087	0.282
Taxable Income:		
$<$ \$ 20,000	0.196	0.397
\$ 20,000 - \$ 50,000	0.247	0.431
$>$ \$ 50,000	0.557	0.497
Diagnosed with:		
Cancer	0.084	0.277
Breast Cancer	0.021	0.143
Number of Person-Years:	42875	

Table 2: Demographics Summary Statistics

Variable	Mean	Std. Dev.	#Person-Years
Smoking Status			42836
Current Smoker	0.183	0.387	
Cigarette Consumption			7743
Smokes 1 to 9 cig/day	0.335	0.472	
Smokes 10 to 19 cig/day	0.360	0.480	
Smokes 20 or more cig/day	0.305	0.460	
Alcohol			42820
Drinks Alcohol	0.527	0.499	
Frequency of Alcohol Consumption[1]			26012
Never drinks	0.459	0.498	
Less than 1 drink per month	0.157	0.364	
One drink per month	0.112	0.316	
Several drinks per month	0.085	0.279	
One drink per week	0.091	0.288	
Several drinks per week	0.073	0.260	
Drinks everyday	0.022	0.147	
Exercise			42624
Never	0.162	0.368	
1 or 2 times/week	0.181	0.385	
3 to 6 times/week	0.294	0.456	
7 times/week	0.326	0.469	
8 to 14 times/week	0.016	0.125	
More than 14 times/week	0.021	0.143	

[1] This includes only waves 2005, 2007, 2009, and 2011.

Table 3: Health Behaviors Summary Statistics

of 55% as reported by the National Center for Health Statistics (Schoenborn and Adams, 2010) for the period 2005-2007.[12] As the survey questions concerning alcohol consumption were not consistently worded across waves, we report statistics only for the last four waves (2005, 2007, 2009, and 2011).[13]

Table 4 presents details about respondents with breast cancer. Individuals in the sample

Variable	**Mean**	**Std. Dev.**	**# Person-Years**
Years Since BC Diagnosis	11.441	12.155	873
Age at BC Diagnosis	50.507	14.997	889
Currently[1]			
Cured	0.695	0.461	491
In Remission	0.189	0.392	491
In Treatment	0.116	0.321	491

[1] These questions are asked starting only in 2005.

Table 4: Descriptive Statistics for Individuals with Breast Cancer

responded to the following question: "Has a doctor ever told you that you have or had cancer or a malignant tumor?" If the respondent answered "yes," follow-up questions were asked regarding the type of cancer and the stage. The majority of our respondents are "cured," while approximately 12% are in treatment.[14] As can be seen in Table 4, the sample average age for a breast cancer diagnosis is approximately 50.

In Table 5, we report prevalence of breast cancer diagnosis by demographic groups. The proportion of respondents having breast cancer is larger among whites than among individuals of other races. This is in line with national statistics, which indicate that white women have the highest probability of getting diagnosed with breast cancer (American Cancer So-

[12] They report the proportion of current drinkers, which refer to adults who have had at least 12 drinks in their lifetime and at least one drink in the past year. Looking at these numbers disaggregated by race, we find in our sample that 61% of the white respondents and 43% of the blacks ever drink alcoholic beverages. This also matches the numbers in the National Center for Health Statistics which report 59% and 40% of current drinkers for whites and blacks respectively.

[13] For the first three waves (1999, 2001, and 2003), people are asked how many drinks they have *on average* per day: "In the last year, on average, how often did you have any alcohol to drink? Would you say, less than one a month, about once a month, several times a month, about once a week, several times a week, or every day?". For the last four waves , the categories were changed and the questions about daily consumption referred to *days when respondents drink*: "In the last year, on the days you drank, about how many drinks did you have?". In later regressions, we also use data only from years 2005, 2007, 2009, and 2011 when looking at alcohol behaviors.

[14] Cancer is considered as "cured" when doctors cannot detect cancer five years after diagnosis (American Cancer Society, 2006). Questions about whether the respondent is currently in treatment, in remission, or has been cured are asked only starting in 2005. The sample size is therefore smaller.

	Proportion of Breast Cancer Diagnoses			
Variable	**Mean**	**Std. Dev.**	**Person-Years**	**p-value**[1]
Race				0.000***
White	0.025	0.156	24814	
Black	0.016	0.126	13166	
Other	0.012	0.107	4895	
Age				0.000***
Younger than 30	0.000	0.019	8643	
Between 30 and 59	0.016	0.126	27012	
60 and older	0.062	0.242	7220	
Family Composition				0.000***
Have Children	0.023	0.149	34732	
Childless	0.012	0.110	8143	
Age at First Child				0.034*
Younger than 35	0.023	0.150	33444	
35 and older	0.016	0.124	1288	
Education				0.042*
No Degree School	0.023	0.150	7372	
High School	0.022	0.147	17800	
Associate or Bachelor	0.018	0.135	13955	
>Bachelor	0.018	0.134	3748	
Family Income				0.000***
<20,000$	0.029	0.168	8404	
≥20,000$ & <50,000$	0.016	0.127	10578	
>50,000$	0.020	0.139	23893	

[1] The reported p-values are from multivariate tests on equal means.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Proportion of Breast Cancer Diagnoses Disaggregated by Demographics

ciety, 2005). However, black women are less likely to use diagnostic services, and, when they are diagnosed, it is typically at a later stage (American Cancer Society Statistics, 2003).[15] Childless women and women whose first birth is after age 35 have an increased risk of developing breast cancer (Britt, Ashworth, and Smalley 2007), which is also reflected in our data. However, conditional on having children, the proportion of breast cancer patients is larger for women who had their child at 35 years old or later. This is consistent with the fact that a higher age at first full-term pregnancy is considered a risk factor for breast cancer (for example, Kelsey, 1993).

Next, we examine relationships between risky health behaviors and breast cancer prevalence. Table 6 displays breast cancer diagnosis among individuals with differing smoking, drinking, and exercise habits.[16] The first few rows show that the proportion of breast cancer patients is the largest among former smokers. Among smokers, breast cancer prevalence is the highest for respondents who smoke more than 19 cigarettes per day.

Regarding alcohol consumption behaviors, prevalence is lower in the group of respondents who drink alcohol. Among those who drink, breast cancer prevalence is the highest for individuals who drink every day.

The bottom panel of table 6 presents statistics for physical activity. The respondents were asked about weekly exercise frequency for heavy and light workouts. Specifically, they were asked "How often do you participate in vigorous/light physical activity or sports?" A problem with this wording is that there is no information about the measure of time spent by a person doing physical activity.[17] In our analysis, we first aggregate light and heavy physical activities into one variable called "exercise." Second, we define the following six categories: no exercise (neither light nor heavy), exercise $1-2$ times a week, exercise $3-6$ times a week, exercise 7 times a week, exercise $8-14$ times a week, and exercise more than 14 times a week.[18] The proportion of breast cancer patients is the largest among people

[15] Diagnosis requires going to the doctor, and women without adequate insurance are going to be less likely to go to the doctor.

[16] There are some women in the sample who have breast cancer but have not yet been diagnosed. However, given that the woman does not know she has breast cancer, this will not influence her actions and hence will not impact our results.

[17] Specifically, heavy exercise refers to "heavy housework, aerobics, running, swimming, bicycling or similar that causes heavy sweating or large increases in breathing or heart rate" (PSID, 2005). Light exercise includes "walking, dancing, gardening, golfing, bowling or similar that causes only light sweating or slight to moderate increases in breathing or heart rate" (PSID, 2005). See the discussion in Berniell et al. (2013).

[18] Some persons report extreme values which could indicate some misunderstanding of the question.

Variable	Proportion of Breast Cancer Diagnoses Mean	Std. Dev.	Person-Years	p-value[1]
Smoking Status				0.000***
Current Smoker	0.014	0.116	7852	
Former Smoker	0.036	0.186	9026	
Never Smoked	0.018	0.132	25929	
Cigarette Consumption				0.037*
Smokes 1 to 9 cig/day	0.010	0.102	2592	
Smokes 10 to 19 cig/day	0.012	0.108	2789	
Smokes 20 or more cig/day	0.019	0.137	2362	
Alcohol				0.000***
Drinks Alcohol	0.018	0.133	22561	
Never Drinks Alcohol	0.024	0.152	20259	
Frequency of Alcohol Consumption[2]				0.058
Less than 1 drink per month	0.019	0.135	4082	
One drink per month	0.017	0.128	2920	
Several drinks per month	0.014	0.117	2221	
One drink per week	0.017	0.129	2376	
Several drinks per week	0.025	0.157	1894	
Drinks everyday	0.031	0.174	574	
Exercise				0.000***
Never	0.032	0.177	6901	
1 or 2 times/week	0.019	0.135	7710	
3 to 6 times/week	0.019	0.136	12550	
7 times/week	0.018	0.134	13896	
8 to 14 times/week	0.012	0.108	673	
More than 14 times/week	0.020	0.140	894	

[1] The reported p-values are from multivariate tests on equal means.

[2] This only considers waves 2005, 2007, 2009 and 2011.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Proportion of Breast Cancer Diagnoses Disaggregated by Health Behaviors

who never exercise, while it is the lowest among people who exercise more than 14 times per week. The main point that emerges from table 6 is that breast cancer incidence differs with the degree an individual engages in lifestyle behaviors. In the next sections, we examine this in more detail.

3 Engaging in Risky Behavior

In this section we present and estimate a model that allows us to learn about the impact of breast cancer diagnosis on engaging in risky behaviors. In the subsequent sections, we use these estimates to determine the value of engaging in risky lifestyle behaviors for women.

3.1 Econometric Specification

In our framework, a woman (indexed by i) makes a lifestyle choice (indexed by l) in each period (indexed by t), where the lifestyle behaviors may be influenced by breast cancer diagnosis. The lifestyle choices concern how much to smoke, how much to consume alcohol, and how much to engage in physical activity. Let y^*_{ilt} be a latent variable measuring the continuous quantity of lifestyle activity l chosen by individual i at time t. Specifically, the baseline model is given by

$$y^*_{ilt} = 1\left(y^*_{ilt-1} > 0\right)\alpha_l + X_{it}\eta_l + b_{it}\delta_l + \mu_{il} + \varepsilon_{ilt}, \tag{1}$$

Lifestyle choices exhibit persistence, which may be due to addiction (such as smoking and drinking alcohol) or habit persistence (such as exercise).[19] Therefore, we allow individual i's lifestyle choices at time t to depend on whether she participated in that behavior in the immediate past $1(y^*_{ilt-1} > 0)$. Exogenous, possibly time-varying individual demographic variables (X_{it}) that are likely to influence lifestyle choices include i's age, her marital status, whether she has children, her income, and her education level.

There may be heterogeneity that we do not observe in the data that influences choices and has a persistent nature. Unobserved heterogeneity likely to influence lifestyle choices includes a person/behavior-specific random effect μ_{il}, which captures things such as taste for alcohol or dislike of exercise, and an idiosyncratic effect ε_{ilt}.

[19] Economists do not distinguish between habit-formation and addiction; both are modeled as consumption decisions today affecting future utility. We follow this approach.

Whether a woman has been diagnosed with breast cancer (captured by dummy b_{it}) may impact her decision to engage in risky behaviors, for example, if she feels that these behaviors may reduce her longevity more severely than prior to the breast cancer diagnosis. To the extent that smoking, drinking, or exercise are risk factors for getting breast cancer, one may be concerned that b_{it} is a function of prior choices. In effect, causation may run in both directions. We address issues of endogeneity and unobserved heterogeneity using Wooldridge fixed effects techniques that we describe momentarily. Finally, we need to include an initial value of the risky decisions at time $t = 0$. These are likely to be endogenous, and we follow previous literature (à la Heckman, 1981) to control for endogenous initial conditions. We specify the initial period values as

$$y^*_{il0} = C_i \varsigma_l + X_{i0}\eta_l + b_{i0}\delta_l + \mu_{il} + \varepsilon_{il0}, \tag{2}$$

$$\varepsilon_{il0} \sim iidN(0, \sigma^2_\varepsilon),$$

where C_i is a set of variables affecting only initial choices. For smoking behaviors, these include age when i started smoking.[20] Unfortunately, the PSID does not contain any information on the age at which respondents started drinking or exercising. For these lifestyle choices, we include the level of drinking or exercising behavior observed in the first period of the data as C_i. In this approach, there may be a concern about the value of μ_{il}. One possibility is to treat it as nonrandom, which would imply that μ_{il} and y^*_{il0} are independent. However, μ_{il} and y^*_{il0} may not be independent, so we follow Wooldridge (2002) that builds on Chamberlain (1984) and specify the construction of the fixed effect conditional on the initial condition as

$$\begin{aligned} \mu_{il} &= \pi_0 + \pi_1 y^*_{il0} + \overline{X}_i \pi_2 + a_{il}, \qquad (3) \\ a_{il} &\sim N(0, \sigma^2_a) \end{aligned}$$

where $\overline{X}_i$ denotes the mean over time of the explanatory variables (excluding the year fixed effects). As discussed in Wooldridge (2005), the random component of the fixed effect then can be integrated out to yield the likelihood function of the random effects Probit model

[20] For those who do not smoke, the initial condition is set to zero. This is an innocuous normalization because we control for those who have never smoked. A separate concern is that age started smoking might be endogenous. However, most of the literature (e.g., Wooldridge, 2005) ignores this issue.

with time-t, observation-i explanatory variables: $(X_{it}, y_{il,t-1}, ...y_{il0}, \overline{X}_i)$ (we define y_{ilt} momentarily).

3.2 Estimation Methodology

Due to data restrictions that we discuss in section (4), we estimate three models corresponding to the lifestyle activities separately. Using equation (1), define

$$Y_{ilt}(\mu_{il}) = 1\left(y^*_{ilt-1} > 0\right)\alpha_l + X_{it}\eta_l + b_{it}\delta_l + \mu_{il}$$

as the deterministic part of y^*_{ilt} after conditioning on μ_{il} for $t \geq 1$; using equation (2), define

$$Y_{il0}(\mu_{il}) = C_i\varsigma_l + X_{i0}\eta_l + b_{i0}\delta_l + \mu_{il};$$

and, using equation (3), define

$$\overline{\mu}_{il} = \pi_0 + \pi_1 y^*_{il0} + \overline{X}_i\pi_2.$$

We should note that each behavior is reported in the data as a bracketed variable. We define $m = 1$ as not participating in the activity and let the quantity of activity increase as m increases with

$$y_{ilt} = m \text{ iff } \kappa_{lm} \leq y^*_{ilt} < \kappa_{lm+1}, \;\; m = 1, 2, .., M_l, \tag{4}$$

where κ_{lm} are cutoff points to be estimated. Assume without loss of generality that $\kappa_{l1} = -\infty$, $\kappa_{l2} = 0$, and $\kappa_{lM_l+1} = \infty$.

The vector of parameters to estimate for model l is $\theta_l = (\alpha_l, \eta_l, \delta_l, \varsigma_l, \pi_0, \pi_1, \pi_2, \sigma_\varepsilon, \sigma_a, \kappa_l)$, and the log likelihood contribution for i is

$$L_{il} = \log \int \left[\prod_{t=1}^{T}\left(\prod_{m=1}^{M_l}\Delta_{ilm}\mu_{il}^{1(y_{ilt}=m)}\right)\left(\prod_{m=1}^{M_l}\Delta_{ilm}\left(\frac{\mu_{il}}{\sigma_\varepsilon^2}\right)^{1(y_{il0}=m)}\right)\frac{1}{\sigma_a}\phi\left(\frac{\mu_{il}-\overline{\mu}_{il}}{\sigma_a}\right)d\mu_{il}\right]$$

where

$$\Delta_{ilm}\left(\frac{\mu_{il}}{\sigma}\right) = \Phi\left[\frac{\kappa_{lm+1} - Y_{ilt}(\mu_{il})}{\sigma}\right] - \Phi\left[\frac{\kappa_{lm} - Y_{ilt}(\mu_{il})}{\sigma}\right]$$

for $\sigma = 1$ or σ_ε^2. The log likelihood function $L_l = \sum_i L_{il}$ can be evaluated using a straightforward quadrature method (Butler and Moffitt, 1982).[21]

[21] More complex error structures probably would require use of simulation methods (Stern, 1997).

3.3 Parameter Estimates

Our parameter estimates indicate that breast cancer diagnosis and recency of diagnosis impacts lifestyle choices. However, the impact of diagnosis has a different effect on smoking, drinking, and exercising, and the impact also depends upon the recency of the diagnosis. We first start by discussing the impact of breast cancer diagnosis on smoking behavior. We consider four categories of daily smoking intensity: (i) does not smoke; (ii) smokes but fewer than 10 cigarettes a day; (iii) smokes between 10 and 19 cigarettes a day; or (iv) smokes more than 20 daily (which is more than a pack of cigarettes). Table 7 presents random-effects ordered probit estimates where the explanatory variables include smoking behavior in the previous year, demographics, as well as breast cancer variables.

Dependent Variable: Ordered Variable for Number of Cigarettes Smoked	(1)	(2)	(3)	(4)
Lagged Behavior				
Smoker Last Period	2.432***	1.646***	2.433***	1.648***
	(0.0298)	(0.0450)	(0.0298)	(0.0450)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.0957	-0.150		
	(0.0984)	(0.142)		
Recent Breast Cancer Diagnosis			-0.289**	-0.326*
			(0.140)	(0.171)
Other Controls				
Aged in 30s, 40s, or 50s	-0.0279	0.172***	-0.0272	0.172***
	(0.0329)	(0.0509)	(0.0329)	(0.0509)
Aged 60 or Older	-0.519***	-0.160	-0.520***	-0.164
	(0.0513)	(0.103)	(0.0511)	(0.103)
White	0.474***	0.701***	0.473***	0.700***
	(0.0527)	(0.0842)	(0.0527)	(0.0841)
Black	0.0807	0.196**	0.0798	0.195**
	(0.0550)	(0.0882)	(0.0549)	(0.0881)
Married	-0.227***	-0.259***	-0.227***	-0.259***
	(0.0296)	(0.0394)	(0.0296)	(0.0393)
Have Children	0.00395	-0.0321	0.00392	-0.0321
	(0.0417)	(0.0632)	(0.0417)	(0.0631)
Highest Education is High School	-0.241***	-0.352***	-0.241***	-0.352***
	(0.0361)	(0.0516)	(0.0361)	(0.0516)
Highest Education is University Degree	-0.505***	-0.700***	-0.505***	-0.700***
	(0.0422)	(0.0605)	(0.0422)	(0.0604)
Highest Education is Post Graduate	-0.896***	-1.268***	-0.895***	-1.266***
	(0.0748)	(0.107)	(0.0748)	(0.107)
Income Less than 20K	0.102***	0.109***	0.102***	0.109***
	(0.0346)	(0.0418)	(0.0346)	(0.0418)
Income Between 20 and 50K	0.0953***	0.106***	0.0949***	0.105***
	(0.0310)	(0.0375)	(0.0310)	(0.0375)
Initial Conditions Included	no	yes	no	yes
Number of Observations	33,967	33,942	33,967	33,942
Number of Individuals	8,019	8,010	8,019	8,010

Notes: Standard errors in parentheses. * indicates significance at 10% level; ** at 5%; and *** at 1%.
All regressions include cut-off points, individual heterogeneity variance and year fixed effects.
The initial conditions specifications include the mean over time of all time varying regressors.

Table 7: Random-Effects Ordered Probit Regressions for Smoking

The signs and significance of the control variables are intuitive and consistent with results from other studies. First, past smokers are more likely to be current smokers, and the significant positive effect persists after controlling for unobserved heterogeneity (in columns

2 and 4). Our finding is consistent with numerous studies that have shown that smoking exhibits true state dependence (i.e., the effect is significant after controlling for unobserved heterogeneity). Our results indicate that white women smoke more than black women (see Schoenborn and Adams, 2010). We also find that married women smoke less than those who are not married as do women with a higher education relative to other education categories. Finally, we find that individuals with lower incomes (under $\$50,000$) smoke more than higher-income women.

The first two columns indicate that whether an individual has been diagnosed with breast cancer has no significant impact on smoking behavior conditional on past behavior and demographic variables. However, as columns (3) and (4) show, if the woman was diagnosed with breast cancer less than five years ago, she will significantly decrease her smoking behavior (-0.289) with this effect being robust to including initial conditions (column 4, -0.326). The differential impact of the time of diagnosis on smoking behavior could arise from a few sources. First, the individual may react to a diagnosis by curbing unhealthy habits such as smoking, but this effect may deteriorate over time as the individual survives past the initial stages. Second, the woman may be undergoing treatment which makes smoking more difficult in the short term due to lack of energy, for example.

Table 8 presents the results of a random-effects ordered probit regression for number of alcoholic drinks, where the dependent variable is ordered according to: (i) a non-drinker, (ii) a woman who drinks at most once a week on average, and (iii) a woman who drinks more than once a week on average. As with smoking, our results indicate that past drinking behavior is a positive significant indicator of current drinking behavior, and this effect remains after controlling for initial conditions in columns (2) and (4). The other control variables imply that women aged 60 or older drink less than younger women and that white women drink more than black women. In addition, we find that married women drink less often as do those with children. Drinking more often is more likely among those with higher education relative to other groups and among those with a larger income. In contrast to smoking behaviors, women do not change their alcohol consumption after a breast cancer diagnosis regardless of when the diagnosis was made.

Dependent Variable: Ordered Variable for Number of Alcoholic Drinks	(1)	(2)	(3)	(4)
Lagged Behavior				
Number of Drinks Last Period	0.220***	0.0513***	0.220***	0.0513***
	(0.0111)	(0.0119)	(0.0111)	(0.0119)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.0791	-0.101		
	(0.136)	(0.142)		
Recent Breast Cancer Diagnosis			-0.0112	-0.0874
			(0.180)	(0.186)
Other Controls				
Aged in 30s, 40s, or 50s	0.0125	0.104**	0.0116	0.103**
	(0.0481)	(0.0498)	(0.0480)	(0.0498)
Aged 60 or Older	-0.394***	-0.163**	-0.398***	-0.167**
	(0.0673)	(0.0699)	(0.0670)	(0.0696)
White	0.849***	0.716***	0.848***	0.715***
	(0.0737)	(0.0764)	(0.0736)	(0.0764)
Black	0.137*	0.148*	0.136*	0.148*
	(0.0777)	(0.0811)	(0.0777)	(0.0811)
Married	-0.192***	-0.151***	-0.192***	-0.151***
	(0.0430)	(0.0444)	(0.0430)	(0.0444)
Have Children	-0.474***	-0.391***	-0.474***	-0.391***
	(0.0591)	(0.0610)	(0.0591)	(0.0610)
Highest Education is High School	0.465***	0.467***	0.465***	0.467***
	(0.0605)	(0.0629)	(0.0605)	(0.0629)
Highest Education is University Degree	0.804***	0.802***	0.804***	0.802***
	(0.0644)	(0.0669)	(0.0644)	(0.0669)
Highest Education is Post Graduate	1.008***	1.017***	1.009***	1.017***
	(0.0818)	(0.0849)	(0.0818)	(0.0849)
Income Less than 20K	-0.0721	-0.0563	-0.0722	-0.0564
	(0.0452)	(0.0467)	(0.0452)	(0.0467)
Income Between 20 and 50K	-0.0615	-0.0613	-0.0614	-0.0612
	(0.0388)	(0.0401)	(0.0388)	(0.0401)
Initial Conditions Included	no	yes	no	yes
Number of Observations	18,082	18,036	18,082	18,036
Number of Individuals	7,175	7,147	7,175	7,147

Notes: Standard errors in parentheses. * indicates significance at 10% level; ** at 5%; and *** at 1%.
All regressions include cut-off points, individual heterogeneity variance and year fixed effects.
The initial conditions specifications include the mean over time of all time varying regressors.

Table 8: Random-Effects Ordered Probit Regressions for Alcohol Consumption

We present the results of the random-effects ordered probit for exercise frequency in Table 9. Exercise frequency is based on the number of exercise sessions per week as discussed in section (2) where the categories are whether one participates in exercise (i) no times, (ii) $1-2$ times, (iii) $3-6$ times, (iv), 7 times, (v) $8-14$ times, or (vi) more than 14 times, per week. The control variables indicate that, the older the woman is, the less physical activity she participates in. The results also show that being white is associated with higher levels of physical activity. Our findings also indicate that married women engage in more physical activity relative to non-married women. Furthermore, the higher the level of education the woman has, the more she engages in weekly physical activity. Finally, individuals with income less than $\$20,000$ engage in less exercise relative to individuals with income between $\$20,000$ and $\$50,000$.

Dependent Variable: Ordered Variable for Exercise Frequency	(1)	(2)	(3)	(4)
Lagged Behavior				
Exercise Frequency Last Period	0.173***	0.126***	0.174***	0.126***
	(0.00727)	(0.00731)	(0.00727)	(0.00731)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.144***	-0.167***		
	(0.0505)	(0.0516)		
Recent Breast Cancer Diagnosis			-0.138**	-0.156**
			(0.0698)	(0.0705)
Other Controls				
Aged in 30s, 40s, or 50s	-0.134***	-0.147***	-0.135***	-0.148***
	(0.0194)	(0.0197)	(0.0194)	(0.0197)
Aged 60 or Older	-0.381***	-0.392***	-0.386***	-0.399***
	(0.0257)	(0.0261)	(0.0256)	(0.0260)
White	0.155***	0.134***	0.154***	0.133***
	(0.0257)	(0.0262)	(0.0256)	(0.0262)
Black	-0.0624**	-0.0664**	-0.0629**	-0.0670**
	(0.0274)	(0.0280)	(0.0274)	(0.0280)
Married	0.0547***	0.0565***	0.0546***	0.0564***
	(0.0167)	(0.0170)	(0.0167)	(0.0170)
Have Children	0.0172	0.0174	0.0169	0.0171
	(0.0231)	(0.0235)	(0.0231)	(0.0235)
Highest Education is High School	0.113***	0.103***	0.113***	0.103***
	(0.0223)	(0.0227)	(0.0223)	(0.0227)
Highest Education is University Degree	0.163***	0.154***	0.163***	0.154***
	(0.0239)	(0.0243)	(0.0239)	(0.0243)
Highest Education is Post Graduate	0.198***	0.199***	0.198***	0.199***
	(0.0322)	(0.0328)	(0.0322)	(0.0328)
Income Less than 20K	0.0482**	0.0393*	0.0479**	0.0389*
	(0.0199)	(0.0201)	(0.0199)	(0.0201)
Income Between 20 and 50K	0.0639***	0.0572***	0.0638***	0.0572***
	(0.0174)	(0.0176)	(0.0174)	(0.0176)
Initial Conditions Included	no	yes	no	yes
Number of Observations	33,851	33,851	33,851	33,851
Number of Individuals	8,009	8,009	8,009	8,009

Notes: Standard errors in parentheses. * indicates significance at 10% level; ** at 5%; and *** at 1%.
All regressions include cut-off points, individual heterogeneity variance and year fixed effects.
The initial conditions specifications include the mean over time of all time varying regressors.

Table 9: Random Effects Ordered Probit Regressions for Exercising

As the results in columns (1) and (2) show, a diagnosis of breast cancer significantly impacts the amount of exercise in a negative way. Perhaps this result is not so surprising given that women often undergo treatment after a breast cancer diagnosis that can weaken them and make it more difficult to engage in extra physical activity. The results in columns (3) and (4) show that women also decrease their amount of physical activity after a recent diagnosis, which is not surprising.

4 Modeling Value of Risky Behavior

In this section, we construct models of choices concerning risky behavior, show how they are informed by the empirical model in the previous section, and use them to say something about the value of each risky behavior. Our approach is in the spirit of Chetty (2008, 2009), Bernheim and Rangel (2009), and Einav, Finkelstein, and Cullen (2010). The advantage of this approach is that the ordered logit estimation associated with the previous section is wellunderstood and straightforward to implement. The disadvantage is that we are limited to some degree with respect to what we can add to the model by our ordered logit specification. For example, we can make only weak statements about dynamic effects because the ordered logit models allow only for a single lagged effect. A good comparison paper with a complete structural model is Arcidiacono, Sieg, and Sloan (2007). Their model accounts for many important details that are missing from the nonstructural literature, but their model is much harder to estimate and may be less robust to important assumptions.

To quantify the value of smoking, drinking, and exercising, we first present a model of the utility obtained from living, which depends on lifestyle behaviors. Using this model and the estimates presented in section 3.3 together with additional data linking risky behavior to mortality (for those with and without breast cancer), we determine the implied monetary value of these risky lifestyle choices for women.

4.1 Utility Flows Associated with Risky Behavior

To determine the value of risky behavior, we first must specify the utility flow one obtains as a function of risky behavior. One difficulty associated with this approach is that publicly available information on how risky behaviors impact mortality for those with and without breast cancer is limited in that it is not available for differing intensities of the behavior nor does it link joint behavior decisions (e.g., the impact of both smoking and drinking on mortality).[22] For these reasons, our framework treats risky behavior as an indicator function for whether a woman i engages in the behavior and does not incorporate interactions of the behaviors. We define a_{ilt} as an indicator for whether i engages in risky activity l ($= 1$ for smoking, $= 2$ for drinking, and $= 3$ for exercise) at age t. In the context of the previous specification, given in equation (1), this is expressed as $a_{ilt} = 1\left(y^*_{ilt} > 0\right)$.

We model the utility a woman gets from participating in risky behavior l at age t as

$$U_i\left(a_{ilt}\right) = 1 + \gamma_{ilt} a_{ilt}. \tag{5}$$

Woman i gets (possibly negative) direct utility γ_{ilt} from engaging in activity l at t, and she also recognizes that engaging in such an activity will have some effect on her survival probability. We assume that being diagnosed with breast cancer affects i's decision concerning a_{ilt} only because breast cancer interacts with activity l in the survivor probability

[22] There is also evidence that alcohol consumption increases the probability of being diagnosed with breast cancer (e.g., Rehm et al., 2003) which we ignore.

function, which we discuss shortly. We assume that breast cancer has no effect on the direct enjoyment i gets from the activity; i.e., $U_i(a_{ilt})$ is not affected by breast cancer. The "1" in equation (5) represents the utility of life at t excluding risky lifestyle choices. If i decides not to engage in any risky behavior, she obtains a positive utility from life of 1. The γ_{ilt} terms are measures of the value of participating in behavior l relative to the utility of living.[23] This is problematic for drinking where evidence (e.g., Rehm et al., 1997; Corrao et al., 1999) suggests that the effect of drinking on mortality is J-shaped. We discuss the case of drinking in more detail in section 4.2.2. Finally, we allow for heterogeneity across women in the extra utility that each woman gets from each risky behavior by allowing γ_{ilt} to vary with i. We discuss in section 4.4 how we use the estimates reported in section 3.3 to inform us about the value of γ_{ilt}.

4.2 Survival Probabilities

We wish to determine how a woman makes trade-offs among risky behaviors when she takes into account that these behaviors can impact her survival. Hence, we wish to learn about how her lifetime discounted utility is impacted by engaging in each risky behavior and how that is affected by a breast cancer diagnosis. The lifetime value of a risky activity combines the per-period utility one gets from the activity with survival probabilities that depend on both participation in the activity and breast cancer diagnosis. We let $p_{s|t}\left(c_i, \overrightarrow{a}_{il,s|t}\right)$ represent the probability that an individual survives to age s conditional on being alive at t. This survival probability depends upon the age, c_i, when the woman was diagnosed with breast cancer and her risky lifestyle choices $\overrightarrow{a}_{il,s|t} = (a_{ilt}, a_{ilt+1}, .., a_{ils})$. Note that we assume that each risky activity has only a one-period effect on the survival probability.[24] We realize that this may not be realistic for some activities, but in order to identify a more complex survivor function we would require much richer data than is available.[25] Note, however, that we do allow for persistence in choices among risky behaviors.

[23] Note that this is general because a_{ilt} is binary. All that can be modelled is the change in utility as one goes from $a_{ilt} = 0$ to $a_{ilt} = 1$. The parameter γ_{ilt} is this change. However, the specification excludes any interaction effects due to data limitations as mentioned above.

[24] This follows from the specified assumption that activities prior to s have no effect on survival conditional on being alive at s.

[25] Arcidiacono, Sieg, and Sloan (2007) allow for prior smoking and drinking to affect health which then is allowed to affect survival. They find statistically significant effects insignificant effects with respect to this mechanism for smoking and statistically insignificant effects for drinking. But the lag structure is very limited because of the short length of the panel used in estimation.

We can decompose

$$p_{s|t}\left(c_i, \overrightarrow{a}_{il,s|t}\right) = \prod_{\tau=t}^{s-1} p_{\tau+1|\tau}\left(c_i, a_{il\tau}\right)$$

where

$$p_{\tau+1|\tau}\left(c_i, a_{il\tau}\right) = p_{\tau+1|\tau}(\infty, 0) + b^*_{i\tau}\lambda_b + a_{il\tau}\left[\lambda_l + b^*_{i\tau}\lambda_{lb}\right], \tag{6}$$

$p_{\tau+1|\tau}(\infty, 0)$ is the one-year survival probability for a woman without breast cancer engaging in no risky behaviors,[26]

$$b^*_{i\tau} = 1\left(0 \leq \tau - c_i < 5\right)$$

is an indicator for whether the breast cancer diagnosis is recent, λ_b is the effect of having breast cancer on survival, λ_l is the effect of the risky behavior l on survival, and λ_{lb} is the interaction effect of breast cancer and the risky behavior l.

The first term needed for analysis is $p_{s|t}(\infty, 0)$ for all $s > t$. The first columns of Table 10 present the 5-year survivor probabilities by Age and Race and were obtained from National Vital Statistics Reports (2015). These are available for women who are at least 30 years old, so we limit our analysis in this section to women aged 30 or older. The last column presents the annual hazard rate $p_{\tau+1|\tau}(\infty, 0)$, which we determined by assuming that it is constant within each 5-year period.[27]

[26] The first argument is ∞ indicating that she may never be diagnosed with breast cancer up to time ∞.

[27] For example, for white women, the 5-year survival probability between ages $40-45$ is $0.984/0.992 = 0.992$. Using the 5-year constant hazard rate assumption, the annual survival probability is $0.992^{1/5} = 0.9984$, and the annual hazard rate is $1.0 - 0.9984 = 0.0015$.

	Survivors		Survivor Function Estimate		Annual Hazard Rate Estimate	
Age	White	Black	White	Black	White	Black
0	100000	100000				
30	98717	97878	1.000	1.000		
35	98358	97324	0.996	0.994	0.0007	0.0011
40	97879	96552	0.992	0.986	0.0010	0.0016
45	97152	95419	0.984	0.975	0.0015	0.0023
50	95996	93658	0.972	0.957	0.0024	0.0037
55	94278	91045	0.955	0.930	0.0036	0.0056
60	91929	87402	0.931	0.893	0.0050	0.0080
65	88535	82581	0.897	0.844	0.0074	0.0110
70	83371	75956	0.845	0.776	0.0117	0.0160
75	75747	67206	0.767	0.687	0.0183	0.0230
80	64517	55549	0.654	0.568	0.0297	0.0347
85	48829	40709	0.495	0.416	0.0486	0.0534
90	29346	24558	0.297	0.251	0.0798	0.0793
95	11777	11057	0.119	0.113	0.1197	0.1100
100	2544	3278	0.026	0.033	0.1568	0.1407

Source: "Table B: Number of Survivors Out of 100,000 Born Alive, by Age, Race, Hispanic Origin, Race for Non-Hispanic Population, and Sex: United States, 2011." *National Vital Statistics Reports* . 64(11). September 22, 2015. http://www.cdc.gov/nchs/data/nvsr/nvsr64/nvsr64_11.pdf.

Table 10: Survivor Functions Conditional on Being Alive at Age 30

Next, we require data on λ_b, the effect of having breast cancer on survival. Based on data from SEER, Howlader et al. (2016) find that a breast cancer diagnosis reduces the baseline survival probability by 0.92 for whites and 0.81 for blacks. If we denote this reduction by P, then the 5-year survival probability becomes $p_{t+5|t}(c,0) = Pp_{t+5|t}(\infty,0)$. Rearranging, we have $p_{t+5|t}(c,0)/p_{t+5|t}(\infty,0) = P$. In the notation of the model, this yields

$$p_{t+5|t}(c,0) = \exp\{-5\lambda_b\} p_{t+5|t}(\infty,0)$$
$$\lambda_b = \frac{-\log P}{5}, \tag{7}$$

which implies $\lambda_b = 0.0167$ for whites and $\lambda_b = 0.0421$ for blacks. Data from NCI (2016), shown in Figure 1, show how breast cancer diagnosis varies by age (and race). Notice that, conditional on race, λ_b is similar across ages of diagnosis up to age 74. After age 74, there is a large increase in λ_b. Figure 2 shows how the variation in death rates translate into variation in survivor functions. Without breast cancer, whites live longer than blacks by a moderate amount. However, differences in mortality from breast cancer across race lead to large variation in survivor probabilities.

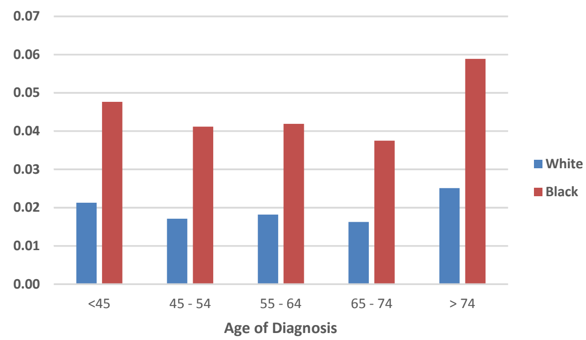


Figure 1: Breast Cancer Hazard Rate by Race and Age of Diagnosis

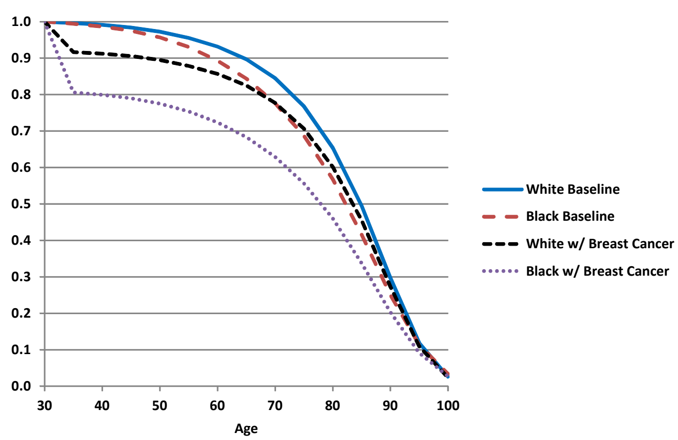


Figure 2: Survivor Probabilities by Race and Breast Cancer Status

The remaining components of equation (6) are λ_l, the effect of the risky behavior l on survival, and λ_{lb}, the interaction effect of breast cancer and behavior l. Therefore we require terms that vary by activity. For each activity, we searched the literature on the effects of the activity for women by breast cancer status.[28]

4.2.1 Survivor Probability Terms Associated with Smoking

We start our discussion with smoking. Braithwaite et al. (2012) find that, compared with people who have never smoked, women who were current smokers had a twofold higher rate of dying from breast cancer.[29] We interpret the results to mean that $\lambda_{1b} = 2\lambda_b$.

Figure 3 shows how the independent effects of smoking affect survivor probabilities with and without a breast cancer diagnosis.[30] The solid (blue) curve is the survivor probability for American non-smoking women without breast cancer starting at age 30. The dotted (purple) curve is the survivor curve for American non-smoking women diagnosed with breast cancer at age 30. Note that the difference in survivor curves occurs all in the five years following diagnosis. This occurs because one is considered cured if there is no sign of breast cancer after 5 years. Next, based on the relative risk factors from the Surgeon General (CDCP 2001, Table 3.1), the dashed curve (red) following the solid curve and then deviating is the survivor cure for smokers without breast cancer. It shows that the effects on mortality of smoking are small at young ages but then have a large effect on mortality. The dashed curve (black) that is the lowest of the four is the survivor curve for smokers with a breast cancer diagnosis at age 30. It's shape is based on the value of λ_{1b} and the smoking survivor curve after the breast cancer danger is past. Note that it would be difficult for the specification of the effect of smoking on survival used in Arcidiacono, Sieg, and Sloan (2007) to fit these survival curves because the effect of smoking on survival varies significantly over age.

[28] We do not claim to have addressed the possible econometric issues associated with estimates from other studies (e.g., endogeneity, measurement error). However, our approach illustrates how one can use available mortality estimates along with estimates similar to those in section 3.3 to measure the value of the risky behaviors.

[29] The hazard ratio is 2.01, and the 95% confidence interval is $(1.27, 3.18)$.

[30] Data sources used for Figure 3 are Table B in National Vital Statistics Reports (2015) and Table 3.1 in CDCP (2002).

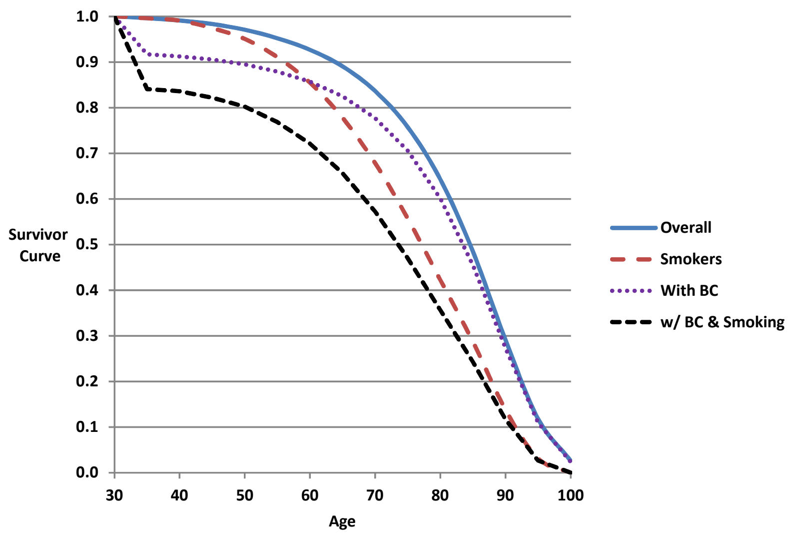


Figure 3: Survivor Probabilities for Smokers by Breast Cancer Status

4.2.2 Survivor Probability Terms Associated with Drinking

Next, we continue our discussion with drinking. The relationship between alcohol consumption and breast cancer survival does not seem to be very clear; studies report mixed findings. Kwan et al. (2010) find that, for women with early-stage breast cancer, drinking the equivalent of 3 to 4 drinks per week increases the breast cancer death rate by 1.5. However, Newcomb et al. (2013) find no evidence for an association with post-diagnosis alcohol intake and breast cancer survival. We use the 1.5 estimate from Kwan et al. (2010) as an illustrative example: $\lambda_{2b} = 1.5\lambda_b$. With respect to the impact of drinking on survival (λ_2) researchers including Rehm et al. (1997) and Corrao et al. (1999) show a J-shaped effect of alcohol consumption on mortality rate for men and women. However, Rehm, Greenfield, and Rogers (2001) suggest that the curvature for women is statistically insignificant, Friedman and Kimball (1986) suggest it is statistically insignificant for both genders, and we think that the reported J-shape reported in Rehm et al. (1997) and Corrao et al. (1999) is suspect.[31] Further, Rehm, Greenfield, and Rogers (2001) find that the effect of alcohol consumption on mortality is more complicated depending on, among other things, the frequency of drinking,

[31] The drinking level with the lowest reported all-causes mortality rate is at 20 grams per day. This is equivalent to 1.33 glasses of wine per day. The higher drinking level with the same all-causes mortality rate as abstention from drinking is approximately 75 grams per day (or 5 glasses of wine per day). Very few people drink 75 grams per day of alcohol (Cook, 2007). Yet, the reported confidence interval at 75 grams per day is the same as at 20 grams per day.

the average amount consumed on each occasion, and the frequency of binge drinking. If we wanted to analyze the implications of a J-shaped effect, we would have to relax the binary assumption about a_{i2t}. This would significantly complicate the analysis with little gain in insight. We could treat a_{i2t} as binary and choose a threshold that captures the most important effect of drinking. Unfortunately, the J-shaped mortality curve in, for example, Corrao et al. (1999) is in terms of grams of alcohol per day. Thus, we also need to translate results in the source on survival effects into units consistent with those used in the PSID.

Klijs, Mackenbach, and Kunst (2011) provide evidence (Table 2) that, relative to people who consume between $1-14$ drinks per week, mortality is 1.19 times greater for people who consume more than 14 drinks per week, and it is 1.43 times higher for people who do not drink. For illustrative purposes, we build on these estimates and assume that the two relevant groups for alcohol consumption are drinking and not drinking and $\lambda_2 = -(1/1.43) = -0.699$.[32] This assumption, along with $\lambda_{2b} = 1.5\lambda_b$, implies that drinking has bad short-term effects if diagnosed with breast cancer but good long-term effects. The implications of these assumptions are displayed in Figure 4. Without breast cancer, drinking increases survival probabilities significantly. With breast cancer, drinking starts off having a detrimental effect on morality, but, after age 67, the effect of drinking on survival probability is positive. This occurs because of the assumed negative effect of drinking on survival probability while diagnosed with breast cancer ($\lambda_{2b} = 1.5\lambda_b$) and the assumed positive effect of drinking 5+ years after diagnosis.

4.2.3 Survivor Probability Terms Associated with Exercising

Our last risky behavior is (not) engaging in exercise. Holmes et al. (2005) find that women who exercise a moderate amount have a probability of dying from breast cancer 80% of that for women who never exercise. We interpret the results to mean that $\lambda_{3b} = -0.2$. Gregg et al. (2003), Gulati et al. (2003), and Mora et al. (2003) find reductions in all-causes mortality on the order of 30% among otherwise healthy women. Based on these studies, we assume that $\lambda_3 = -0.3$.

[32] The non-drinker curve replaces the overall curve by solving

$$\begin{aligned} \lambda_{\text{overall}} &= 0.3\,(1.43)\,\lambda_{\text{drinker}} + 0.7\lambda_{\text{drinker}} \\ \lambda_{\text{nondrinker}} &= 1.43\lambda_{\text{drinker}} \end{aligned}$$

for $\lambda_{\text{nondrinker}}$. The weights, 0.3 and 0.7, are the proportions of the population that do not drink and that drink respectively (Cook, 2007).

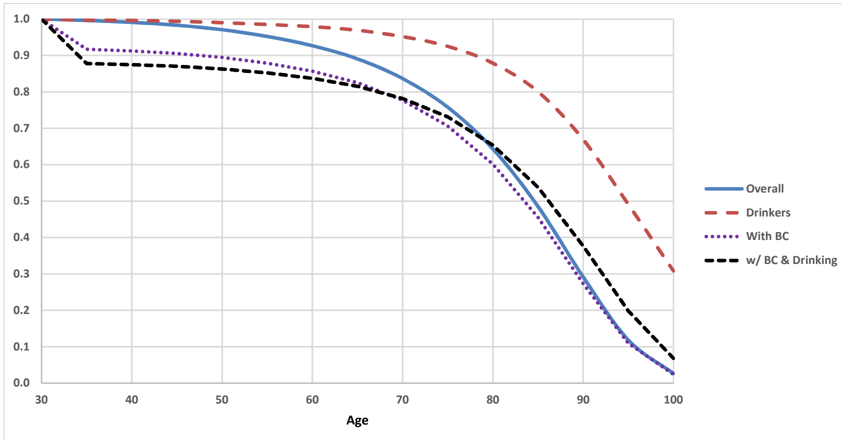


Figure 4: Survivor Probabilities for Drinkers by Breast Cancer Status

Figure 5 shows how the independent effects of exercise affect survivor probabilities with and without a breast cancer diagnosis.[33] With breast cancer, exercise starts off having a helpful effect on morality, and, even 5+ years after diagnosis, the effect of exercise on survival probability is positive. This occurs because of the assumed positive effect of exercise on survival probability while diagnosed with breast cancer ($\lambda_{3b} = -0.2$) and the assumed positive effect of drinking 5+ years after diagnosis ($\lambda_3 = -0.3$).

4.3 Value of Life

We now have all the components of the survivor probabilities we need to compute the value of life. We specify the discounted value of life conditional on $\overrightarrow{a}_{il,s|t}$ as

$$V_{it} = \sum_{s=t}^{T} \beta^{s-t} p_{s|t} \left(c_i, \overrightarrow{a}_{il,s|t} \right) U_i \left(a_{ils} \right)$$

where β is the one-period discount factor and $U_i \left(a_{ils} \right)$ is her utility function at time s, defined in equation (5). The change in value of life associated with a change in activity l at age t is

[33] The nonexercise curve replaces the overall curve by solving

$$\begin{aligned} \lambda_{\text{overall}} &= \frac{0.3}{0.7} \lambda_{\text{exercise}} + 0.7 \lambda_{\text{exercise}} \\ \lambda_{\text{nonexercise}} &= \frac{1}{0.7} \lambda_{\text{exercise}} \end{aligned}$$

for $\lambda_{\text{nonexercise}}$. The weights, 0.3 and 0.7, are the proportions of the population that do not exercise and that do exercise respectively (Blair, 2009).

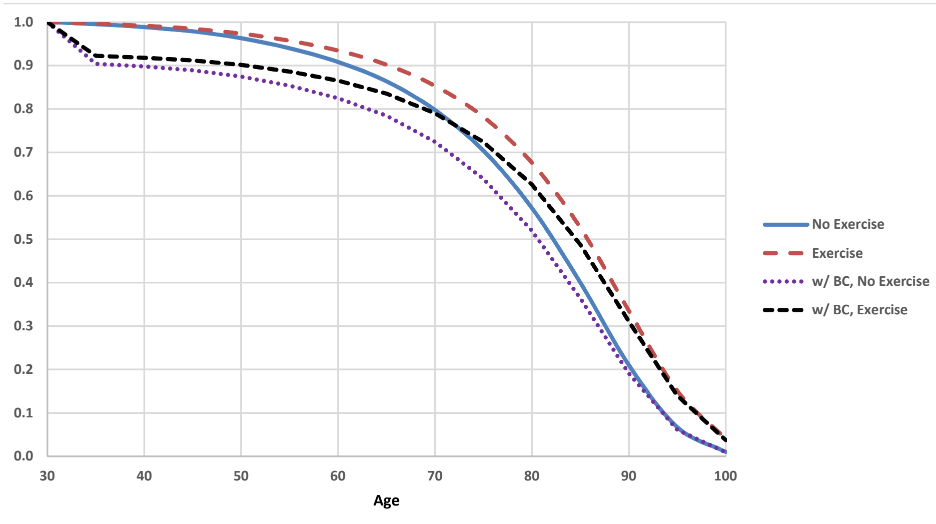


Figure 5: Survivor Probabilities for Exercisers by Breast Cancer Status

given by

$$\begin{aligned} \frac{\Delta V_{it}}{\Delta a_{ilt}} &= (V_{it} \mid a_{ilt} = 1) - (V_{it} \mid a_{ilt} = 0) \\ &= \sum_{s=t}^{T} \beta^{s-t} \left[U_i\left(a_{ils}\right) \frac{\Delta p_{s|t}\left(c_i, \overrightarrow{a}_{il,s|t}\right)}{\Delta a_{ilt}} + p_{s|t}\left(c_i, \overrightarrow{a}_{il,s|t}\right) \frac{\Delta U_i\left(a_{ils}\right)}{\Delta a_{ilt}} \right] \end{aligned} \tag{8}$$

We assume that i makes a one-time decision to permanently change behavior. For example, for smoking, equation (8) is the difference in the value of life from continuing to smoke forever and stopping smoking forever.[34] Note that $\Delta U_i\left(a_{ils}\right)/\Delta a_{ilt} = \gamma_{ils}$ for all s because of the assumption about permanency of the change.

4.4 Computing the Marginal Utility from Risky Choices

In order to compute the value of life, we need to determine the value of γ_{ilt}, which is the marginal utility obtained from engaging in risky choice l (see equation 5). As we mentioned previously, we use the estimates obtained from our model in Section 3.1 to inform us about γ_{ilt}. To see the link, first note that the deterministic component of equation 1 for women

[34] This implies a time inconsistency in that i made a decision some time τ in the past about $\overrightarrow{a}_{il,\infty|\tau}$ which is now changing at t. We ignore this problem as it is not really tied to the point of the paper.

without breast cancer ($c_{it}=0$)[35] can be written as

$$\psi^*_{ilt}=\psi_{ilt}+E\left(\varepsilon_{ilt}\mid b_{it}\right)=\frac{\partial V_{it}}{\partial a_{ilt}}. \tag{9}$$

Given equation 8, this implies

$$\psi^*_{ilt}=\sum_{s=t}^{T}\beta^{s-t}\left[\left(1+\gamma_{ils}\right)\frac{\Delta p_{s|t}\left(0,\overrightarrow{a}_{il,s|t}\right)}{\Delta a_{ilt}}+\gamma_{ils}p_{s|t}\left(0,\overrightarrow{a}_{il,s|t}\right)\right],$$

which shows the relationship between the deterministic component of equation 1 and γ_{ilt} for women without breast cancer.

For ease of exposition, we express this equation in matrix notation as

$$\psi_{il}=\varpi^0_{il}+\varpi^1_{il}\gamma_{il} \tag{10}$$

where $\psi_{il}=(\psi_{il1}\ \psi_{il2}\ ...\ \psi_{il\bar{t}})'$, $\varpi^0_{il}=(\varpi^0_{il1}\ \varpi^0_{il2}\ \ ...\varpi^0_{il\bar{t}})'$, $\gamma_{il}=(\gamma_{il1}\ \ \gamma_{il2}\ ...\gamma_{ilT})'$,

$$\begin{aligned}\varpi^0_{ilt} &= \sum_{s=t}^{T}\beta^{s-t}\frac{\Delta p_{s|t}\left(0,\overrightarrow{a}_{i,s|t}\right)}{\Delta a_{ilt}},\ \text{and}\\ \varpi^1_{ilts} &= \begin{cases}\beta^{s-t}\left[\frac{\Delta p_{s|t}\left(0,\overrightarrow{a}_{i,s|t}\right)}{\Delta a_{ilt}}+p_{s|t}\left(0,\overrightarrow{a}_{i,s|t}\right)\right] & \text{if } s\geq t\\ 0 & \text{if } s<t\end{cases},\end{aligned}$$

and

$$\varpi^1_{il}=\begin{pmatrix}\varpi^1_{il11} & \varpi^1_{il12} & \cdots & \varpi^1_{il1T-t}\\ \varpi^1_{il21} & \varpi^1_{il22} & \cdots & \varpi^1_{il2T-t}\\ \vdots & \vdots & \ddots & \vdots\\ \varpi^1_{il\bar{t}1} & \varpi^1_{il\bar{t}2} & \cdots & \varpi^1_{ilTT-t}\end{pmatrix}.$$

More generally, equation 1 can be expressed as

$$\begin{aligned}E\left(y^*_{ilt}\mid a_{it}\right) &= \psi_{ilt}+b_{it}\delta_l+E\left(\varepsilon_{ilt}\mid a_{it}\right)+\eta_{it},\\ \eta_{it} &= \varepsilon_{ilt}-E\left(\varepsilon_{ilt}\mid a_{it}\right)\end{aligned}$$

---

[35] Notice that y^*_{ilt} is the net value of participating in activity l, and its expected value conditional on observables is the same thing as lifetime utility conditional on participating in activity l minus lifetime utility conditional on not participating in activity l; this is the definition of $\partial V_{it}/\partial a_{ilt}$.

where ψ_{ilt} is the deterministic component of y^*_{ilt} given in equation 1 excluding any new breast cancer diagnosis effect, b_{it} is an indicator for a new diagnosis of breast cancer, as in equation 1, δ_l is the estimated effect of having a relevant breast cancer diagnosis on y^*_{ilt}, and ε_{ilt} is an idiosyncratic effect distributed normally as in Section 3.1 and independent of explanatory variables including b_{it}. Given the normality assumption for the distribution of ε_{ilt},[36]

$$E\left(\varepsilon_{ilt} \mid a_{it}\right) = \frac{\phi\left(\psi_{ilt}\right)}{\Phi\left(\psi_{ilt}\right)\left[1-\Phi\left(\psi_{ilt}\right)\right]} a_{it} - \frac{\phi\left(\psi_{ilt}\right)}{1-\Phi\left(\psi_{ilt}\right)}. \tag{11}$$

For each observation i and activity l, there are $T-t$ elements of γ_{il} to estimate but only $\bar{t}$ years to use in estimation. Thus, we must impose some restrictions on γ_{il}. We assume that $\gamma_{ilt} = \overline{\gamma}_{il}\ \forall t$. Then, we minimize

$$L\left(\overline{\gamma}_{il}\right) = \left(\psi_{il} - \varpi^0_{il} - \varpi^1_{il}\iota\overline{\gamma}_{il}\right)' \left(\psi_{il} - \varpi^0_{il} - \varpi^1_{il}\iota\overline{\gamma}_{il}\right)$$

where ι is a $(T-t) \times 1$ vector of 1's. The first order condition is

$$-\left(\varpi^1_{il}\iota\right)' \left(\psi_{il} - \varpi^0_{il} - \varpi^1_{il}\iota\overline{\gamma}_{il}\right) = 0$$

which can be written as

$$\overline{\gamma}_{il} = \left[\left(\varpi^1_{il}\iota\right)' \left(\varpi^1_{il}\iota\right)\right]^{-1} \left(\varpi^1_{il}\iota\right)' \left(\psi_{il} - \varpi^0_{il}\right).$$

For each observation i and activity l, ψ_{il} comes from our estimates in Section 3.3. Given the $p_{s|t}\left(c_i, \overrightarrow{a}_{il,s|t}\right)$ estimates and a choice of β, we construct ϖ^1_{il} and ϖ^0_{il}. Thus, we are able to obtain $\overline{\gamma}_{il}$ for each observation and activity.

Figure 6 shows F_γ, the distribution of γ for smoking, across the sample for two values of β. One can see that the marginal utilities of smoking (γ's) decline and spread out as β

[36]

$$\begin{aligned}
E\left(\varepsilon_{ilt} \mid a_{it}\right) &= \frac{\phi\left(-\psi_{ilt}\right)}{1-\Phi\left(-\psi_{ilt}\right)} a_{it} - \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)}\left(1-a_{it}\right) \\
&= \left[\frac{\phi\left(-\psi_{ilt}\right)}{1-\Phi\left(-\psi_{ilt}\right)} + \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)}\right] a_{it} - \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)} \\
&= \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)\left[1-\Phi\left(-\psi_{ilt}\right)\right]}\left[\Phi\left(-\psi_{ilt}\right) + 1 - \Phi\left(-\psi_{ilt}\right)\right] a_{it} - \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)} \\
&= \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)\left[1-\Phi\left(-\psi_{ilt}\right)\right]} a_{it} - \frac{\phi\left(-\psi_{ilt}\right)}{\Phi\left(-\psi_{ilt}\right)} \\
&= \frac{\phi\left(\psi_{ilt}\right)}{\Phi\left(\psi_{ilt}\right)\left[1-\Phi\left(\psi_{ilt}\right)\right]} a_{it} - \frac{\phi\left(\psi_{ilt}\right)}{1-\Phi\left(\psi_{ilt}\right)}.
\end{aligned}$$

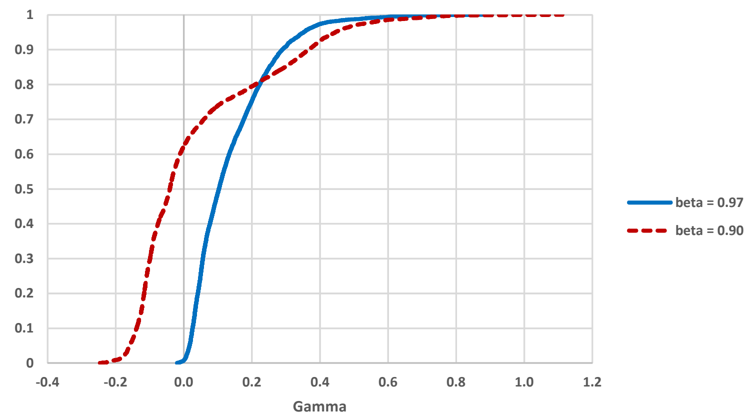


Figure 6: Distribution of Marginal Utility of Smoking for Different Discount Factors

declines from $\beta = 0.97$ to $\beta = 0.90$. This occurs because, as β declines, individuals do not value living longer as much and therefore need lower values of γ to explain $\widehat{F}_{\psi}$, the sample distribution of ψ from equation (9) associated with true distribution F_{ψ}. In the remainder of the analysis, we assume $\beta = 0.90$.[37] We provide more detailed motivation for this choice in the Appendix.

Figure 7 shows the γ distributions for all three risky behaviors using $\beta = 0.90$. The "Smoking" curve in Figure 7 is the same as the "beta = 0.90" curve in Figure 6. The other two curves are for drinking and exercise. Both the drinking distribution and exercise distribution have more of their mass at $\gamma > 0$. This reflects the number of people in the data who participate in drinking and exercise relative to smoking. Also, the "exercise" distribution has a much shorter right tail than the other two distributions; this is caused by a lack of observations in the sample where choosing to exercise seems to be a very low probability event. The median values of the marginal utilities γ are -0.126 for smoking, 0.034 for drinking, and 0.176 for exercise. The 10% and 90% deciles are $(-0.271, 0.018)$ for smoking, $(-0.169, 0.240)$ for drinking, and $(0.056, 0.245)$ for exercise. Finally, the proportions of the sample with $\gamma < 0$ are 0.705 for smoking, 0.423 for drinking, and 0.061 for exercise.

4.5 Implied Monetary Value and Trade-off of Risky Behavior

These results allow us to compute the monetary value associated with risky behaviors using $F_{a,\gamma}(a, \gamma)$. We generate the joint distribution from the data because we observe both the

[37] Arcidiacono, Sieg, and Sloan (2007) find that $\beta = 0.78$ fits the data best.

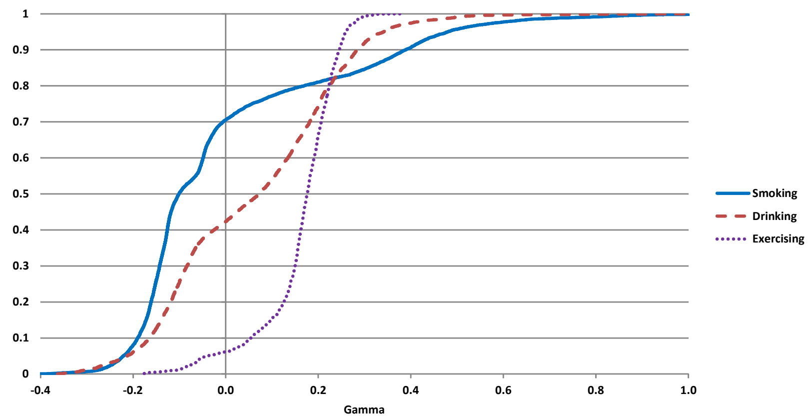


Figure 7: Distribution of Marginal Utilities for Behaviors for Discount Factor =0.90

activity that the woman engages in (i.e., her a) as well as as the estimate of γ. Therefore, the joint distribution is nonparametrically identified. For smoking, the average value of $a\gamma$ among smokers is 0.333 which means the average value of one year of life among smokers is

$$\$x_{smoke}^{\text{smokers}} = \frac{\$200,000}{1.333} = \$150,038.$$

Therefore, the implied value of smoking per year for smokers is $\$200,000 - \$150,038 = \$49,962$.

We can perform similar analyses for drinking and exercise. For drinking, the average value of γ conditional on drinking is 0.173. Following the same steps used for smoking, the implied value of drinking for drinkers is $\$200,000 - \$170,503 = \$29,497$. For exercise, the average value of exercise for women who exercise is 0.164, implying a value of exercising for exercisers of $\$200,000 - \$171,821 = \$28,179$.

Table 11 shows how the change in the value of life from a change in risky behavior (equation **??**) changes with γ_{ilt}. Column (1) shows the change in the value if the woman was not diagnosed with breast cancer. For example, if $\gamma_{ilt} = 0.06$, then the definition of γ_{ilt} implies that utility at t increases by 0.06 if i smokes and then, plugging into equation (**??**), the extra discounted flow of utility over the rest of one's life (temporarily ignoring the independent effect of smoking on survival probabilities) is 0.229. Since we are temporarily ignoring the independent survival probability effects of smoking, $\Delta V_{it}/\Delta a_{tlt} > 0$ iff $\gamma_{ilt} > 0$.

Gamma	Value without Breast Cancer	Value with Breast Cancer		
		Smoking	Drinking	Exercise
-0.05	-0.191	-0.414	-0.305	-0.111
-0.04	-0.153	-0.379	-0.268	-0.072
-0.03	-0.115	-0.343	-0.231	-0.032
-0.02	-0.076	-0.307	-0.194	0.007
-0.01	-0.038	-0.271	-0.157	0.046
0	0.000	-0.235	-0.120	0.085
0.01	0.038	-0.199	-0.083	0.124
0.02	0.076	-0.163	-0.046	0.163
0.03	0.115	-0.128	-0.009	0.202
0.04	0.153	-0.092	0.028	0.241
0.05	0.191	-0.056	0.065	0.280
0.06	0.229	-0.020	0.102	0.319
0.07	0.267	0.016	0.139	0.358
0.08	0.306	0.052	0.176	0.397
0.09	0.344	0.088	0.213	0.436
0.1	0.382	0.123	0.250	0.475

Table 11: Value of Smoking, Drinking, and Exercise

On the other hand, if the woman has been diagnosed with breast cancer, then there is a real trade-off. For example, column (3) shows that smoking has a positive impact on the value of life only if the value placed on smoking is greater than 0.06 ($\Delta V_{it}/\Delta a_{i1t} > 0$ iff $\gamma_{i1t} > 0.06$). This captures the fact that, even if one enjoys smoking, smoking also negatively impacts the value of life by decreasing the survival rate. In other words, one must enjoy smoking by at least 0.06 per period to make up for the lower survivor probabilities associated with smoking when one has breast cancer. Recall that the way to interpret $\gamma_{i1t} = 0.06$ is that smoking would account for about 6% (0.06/1.06) of the total utility one gets from being alive. Column (4) shows that drinking has a positive value of life only if the impact on utility is greater than 0.03 ($\Delta V_i/\Delta a_{2t} > 0$ iff $\gamma_{i2t} > 0.03$). Finally, column (5) shows that an individual finds it valuable to engage in exercise even when it brings disutility ($\Delta V_i/\Delta a_{3t} > 0$ iff $\gamma_{i3t} > -0.03$).

We define γ^*_{lt} as the reservation value of γ_{ilt} with a breast cancer diagnosis: $\Delta V_i/\Delta a_{lt} > 0$ iff $\gamma_{ilt} > \gamma^*_{lt}$. Our analysis shows that some women choose not to engage in smoking because they do not enjoy it ($\gamma_{ilt} < 0$), some choose not to engage even though they enjoy it because it is not worth the mortality risk ($0 < \gamma_{ilt} < \gamma^*_{lt}$), and others engage even though it is risky

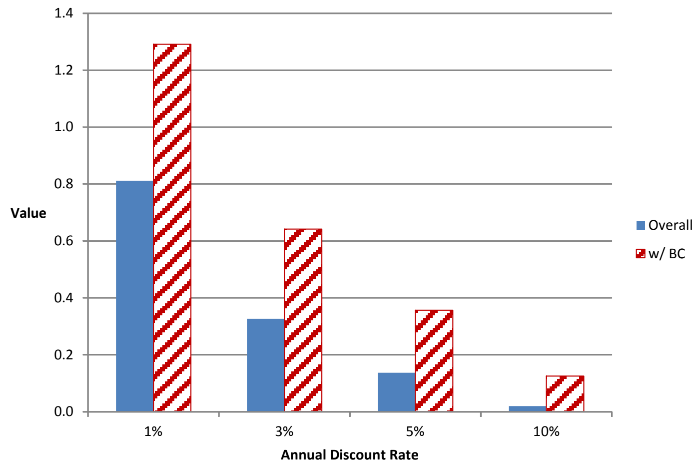


Figure 8: Value to Increased Lifetime Due to Not Smoking

because they enjoy it enough to compensate for the risk ($\gamma_{ilt} > \gamma^*_{lt}$). For exercise, some participate because they enjoy it ($0 < \gamma_{ilt}$), others participate even though they do not enjoy it because the disutility is worth the health benefits ($0 > \gamma_{ilt} > \gamma^*_{lt}$), and others do not participate despite the health benefits because they dislike it so much ($\gamma_{ilt} < \gamma^*_{lt}$).

Because of the differential timing of these effects, the value of the loss of life associated with smoking for the two cases, with and without breast cancer, depends critically on the woman's discount rate. Figure 8 displays this relationship graphically. The solid bars in Figure 8 reflect the discounted expected value of the extra lifetime gains associated with not smoking based on the difference between the overall survival and smoking survival curves in Figure 3. The upward-sloping fill bars in the figure reflect the discounted expected value of the extra lifetime gains associated with not smoking conditional on having breast cancer based on the difference between the "w/BC" curve and the "w/BC & Smoking" curve. These are computed for discount rates of 1%, 3%, 5%, and 10%. Note that, when the annual discount rate is 1%, the loss associated with overall harm is greater than that interacted with breast cancer, while, when the annual discount rate is 10%, the loss associated with breast cancer is much larger.

To fix ideas, consider using a 3% annual discount rate. Then the ratio of the loss associated with smoking with and without a breast cancer diagnosis is 1.97.[38] Thus, one third of

[38] Hewit et al. (2003) examine the health and disability among a nationally representative sample that includes survivors with a range of cancer types. They found that nearly 20% of cancer survivors currently

the "cost" associated with smoking when diagnosed with breast cancer is due to the harmful effects of smoking for everyone, and two thirds are due to the interaction effect of smoking and breast cancer. This can be interpreted in terms of the utility model in equation 5. Now, the added utility associated with smoking is net of the loss associated with smoking overall, implying that the reservation value γ_{lt}^{*} is higher by $0.642 - 0.327 = 0.315$.[39]

5 Conclusions

According to the National Breast Cancer Foundation, one in eight US women are impacted by breast cancer.[40] In 2013, the National Cancer Institute spent more than $550 million to investigate the causes of breast cancer (NCI Annual Factbook).[41] We use longitudinal data from the PSID, starting from 1999 to 2011, to examine to what extent women who are diagnosed with breast cancer change their (potentially risky) lifestyle choices. We develop a framework for valuing the quality of life and longevity that depends on an individuals' observed risky behaviors, which we use to determine the implicit value of engaging in risky behaviors in terms of reduced survival. We find that women who were recently diagnosed with breast cancer smoke less. In contrast to smoking behavior, women do not change their alcohol consumption after a breast cancer diagnosis regardless of when the diagnosis was made. Furthermore, a diagnosis of breast cancer significantly impacts the amount of exercise in a negative way. Perhaps this result is not so surprising given that women often undergo treatment after a breast cancer diagnosis that can weaken them and make it more difficult to engage in extra physical activity.

Our findings allow us to learn more about the trade-offs women are willing to make between participating in unhealthy (but enjoyable) habits and increasing one's life expectancy.

smoked. Another population-based study (Blanchard, et al. 2003) found that 13% of breast cancer survivors continued to smoke after diagnosis, which was less than the smoking rate (21.9%) for noncancer controls.

[39] The height of the "w/ BC" bar for the 3% annual discount rate is 0.642, and the height of the "Overall" bar is 0.327. Unfortunately, we were not able to conduct the same analysis for alcohol consumption due to lack of data. Based on results reported in Table 2 of Klijs, Mackenback, and Kunst (2011), the overall effect of drinking moderately ($1 - 14$ alcoholic beverages/week) increases life expectancy relative to not drinking at all (relative risk, no drinking = 1.43). Thus, if we were to use the same type of analysis for drinking as we did for smoking, we would have to deal with the strong difference in drinking's effect. Also, unfortunately, the data in Klijs, Mackenback, and Kunst (2011) provide no detail on where in the age distribution one observes the effects of drinking.

[40] See https://www.nationalbreastcancer.org/what-is-breast-cancer
Referenced on October 28, 2016

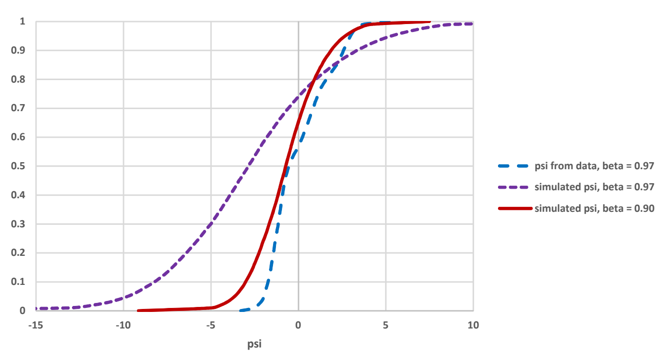
[41] See www.cancer.gov/about-nci/budget/fact-book/data/research-funding.

For a woman diagnosed with breast cancer, our results indicate that a woman will smoke only if the value placed on smoking is greater than 6% of the total utility from being alive. Whereas we find the threshold is lower for drinking, where drinking has a positive impact on the value of life if the value placed on drinking is greater than 3% of the total utility from being alive. Finally, a woman with breast cancer will find it valuable to engage in exercise even when it brings disutility of 3% of the value of living. Using conventional estimates for the value of a year of life, we find that these choices imply smoking is valued at about $\$49,000$ per year for smokers, drinking is valued at about $\$29,500$ per year for drinkers, and exercising is valued at about $\$28,200$ for exercisers.

Appendix

Also of note is that most of F_γ is for positive values of γ, implying that a high proportion of non-smokers would smoke if smoking had better mortality rates. This sounds somewhat surprising; there are many other reasons not to smoke. Figure 5 shows F_ψ and $\widehat{F}_\psi$[42] from three different models. $\widehat{F}_\psi$ is the rough-mesh blue curve. Note that the distribution is tightly distributed.

We consider two other models to explore some possible causes. First, we assume that $\gamma \sim iidN(0, 1/4)$ and $\beta = 0.97$. We think of this F_γ as more in line with our expectations.[43] We use equation (10) along with random draws of γ to simulate F_ψ. The resulting F_ψ moves to the left and spreads out. This result strongly suggests that the tight F_γ for $\beta = 0.97$ displayed in Figure 6 is closely tied to the tight F_ψ. Also, F_ψ moves to the left helping to explain how the high values of γ are caused by the high values of ψ from the sample.



Distribution of Psi for Different Models

[42] The distributions displayed are actually for $\psi + E(u \mid a)$.

[43] It also represents the result of some experimentation with different distributions.

Finally, we perform the same experiment but with decreasing $\beta = 0.90$. In this case, F_ψ is quite similar to $\widehat{F}_\psi$, suggesting that $\beta = 0.90$ can generate F_γ that looks more reasonable.

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