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BREAST CANCER SURVIVAL, WORK, AND EARNINGS

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ABSTRACT

Relying on data from the Health and Retirement Study, we examine differences between breast cancer survivors and a non-cancer control group in employment, hours worked, wages, and earnings. Overall, breast cancer has a negative impact on the decision to work. However, among survivors who work, hours of work and, correspondingly, annual earnings are higher compared to women in the non-cancer control group. These findings suggest that while breast cancer has a negative effect on women's employment, breast cancer may not be debilitating for those who remain in the work force. We explore numerous possible biases underlying our estimates–especially selection–based on information in the Health and Retirement Study, and examine related evidence from supplemental data sources.

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I. Introduction

In recent years, improved detection methods for breast cancer have led to the treatment and survival of a younger population of women more likely to be at working ages, making an inquiry into the impact of breast cancer on labor market outcomes particularly relevant. Between 1983 and 1993, in situ breast cancer rates increased from 2.3 to 6.2 per 100,000 among women under age 50, largely reflecting an increase in the use of mammography (American Cancer Society, 1999). Treatment has improved as well, leading to the largest short-term decline in over 40 years in breast cancer mortality. Breast cancer research has focused on detection and treatment and, to a lesser extent, survivors' quality of life. However, now that five-year survival is expected for most women diagnosed in the early stages of breast cancer (98% according to the American Cancer Society), attention should also be given to objective economic measures of the consequences of surviving breast cancer for labor market outcomes, as part of a broader effort to understand the quality-of-life implications of the disease, and how labor market agents react to cancer survivorship.

In this paper, we use the first wave of the Health and Retirement Study (HRS) in an attempt to understand how breast cancer influences labor market decisions and outcomes. In addition to incorporating numerous individual characteristics into the analysis as controls, we incorporate elements of morbidity by using information on time since diagnosis. We also pay close attention to the potential role of health insurance in mediating the relationship between breast cancer and labor market outcomes. In addition, we replicate, to the extent possible, our basic estimation of labor market outcomes using 1998-99 pilot-study data from a sample of cancer survivors from Detroit, Michigan, and a comparison sample of Detroit residents who responded to the 1999 March supplement of the Current Population Survey (CPS).

As cancer screening is more routinely applied to a working age population, more cancers are likely to be detected in early stages that may have otherwise gone undetected until a later time. Therefore, this research is particularly relevant as it both fills a gap in the literature regarding labor market consequences of cancer and contains information that addresses how early detection of disease may affect labor market behavior.

There is a long way to go to unravel and explain the various behavioral responses to cancer. For example, do employers discriminate against cancer survivors, and if so, why? Does labor supply shift because of health effects, motivational effects, or incentives related to the retention of health insurance? What policies can mediate some of the adverse outcomes for cancer survivors? Answering such questions is part of our longer-term research agenda, and essential to facilitating cancer survivors' continued participation in the labor market. This paper lays out some of the basic facts that are not, to date, established in the existing research.

II. Illness and Labor Market Outcomes

Intuitively, poor health would seem to have a negative impact on labor supply and productivity. A more formal way of thinking about this impact is that under the assumption of utility maximization, the supply of work hours H (the difference between a time endowment T and the demand for leisure hours L) is determined by tastes and a budget constraint. Poor health can affect labor supply by diminishing tastes for work and thereby raising the marginal value of leisure time, reducing productivity, and, put simply, by stealing time away from work for health maintenance (Oi, 1996). Formally, this could be captured by incorporating a health production function into a labor supply model.

On the other hand, the potential for a change in health insurance status may be an important consideration in the decision to exit the labor force, given that breast cancer treatment is expensive and the potential for future medical expenses is great. Under these circumstances, an individual's tolerance for financial and personal risk becomes very important. Friedland (1996) suggests that health insurance creates unusual incentives regarding the decision to work. For people with medical conditions who need specialized (and often expensive) care, obtaining coverage is uncertain. Thus, some people are trapped in a job for fear of losing insurance and others have disincentives for leaving public programs and seeking employment since having a job may mean losing coverage (Friedland, 1996). Therefore, the counterintuitive notion that in the face of illness, labor supply may actually increase or remain unchanged, through the influence of health insurance and its accompanying incentives, is plausible. This tension between health conditions and their negative influence on labor supply, and the demand for health insurance and its potentially positive influence on labor supply, is reflected in the existing empirical research.

In empirical studies, the relationship between poor health or disability, health insurance, and labor supply appears unresolved. Psychiatric disorders, for example, have been shown to significantly reduce employment, work hours, and income (Ettner, et al., 1997; Benham and Benham, 1982). Severity of illness also plays an important role in the decision to reduce participation in the labor force (Famulari, 1992). Conversely, there is some evidence consistent with the demand for health insurance increasing or maintaining labor supply in response to illness. An ill person–particularly someone with a chronic condition requiring specialized care–is motivated to remain at work to maintain health insurance coverage. Empirical studies (e.g., Gruber and Madrian, 1993; Madrian, 1994; Monheit and Cooper, 1994; Kapur, 1998) supporting this position largely address the potential for job lock that may decrease workers' mobility, rather than directly addressing workers' willingness to exit the labor force or curtail hours.

Cancer-specific studies have pointed to some key questions in understanding the direction of influence cancer is likely to have on labor market decisions and outcomes, but they are far from decisive, and do not focus in a very detailed manner on the empirical estimation of the effects of cancer on these decisions and outcomes. In general, studies (e.g., Quigley, 1989; Fow, 1996; Kornblith, 1998; Razavi, et al., 1993; Carter, 1994; Berkman and Sampson, 1993) have focused on survivors' subjective impressions of the impact of cancer on their lives. These studies suggest negative factors that can influence employment including physical disability (e.g., limitations in upper body strength) (Fow, 1996), memory loss (Schagen, et al., 1999), lack of control over schedules, need for transportation, and type of work performed (Greenwald et al., 1989; Satariano and DeLorenze, 1996), and in some cases discrimination on the part of employers (Carter, 1994; Berry, 1993).

Other studies of employment following breast cancer offer another view of employment outcomes. In a study of patients two and three years after their primary treatment, Ganz, et al. (1996) found that breast cancer survivors function at a high level. Sixty-five percent of survivors (n=139) were either working for pay or volunteering their services. The mean numbers of hours worked were 34.4 and 33.2 hours per week among women who were two and three years post-treatment, respectively. This study concluded that women continue to work and perform their usual roles after treatment for breast cancer. Satariano and DeLorenze (1996) had similar findings. In a study of 300 women working at the time of their breast cancer diagnosis, 71% returned to work three months after diagnosis. The implication of these studies is that the overall impact of breast cancer on employment status is minor. However, these studies are not based on national samples, nor do they include a control group. Our analysis contributes to research on this topic along both of these dimensions. In addition, unlike much of the previous research, we control for a number of correlates that can influence the probability of employment, decisions regarding hours of work, and earnings, including individual characteristics and information on health insurance coverage.

Nonetheless, our analysis faces a major limitation. Specifically, we analyze survivors and a control group, without being able to address non-random (conditional on the observables) differences between survivors and non-survivors. This is, of course, a difficult selection problem to solve in the context of health economics. We try to address the issue as best as possible based on the observable information we have. Finally, we would argue that the evidence we present is of interest even if one suspects that our estimates are prone to selection bias, as the evidence at a minimum informs us of some of the differences between cancer survivors and the non-cancer control group, along a number of dimensions that have not been explored in previous research. If selection bias remains important, though, the evidence cannot tell us whether variation in labor market decisions or outcomes accurately reflects the longitudinal developments a cancer survivor would face (rather than reflecting unobservable differences among those who have survived different lengths of time).

III. Data

We use data from the first wave (1992) of the HRS. The HRS is designed to answer research questions regarding the relationship between health, income, wealth, job decisions, and retirement. The cohort is aged 51-61.[1] In most cases, if there are two members of the household (e.g., husband and wife) each is interviewed regarding his/her own employment history, retirement, health, and demographic characteristics. The more financially knowledgeable respondent in the household is interviewed regarding housing, net worth, income, and health

[1]There are follow-up interviews at two-year increments that are not used in this study.

insurance status for the members of the household included in the survey.[2] Only one member of the household must be in the age range of the sample frame; therefore spouses may be interviewed even if they are out of the specified age range, and thus our sample departs from national representativeness for these respondents.

For our non-cancer control group, we selected women who answered "no" to the question, "Has a doctor ever told you that you have cancer or a malignant tumor of any kind?" Given that a cancer diagnosis is a life-altering event, recall bias is not likely to be a problem in the data. Those women that said "yes" to the above question and subsequently indicated that their diagnosis was breast cancer constitute the treatment group. We also use information available in the HRS on the number of years since breast cancer diagnosis, which is likely to be associated with morbidity and the severity of any side effects from treatment, and therefore to have potential labor market consequences. Women in our sample were diagnosed an average of 7 years (standard deviation = 6, range 1-32 years) prior to the interview. For the reader's convenience, we include the HRS questions relating to cancer in Appendix A.

The HRS contains 6,708 women on whom we have information regarding labor force participation and hours worked. We excluded women who were insured by Medicaid (n=319) because Medicaid has been shown to constrain labor supply, particularly for families with high expected medical expenditures (Moffitt and Wolfe, 1992). The non-Medicaid restriction coupled with missing data[3] led to a final sample size of 5,974 women, 156 of whom reported having breast cancer.

[2] If a person was single, he or she was designated the primary respondent. In a married pair or partnership, the person most knowledgeable of household financial matters was designated the primary respondent.

IV. Empirical Approach

Specifications

The outcomes of interest are employment status, usual hours of weekly work, earnings, and wages. Each of these can be expressed as a function of the incidence of breast cancer (BCA), the duration of survival to date (S), variables we take to be exogenous (X), the availability of health insurance (HI), and random or unobserved influences (ε). Generically, we write the employment equation as

$$E_i^* = f(BCA_i, S_i, X_i, HI_i, \varepsilon_i) \qquad (1)$$

where E_i^* represents a latent variable for the propensity for employment. We observe that a woman is employed if E_i^* exceeds some critical value. In the context of economic theory, the function f(.) captures the difference between the offer or market wage and the reservation wage at zero hours of work, and when this difference exceeds zero the woman chooses to work. Of course, there is a potential demand-side influence as well, for example stemming from discrimination against women with cancer. This could pose a barrier to employment or full-time work, or it could influence the market wage. Since we do not interpret the parameter estimates structurally, we need not choose between the interpretations. We estimate the employment equation by assuming a linear additive form for equation (1),

$$E_i^* = \alpha_E + \beta_E\, BCA_i + X_i\gamma_E + \delta_E HI_i + \varepsilon_i \; .\text{[4]} \qquad (2)$$

We then define employment status as a binary variable (E_i) that equals one if the respondent reports positive hours worked and estimate equation (2) as a probit model. For ease of

[3] Missing data were distributed as follows: Medicaid (319), age (120), type of cancer (282), race (13).
[4] Note that we have omitted S_{it} for now; later, we introduce information on length of survivorship.

interpretation, the probit estimates are translated into derivatives of the probability of working with respect to the independent variables.[5]

As noted earlier, we are interested in how health insurance may affect labor market decisions and outcomes (in particular, labor supply), and how it mediates the effects of breast cancer. Of course such insurance is available in large part only for employed women or married women with an employed spouse. It is highly likely that the presence of employer-based health insurance is endogenous to a model estimating the decision to work, and so we approach the estimation of the effect of health insurance, for married women, using information on whether her spouse has health insurance through his employer (Buchmueller and Valletta, 1999). Consequently, when we estimate equation (2) including information on spousal health insurance, we use a sample of married women only.

The other three dependent variables depend critically on the employment decision. Hours worked are zero for those who do not work, and nonzero for those employed (E_i=1). In the standard economic model, the former are generally at a corner solution, while the latter are at an interior solution to the utility maximization problem; thus in principle desired hours of work of the non-employed could be negative but zero is the lowest possible value. Assuming a linear functional form, and assuming that the same variables that affect employment affect hours, the empirical model for observed hours is

$$H_i = \alpha_H + \beta_H BCA_i + X_i\gamma_H + \delta_H HI_i + \eta_i \text{ , if } E_i=1 \qquad (3)$$

$$H_i=0 \text{ , if } E_i=0 \text{ .} \qquad (3')$$

[5] The "derivatives" are computed as the difference in probabilities as the dummy variable takes on the values zero and one, with the other variables at the sample means. The standard errors reported are those making the t-statistics for these derivatives the same as those on the original coefficients, allowing the reader to easily assess the statistical significance of the raw coefficients.

With hours censored in this equation, it is common to attempt to estimate such models using a Tobit or selection-correction model (e.g., Heckman, 1979), in order to recover estimates of the unconditional mean function based on equation (3),

$$E(H_i|BCA_i, X_i, HI_i) = \alpha_H + \beta_H BCA_i + X_i\gamma_H + \delta_H HI_i \ . \qquad (4)$$

The selection-correction model is more appropriate when the second-stage equation (corresponding to H) is for a dependent variable that is not a direct transformation of the dependent variable in the first-stage equation. An example would be the estimation of a wage or earnings equation conditional on employment. A potential pitfall of selection-correction models is that if there are variables that cannot be excluded *a priori* from the second-stage equation, identification comes from restrictions on the functional form (e.g., linearity), as well as distributional assumptions (see Olsen, 1980).

In contrast, when we examine hours, under some conditions the equation determining hours is identical to the equation determining employment, in which case a Tobit model is appropriate. The Tobit model still depends on underlying assumptions. One such assumption is the distributional assumption, and the other is that the behavioral equation determining hours and employment is the same, with employment simply determined by whether desired hours exceed zero. Such an assumption would be violated, for example, when there are fixed costs of employment (Killingsworth, 1983, Chapter 3).[6] Because we would rather not rely on tenuous identifying assumptions, we instead report in the tables the unconditional OLS estimates using the zero values for hours. The coefficient estimates from these regressions measure the slopes of the linear projection of hours on the independent variables (under mild conditions), rather than how the expectation of hours varies with the independent variables; although the former provide biased

[6] In contrast, this assumption would hold in the case of pure top-coding or bottom-coding of a variable, which is *not* the way to conceptualize the censoring of hours at zero.

estimates of the latter, it is still possible that the estimates are close to the population parameters, at least near the population means (Wooldridge, 1999). However, in all cases we also estimated (but do not report) Tobit models, which are consistent if the normality assumption holds, but not otherwise; throughout the empirical analysis described below, the results were not sensitive to the choice of estimator. [7]

We also report estimates of a linear conditional mean function

$$E(H_i|BCA_i, X_i, HI_i, E_i=1) \quad . \tag{5}$$

Again, such a regression in general provides biased estimates of the slopes of the unconditional mean function (unless the conditional expectation of η is uncorrelated with the regressors), but still is informative about how the exogenous variables are related to hours of work for those at work.[8]

We next turn to estimation of the effects of breast cancer on wages (W) and earnings (Y). Earnings are defined as the respondent's annual earnings. Wages were reported on an hourly basis by many HRS respondents (n=1956). For respondents who reported their earnings in weekly, bi-weekly, monthly, or annual increments, we divided their reported earnings by their average hours worked during the specified time frame. For example, if the respondent works an average of 40 hours per week and earnings were reported bi-weekly, we divided bi-weekly earnings by 80. Estimation of earnings and wage effects faces the same issues as the estimation of hours effects, but here uncovering the unconditional mean would require a selection-correction model, consisting of the employment probit and either one of

$$W_i = \alpha_W + \beta_W BCA_i + X_i\gamma_W + \mu_i \;\;, \text{ if } E_i=1 \tag{6}$$

[7] Results are available from the authors upon request.
[8] Wooldridge (1999) shows that if we assume that the decision to work follows a probit, and we assume that the conditional expectation of log(H) is normal with mean linear in the included variables and constant variance, then this

or

$$Y_i = \alpha_Y + \beta_Y BCA_i + X_i\gamma_Y + \nu_i \ \text{, if } E_i{=}1 \quad .^{9} \tag{7}$$

In the case of estimating a selection-correction model for wages or earnings, identification seems untenable. The employment decision fundamentally depends on the market wage and the reservation wage, but it is not clear what variables affect the reservation wage only, and hence can be excluded from the wage equation; this argument is even stronger in the case of earnings, since earnings reflect hours of work. Therefore when we analyze wages and earnings we focus on the estimates of the conditional functions (6) and (7), recovering estimates of the linear projections of W_i or Y_i on the independent variables for those working, although, as mentioned previously, these are generally biased estimates of the unconditional mean function. The only exception is that we also report OLS estimates of the unconditional earnings equation, to provide a summary of the combined effects of employment, hours, and wage changes caused by breast cancer. These estimates must be interpreted with care, as they neither reflect wage equation parameters nor labor supply parameters.[10]

Econometric Issues

To this point we have been relatively silent on the assumptions surrounding the unobservable error terms (ε, η, μ, and ν) in the equations we estimate. Obviously, we would like our estimates to reflect causal effects of breast cancer on the labor market decisions and outcomes we analyze. This requires, of course, that the residual terms be uncorrelated with the right-hand-side variables. This is potentially problematic with respect to both BCA and S. Even if we take

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regression provide the maximum likelihood estimates of the conditional mean function. When we estimated our conditional hours models using the log of hours, the qualitative conclusions were unchanged.

[9] Note that we excluded health insurance variables from the wage equation as it is unlikely to affect productivity. We also excluded health insurance from the earnings equation because of potential endogeneity. In our analysis, we estimated (but do not report) equation (7) for married women, controlling for whether her spouse had health insurance through an employer. The results were qualitatively unchanged.

the incidence of breast cancer as random conditional on the other observable control variables, in order for a breast cancer patient to appear in our data set, she must have survived the breast cancer for some time. In the HRS sample, 76% of the patients had survived three or more years. Thus, a causal interpretation of our estimates requires that survival, also, be unrelated to the unobservables, and the estimation of specifications including S (the number of years of survival thus far), requires that this survival duration also be unrelated to the unobservables.

To fully address this issue, we would require longitudinal data on women before and after the onset of breast cancer.[11] Under weaker assumptions (that the unobserved residuals are fixed over time for individuals), we could recover causal estimates by comparing changes in behavior for cancer patients to changes in behavior for the non-cancer control group over a similar period. Such data are by and large absent in the HRS. Therefore, we proceed in two other ways. First, we have available a number of control variables, such as wealth, race, age, and education that are plausibly correlated with survival outcomes as well as labor market behavior. It is therefore instructive to compare the estimated effects of cancer incidence and survival time with and without these controls. If the inclusion of these controls has much influence on the estimated effects, then an additional role for unobservables seems relatively more likely. On the other hand, if the inclusion of these controls has no influence, it seems less likely that other unobserved characteristics would be important.

Second, we compare results across our various dependent variables to see whether there are patterns consistent with selection explanations of the findings. In particular, it seems likely that if important unobservable variables in the employment, hours, wage, and earnings equations

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[10] Again, we also estimated Tobit models corresponding to the unconditional earnings specifications, and obtained similar findings; results are available from the authors upon request.

are unobserved components of ability or productivity, then they ought to be positively related with all of the outcomes explored. If this unobserved ability or productivity is also correlated with factors increasing the likelihood of surviving cancer, then any estimates of the effects of breast cancer on these outcomes would be upwardly biased. Thus, a consistent finding of positive impacts of cancer on each of these labor market outcomes would suggest a potential selection problem. We also consider evidence from specific hypotheses that might generate causal effects of breast cancer on the labor market outcomes we study.

Finally, it has been argued that labor market decisions and health should be jointly considered (Grossman, 1972; Olson, 1998), because people who are inclined to invest in attributes (e.g., education) that improve their labor market outcomes are also more inclined to invest in health. We think this is a potentially interesting but also a potentially futile challenge given our data, since we know very little about respondents' risk factors (e.g., family history, oral contraceptive use, nulliparity, estrogen replacement use, high fat diets, and environmental risks) for breast cancer. Thus, treating the incidence of breast cancer as essentially random, other than a few known exogenous predictors out of individuals' control, such as age and race,[12] seems a reasonable approximation to reality. However, we do not want to dismiss this problem, because as noted above we are really estimating the effects of being diagnosed with and surviving breast cancer, and survival is more plausibly related to past and present behavioral and environmental variables.

[11] The first wave of the HRS does not collect this information retrospectively. In principle, subsequent waves of the study could be used to construct such data, but the incidence of cancer would likely be too low to generate a sizable treatment group among those initially cancer-free.

[12] Caucasian women are slightly more likely to develop but also to survive breast cancer compared to other women.

Control Variables

The regressor of primary interest is a 0-1 indicator for whether or not women had breast cancer. We also incorporate information on the duration of survival to date. For the HRS sample, we report results distinguishing between those diagnosed two years or fewer prior to the interview, and those diagnosed three or more years prior to the interview. The literature offers little guidance on how to specify the effects of breast cancer in multivariate analyses predicting labor market outcomes. We solved this problem empirically. Our alternatives were to enter breast cancer as either a binary variable indicating the presence or absence of breast cancer or as an ordinal or continuous variable indicating the years since diagnosis. An argument can be made for a continuous specification based on ease of interpretation and parsimony. However, a single-year interval between the time since diagnosis may be unequal in its impact on employment, indicating a nonlinear relationship between years since diagnosis and the labor market decisions and outcomes we study. We entered years since diagnosis into our preliminary estimations a number of ways (continuously and as dummy variables) in separate regression equations and used F-tests to examine the relative contributions of the restricted and unrestricted models. Based on our analysis, we found three primary distinctions among women: no cancer, cancer diagnosed in two or fewer years prior to the interview, and cancer diagnosed three or more years prior to the interview.

We also controlled for demographic characteristics including age, marital status (never married, separated/widowed/divorced, married), race (Hispanic, African-American/non-Hispanic, or Caucasian/Other/non-Hispanic), education (no high school diploma, high school diploma, some college, college degree), and wealth. Age is specified as a continuous variable and as a dummy variable for women over age 65. The dummy variable controls for Medicare insurance coverage and the typical age at which one retires. We include terms for spousal insurance through his employer (for married women only), region of country (Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific, and New England), and urban residence. For brevity, we do not report coefficients for the regions or urban residence.

V. Results

Descriptive Statistics

Table 1 presents descriptive statistics for the dependent and independent variables from the HRS. The prevalence estimate of breast cancer is 2.6% (n=156). Approximately 64% of all women are currently working. They work an average of 38.5 hours per week, and have average annual earnings of $18,430. The average hourly wage for women in our sample is $31.24, which is unreasonably high. However, note that the standard deviation is very large ($483.89) and wages range from $.28 to $27,900 per hour. The hourly wage variable is constructed for many women who report wages on a non-hourly basis (e.g., weekly). In these cases, we divide earnings by an estimate of hours worked per period. Perhaps the unusually high and low values for wages are due to errors in data reporting. We later test the sensitivity our estimations to the high and low extremes by imposing cutoffs ($2.75 to $200) and by applying our model to the sample that report being paid on an hourly basis. Wealth is a highly skewed variable with a mean of $229,531 and median of $98,500. Fifty-five percent of married women's husbands have health insurance coverage through their employer-based policy. Overall, this sample can be described as predominantly Caucasian/other, married, middle-aged (mean age is 54), and as having a high school education or better.

Women with breast cancer are similar to the rest of the HRS sample in their demographic characteristics with the following exceptions. More breast cancer survivors are older, Caucasian/other and married, and have achieved higher education compared to women without breast cancer. These differences are consistent with what we would expect regarding who gets and survives breast cancer for some time. The average time since breast cancer diagnosis is 7 years, with three-quarters of the sample having survived for three or more years. Thus, we do not expect treatment-related morbidity to affect these women's labor market outcomes. Even so, several differences in labor market variables are apparent in this descriptive analysis. Fewer breast cancer survivors work (54% versus 64%). Among those who do work, though, breast cancer survivors work more hours per week and earn more per year.

Probability of Working

Table 2 provides the probit model estimates for the probability of working. In the first column, breast cancer is defined as a dummy variable, and its coefficient (-.09, $p<.05$) is negative and statistically significant. At the mean for all covariates, we estimate the probability of women with breast cancer working to be nine percentage points lower than for women who do not have breast cancer. This is consistent with the means in Table 1. In the second column, we differentiate between women diagnosed with breast cancer within the last two years and those diagnosed three or more years ago. The coefficient for women diagnosed three or more years prior to the interview is negative and statistically significant ($p<.10$). At the mean for all covariates, women who were diagnosed three or more years prior to the interview were eight percentage points less likely to work.

Other coefficients that were significant include household income, which had a negative influence on the decision to work, albeit very small. Age also had a negative impact on the work decision. More educated women were more likely to work. The influences of age, education, and wealth are consistent with what one would expect according to standard labor supply theory.

In Table 3, we test the effect of a spouse holding employer-based health insurance on the probability of working among married women in HRS sample. The magnitude and significance of the coefficient on breast cancer (column 1) increases slightly to -.11 ($p<.01$) relative to Table 2, column 1. If a spouse has employer-based insurance, women were 10 percentage points less likely to work. An interaction term for having a spouse with employer-based health insurance and breast cancer was not statistically significant (not reported). Thus, the hypothesis that breast cancer survivors who have the option of health insurance through their spouses are less likely to work–or equivalently that those without such insurance are more compelled to work–is questionable.

Hours Worked

Table 4 shows the results from our conditional and unconditional OLS models for hours worked. In the model predicting hours conditional on employment, we find a counterintuitive result, although one that replicates what we saw in the means. Employed breast cancer survivors are estimated to work 3.24 ($p<.05$) hours more a week than other employed women. When we specify years since diagnosis, we see that in the years immediately following diagnosis, women with breast cancer do not work a different number of hours than women without cancer. In subsequent years following diagnosis, however, women with breast cancer work an average of approximately four ($p<.01$) additional hours per week. The signs and significance of the remaining coefficients are as one would expect.

In the unconditional OLS models (columns 3 and 4), the point estimates of the coefficients on breast cancer are negative and statistically insignificantly different from zero. The lack of any relationship in these columns reflects the apparently offsetting negative influence of breast cancer on employment and the positive influence on hours conditional on work. As a summary measure, these regressions do not provide statistical evidence of an overall effect of breast cancer on hours of work.

Perhaps breast cancer survivors are responding to minimum hours constraints needed to retain health insurance. To examine this question, we tested whether insurance constraints potentially explain the higher hours of work of married breast cancer survivors (n=59). Specifically, for the married sample, we included an interaction between breast cancer and a spouse employer-based insurance, to see whether the hours effect is more negative relative to married women whose spouses do not have health insurance through their employer. However, the evidence (not reported) does not point to any statistically significant differential effects of breast cancer on hours of work by husbands' insurance.

Earnings

In a comparison of mean annual earnings, we found that among working women, those who had been diagnosed with breast cancer earn on average nearly $2,300 more than other women, an advantage of approximately 12% (Table 1). In Table 5, when we estimate a log earnings equation conditional on working, controlling for other variables that are likely to affect earnings, we continue to find that breast cancer survivors earn more than the non-cancer control group. Following the suggestions of Halvorsen and Palmquist (1980) for interpreting dummy variables in semilogarithmic equations (i.e., $(e^{\beta} - 1) \times 100$), breast cancer survivors have 20% ($p<.05$) higher earnings than the non-cancer control group. When we further controlled for years since diagnosis, women diagnosed three or more years prior to the interview earn approximately 23% more than the non-cancer control group.

Columns 3 and 4 of Table 5 show the unconditional OLS estimations for log annual earnings. In these models, the estimated coefficients for the breast cancer variables are negative, but statistically insignificant, with much larger standard errors. The estimates of the unconditional OLS models of earnings are consistent with our previous findings, reflecting offsetting effects of higher earnings conditional on working, but a substantially lower probability of working.

Wages

The apparent positive earnings effect of breast cancer survival for working women could be driven by the positive relationship between breast cancer survival and hours that we saw in Table 4. It could also reflect a positive wage effect. Table 6 reports similar specifications to those for annual earnings, but now using the hourly wage as the dependent variable. In the first two columns we use the full HRS sample of working women, constructing an hourly wage when necessary, as explained earlier. This evidence suggests that breast cancer survivors' wages are higher than the wages of women in the control group; in particular, the evidence emerges for those women diagnosed three or more years prior to the survey ($p<.10$).

We observed earlier that the constructed wage data likely contained some egregious errors. Therefore, we dropped observations with wages below \$2.75 an hour and above \$200 an hour, and re-estimated the wage equations. These estimations are shown in columns 3 and 4 in Table 6. By imposing the cutoffs, the sample size decreased slightly, and the distribution approaches normality with a log transformation. In column 3, we find a statistically significant ($p<.01$) coefficient on breast cancer. Breast cancer survivors earn approximately 12% more per hour than other women. In column 4, we see that women who have survived breast cancer for three or more years earn approximately 15% more per hour than women without breast cancer, while there is no statistically significant differential for those diagnosed within the past two years. In columns 5 and 6, we take this one step further, estimating the wage equations for the sample of women (n=1956) who reported their wages in hourly terms, to further reduce errors from constructing wages. Once again, we see that breast cancer survivors of three or more years earn approximately 14% more per hour than other women. The coefficient for women diagnosed within two years changes sign and is sizable, but not statistically significant.

Assessing Selection Bias

The results to this point indicate that while breast cancer survivors have lower employment probabilities, those who have survived three or more years work more hours, have higher earnings, and earn higher wages, if they are employed. These results are surprising, if one believes that there are any long-lasting debilitating effects of breast cancer. Certainly the opposite case can be made for early-stage cancers, but even if there are not long-lasting effects, the most reasonable expectation might be to find no differentials between the survivors and the non-cancer control group. On the other hand, a positive causal effect is not inconceivable. For example, by virtue of being a "survivor" women could approach their careers with more vigor than they previously had. If a positive causal effect of breast cancer survival on these outcomes is replicated and established in future work, conjectures such as this one must receive more serious attention. However, as this is one of the first systematic empirical studies of this topic, a more appropriate line of inquiry is to attempt to assess whatever evidence is available on whether the estimated relationships described in the previous sub-sections are causal, or are instead driven by selection bias. The numerous analyses we describe in this section are not decisive, but we think they are helpful, and point the way to further consideration of this question in future research.

We first re-interpret some of the earlier evidence. One might view our earlier results on wages through the prism of causality versus selection. Recall that we reported evidence that breast cancer survival was associated with higher hours and higher annual earnings. One potential explanation for these results is that breast cancer survivors are more committed to the labor force and more productive *prior to* their cancer diagnosis. For example, women who survive breast cancer may have higher educational attainment and human capital or more financial resources. In this scenario, the hours and earnings effects are not causal, but reflect selection. If this is true, it seems reasonable to expect that women who survive breast cancer and work may also have higher wages, reflecting a longer-term history of labor market commitment or higher unobserved productivity among those who get and ultimately survive breast cancer.[13] In contrast, while we could easily imagine breast cancer survivors increasing their hours of work and therefore their earnings, workers in general have less control over their wages, which are set by the market, although they could increase their effort. Aside from this qualification the evidence that breast cancer survivors have higher wages is probably more consistent with a selection explanation of our findings than a causal explanation.

Similarly, one might view the earlier employment results through the same prism. If we believed that what was driving the hours and earnings results was that survivors were more committed workers ex ante, we might also expect the probability of employment to be higher for them after surviving breast cancer. The fact that employment appears to be lower is therefore more consistent with the hypothesis that we are observing causal effects. Of course the population of survivors could be more heterogeneous, with some debilitated by the disease and therefore leaving the labor market, while those who remain are a select group of the most committed or most "robust." Thus, additional evidence assessing the validity of a causal interpretation of the estimated effects for employment, hours, earnings, and wages is useful.

[13] The theory of compensating differentials might suggest that women in jobs with higher risk of cancer earn higher wages, although we do not think that this is a major part of the story.

We first report an analysis that compares our findings reported earlier for the probability of work, and hours, earnings, and wages to estimates of models where we do not control for wealth, race, age, and education. These variables have been identified as associated with surviving breast cancer and labor market outcomes. If the exclusion of these controls does not substantively influence the estimated effects of breast cancer survival, then the argument for selection into the treatment group on unobservables is weakened. The results from this analysis are shown in Table 7. By comparing these estimates to those in the earlier tables, the reader can see that the estimated effects on hours, wages, and earnings are virtually unchanged in this table. In contrast, if we were "worsening" the selection on unobservables in this table, we would expect the effects to be larger in Table 7. This provides suggestive evidence that unobservable characteristics associated with breast cancer are not influencing the labor market outcomes we observe, thus providing support for a causal interpretation of our findings.

Our next set of analyses pursues more directly the hypothesis that among breast cancer survivors, those who exhibit higher hours of work, earnings, and wages *ex post* were simply more committed, higher-wage workers *ex ante*. To conduct this sort of analysis in the absence of a long panel, employment history variables such as job tenure and starting wages are critical. Unfortunately, the HRS has rather limited employment history information. The HRS includes job tenure information if the respondent is currently working. If the respondent is not working, job tenure information is collected for the respondent's most recent job, unless the respondent never worked for more than a few months or last worked prior to 1972. Thus, there is a sample for which we can include job tenure as a proxy for labor market commitment or attachment, although it also has independent effects on wages and therefore earnings.

This analysis, for each of the main outcomes considered earlier, is reported in Table 8 for the HRS sample. Because there are some observations for which tenure is unavailable, we first report estimates of the earlier models (only the key breast cancer coefficients) using the smaller sample for which the tenure information is available. Otherwise, the estimated specifications including tenure would not be comparable. Then, in the lower panel we re-estimate the models including the tenure variable. The table reveals that the estimated differentials associated with breast cancer are largely unaffected by the inclusion of the tenure control. In our view, the fact that these relationships are not changed by including a variable strongly related to past labor market commitment undermines a selection explanation of our findings.

The most decisive type of analysis would be a longitudinal analysis that looks at how the relationship between our labor market outcomes and breast cancer differs prior to the cancer diagnosis and after the diagnosis. Unfortunately, the HRS includes only a limited job history section for respondents who worked for more than five years, but otherwise job history information is not collected. There is some information about the start of the current job that is asked of everyone currently working. Since the starting date of the current job is also reported, we can restrict attention to breast cancer survivors whose starting date precedes their diagnosis with cancer. We can then study labor market outcomes at the start of the job and currently, and compare these for the cancer survivors who did not change jobs since diagnosis and the non-cancer control group. However, we can do this only for wages, but not hours or earnings, as HRS respondents were asked their rate of pay and time unit of pay at the start of the job, but not hours. Aside from not being able to study hours (or annual earnings), this also implies that we cannot construct an hourly wage for those paid on something other than an hourly basis. Because of these restrictions, we are left with very few observations on breast cancer survivors. The total sample size falls to 1824, with only 24 women with breast cancer.

For this sample, we estimate wage equation specifications like those reported earlier, comparing the estimated associations between breast cancer and both current wages and starting wages. If we observe a similar positive association for both current wages and starting wages, we would conclude that the breast cancer survivors were simply higher wage earners prior to their diagnosis, in which case the relationship would not be causal.[14] On the other hand, if the positive association appears only for current wages, then we would conclude that this positive effect reflects a causal outcome of cancer survival, again for the sample of women who remain at work. Following on our earlier analysis of wages, we report results with the cutoffs imposed on extreme values for the current wages.[15]

The results are reported in Table 9. The first column reports the regression for log starting wages, while the second reports regressions for log current wages. The latter parallels the specifications reported earlier in Table 6. However, because of changes in the sample, we no longer find a statistically significant relationship between breast cancer and wages.[16] Nonetheless, the estimated coefficient for the log starting wage is -.08, considerably less than that for current wages, although not statistically significantly so. Thus, while the point estimates are consistent with wages rising following breast cancer (although now relative to the starting wage), this longitudinal experiment is probably best judged as uninformative.

Our final analysis tests a specific version of a selection story, namely the hypothesis that the hours differential we find arises because women working part-time are not as attached to the

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[14] Recall that the selection mechanism underlying a positive association with starting wages may stem from survival rather than incidence of breast cancer, and the former is more plausibly positively associated with wages.

[15] Even though the starting wages are not constructed but based only on actual hourly wages, the current wage could be a constructed wage for the same individual.

labor force as full-time workers. When these women are presented with a breast cancer diagnosis, they quit their jobs, whereas women working full-time with a breast cancer diagnosis continue to work. This could also explain the higher earnings of breast cancer survivors, as well as their higher wages (since full-time workers earn a wage premium). If this is true, we should find that breast cancer survivors are relatively more likely to work full-time, and that the hours differential should disappear when we subdivide the sample into full- and part-time workers. The results of this analysis are shown in Table 10. Columns 1 and 2 show no statistically significant effect on the probability of being employed 35 or more hours per week associated with breast cancer. In columns 3 and 4, we do not find that breast cancer has an effect on the number of hours worked per week for women employed full-time. Furthermore, in columns 5 and 6, we show a positive effect for women working less than 35 hours per week and diagnosed with breast cancer. Thus, the data are not consistent with the hypothesis that women employed part-time tend to leave their jobs after a breast cancer diagnosis.

Detroit Analysis

Although we believe the HRS data are currently the best-suited to addressing the effects of cancer on labor market outcomes, they have two shortcomings that we are addressing in ongoing data collection and research that will be carried out over the next five years. First, as already discussed, we do not obtain a usable longitudinal sample of cancer survivors with information before and after diagnosis, and second, even aside from the cross-sectional/longitudinal issue, we do not obtain a large number of cancer survivors.

As a pilot study for our longer-term research efforts, we collected cross-sectional data on cancer survivors in a different fashion. This pilot study includes a smaller sample of cancer survivors, but nonetheless gives us a check on the estimates obtained from the HRS, with which to

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[16] This is also true if we separate out those diagnosed three or more years ago.

verify that the basic qualitative results we have described thus far are not driven by a handful of outliers in the relatively small HRS sample of survivors. If they were, the results would be unlikely replicated in another data set.

For this pilot study, we interviewed breast cancer survivors aged 35 to 75 in 1999, five to seven years after their diagnosis of cancer. Survivors were randomly selected from the Metropolitan Detroit Cancer Surveillance System (MDCSS) that covers the population within the Detroit metropolitan area (Macomb, Oakland, and Wayne counties). Our interview questions replicated a subset of those found in the Current Population Survey. Women answered the survey with very few refusals (9%) once we successfully contacted them. However, we were unable to contact approximately one-third of the patients drawn from the eligible cancer population. The main reason we were unable to contact these patients was lack of current addresses and telephone numbers in the database.

To determine if those we could not contact were systematically different from the survey respondents, we compared patients in the two groups by age, race, zip code of residence, and cancer site in proportion to the eligible population's characteristics. A greater proportion of patients with stage III (i.e., regional disease) cancer were not contacted. Thus, our sample respondents may be less sick than the general population of patients, and our estimates of the detrimental labor market effects of cancer may be understated. No differences were found on the basis of age, race, site, and recorded zip code of residence between the respondents and patients we were not able to successfully contact.

A total of 73 breast cancer survivors completed our survey. With the exclusion of women insured by Medicaid, our sample size was 65. In addition to the questionnaire responses, personnel from the MDCSS matched interviewed patients with their clinical information regarding their stage of cancer at diagnosis and treatments received. We then selected female Detroit Metropolitan Statistical Area (MSA) residents who responded to the 1999 March supplement of the Current Population Survey as our control group. Because the CPS does not collect information regarding cancer, it is possible that some respondents may have cancer, however this number is likely to be small, leaving the control group relatively uncontaminated although possibly biasing our results slightly toward finding no difference between cancer survivors and the control group. We restricted the CPS sample (n=342) to match the age ranges in the treatment sample and excluded respondents insured by Medicaid.

Descriptive statistics for this sample are reported in Table 11, and can be compared with those for the HRS in Table 1. The Detroit sample is considerably more heterogeneous than the HRS. Several distinctions are worth noting between the HRS and the Detroit samples. First, a higher percentage of women are African-American, more women have a high school education or better, and more women are separated, widowed, or divorced. Second, the women are slightly younger (in the CPS sample), but fewer are working compared to the women in the HRS sample (56% versus 64%). Turning to the labor market outcomes of direct interest, in a comparison of breast cancer survivors to the CPS sample, a similar pattern emerges as the one observed in the HRS treatment and control groups. Fewer breast cancer survivors work, but for those who do, they work more hours and have higher earnings than women in the control group.

Table 12 reports the multivariate analyses of labor market outcomes of breast cancer survivors in the Detroit Metropolitan Area. As shown in column 1, the coefficient on the probability of working is statistically insignificant. In column 2, we do not observe a statistically significant effect of breast cancer on hours worked for those who work. However, the sign and size of the coefficient on breast cancer is similar to that observed in the conditional model for the

HRS sample (Table 4, column 1). The estimates in column 3, for annual earnings conditional on working, also mimic the HRS results in showing a positive differential for cancer survivors, although again the estimated effect is not statistically significant. Finally, in column 4, we observe that breast cancer survivors' hourly wages are approximately 30% ($p<.05$) higher compared with the control sample. This finding compares favorably with the findings in Table 6, where we also found a positive wage effect associated with breast cancer.

From this pilot-study sample, for the most part we did not find evidence inconsistent with our previous findings. The signs and sizes of the estimated effects of breast cancer on hours, earnings, and wages were similar to those observed in the HRS. Unfortunately, statistical significance was rarely achieved–perhaps due to the small sample sizes.[17] Nonetheless, the overall similarity of the estimates enhances our confidence in the HRS results, which is particularly important given that some of the HRS results are unexpected.

VI. Discussion

Our finding that breast cancer has a negative effect on working is consistent with what one would expect given the disease and population affected, and our sensitivity analysis indicates that the coefficients on the breast cancer variables for this labor market outcome are robust. However, breast cancer's positive effect on hours worked and earnings is inconsistent with standard views of the natural course of the disease (i.e., it should either reduce the number of hours worked because of recurrences or health effects, or at best be neutral if the cancer remains in remission and has no lasting debilitating effects), which is why we have delved at length into the question of selection bias. We believe that the various analyses of this issue are complementary, although none is

[17] Another potential problem is the significantly higher average age (by 7 years) of breast cancer survivors compared to female CPS respondents. Although we selected the CPS sample based on a common age range, we did not match respondents based on age.

definitive. Nonetheless, the evidence generally suggests that our findings are not driven by selection bias.

We might think that the best-case scenario is that the morbidity associated with breast cancer is negligible for at least some women, so that for these women, who are more likely to continue to work, there are no adverse consequences in terms of labor market outcomes or performance. There are several studies indicating that the morbidity associated with certain types and stages of breast cancer and its treatment may not interfere with work (e.g., Ganz, et al., 1996; Satariano and DeLorenze, 1996). But this explanation is only consistent with no effects, not positive effects. One potential explanation of positive effects is that women may be unwilling to reduce number of hours worked or exit the labor force for fear of not getting another job with equivalent health insurance benefits. Relatively few part-time jobs provide health insurance benefits (Olson, 1998). However, our analysis of the interaction between spousal insurance coverage and breast cancer and their combined effect on hours worked does not support this hypothesis.

We observed similar patterns in the probability of working, hours worked, and earnings for breast cancer survivors in data covering the Detroit metropolitan area from a pilot-study sample, although these relationships were less often statistically significant. The Detroit sample is relatively small, so we are reluctant to attribute too much importance to the specific results it yields. However, what we find informative in the Detroit analysis is that the patterns are similar to those in the HRS, bolstering our confidence in the findings from the latter.

Even in the absence of perfect data, our analysis improves upon what is known in the existing literature. Our study, controlling for a range of correlates, provides the first descriptive information on differences in labor market outcomes between cancer survivors and a non-cancer control group. We also provide the first analysis of objective measures of individuals' economic circumstances after a cancer diagnosis. What the evidence cannot tell us definitively, if selection bias remains important, is whether variation in labor market decisions or outcomes depending on a cancer diagnosis and the number of years since diagnosis accurately reflects the actual longitudinal developments a cancer survivor would face. We are currently collecting longitudinal data to address this issue, and so our future research should lend further insight into the extent of selection bias, and the causal effects of breast cancer survival.

The American Cancer Society estimates that there will be 175,000 new cases of invasive breast cancer this year among women in the United States. In general, the high incidence of certain cancer types among working age people leads to greater productivity costs for cancer compared to other categories of disease. An understanding of the labor market implications of a cancer diagnosis and treatment is particularly relevant as cancer screening (including prostate, colon, and lung in addition to breast) is routinely applied to a working age population where these cancers may have otherwise gone undetected for some time.

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Table 1. Descriptive Statistics: Health and Retirement Study 1992

Variable	All Women (N=5974)	Women without Breast Cancer (N=5818)	Breast Cancer Survivors (N=156)
Employment Characteristics			
Currently Employed	63.91%	64.18%***	53.85%
Mean Hours Worked Per Week (Workers Only)	38.50	38.43**	41.42
	(13.89)	(13.89)	(13.38)
Currently Working 35+ hours per week	74.18%	74.17%	74.70%
Annual Earnings (Workers Only)	$18,430.44	$18,375.20	$20,696.80
	($13,904.30)	($13,895.94)	($14,133.86)
Hourly Wage (Workers Only)	$31.24	$31.40	$24.01
	($483.89)	($489.16)	($111.41)
Breast Cancer			
Mean Number of Years Since BCA Diagnosis	N/A	N/A	7.02
			(5.93)
Two Years or Less Since BCA Diagnosis	N/A	N/A	23.08%
Three Years or More Since BCA Diagnosis	N/A	N/A	76.92%
Health Insurance			
Spouse has coverage through his employer	54.52%	54.41%	58.41%
Age			
Age (Mean)	54.36	54.33***	55.44
	(4.87)	(4.88)	(4.71)
Age >65	.95%	.95%	1.28%
Race/Ethnicity			
Caucasian, other	74.04%	73.84%**	81.41%
African-American	16.84%	16.95%	12.82%
Hispanic	9.12%	9.21%*	5.77%
Marital Status			
Married	74.97%	74.94%	76.28%
Divorced, Separated or Widowed	22.08%	22.12%	20.51%
Never Married	2.95%	2.94%	3.21%
Education			
No High School Diploma	26.60%	26.66%	24.36%
High School Diploma	39.00%	38.95%	41.03%
Some College	19.37%	19.37%	19.23%
College Degree	15.03%	15.02%	15.38%
Mean Wealth	$229,531	$228,697	$260,646
	($500,139)	($500,950)	($469,349)

Notes: Standard deviations are in parentheses for continuous variables. Median wealth is $98,500. * Significantly different from adjacent cell in next column at p≤.10; ** p≤.05;*** p≤.01.

T*able 2*. Probability of Working—All Women, Health and Retirement Study 1992

Independent variable	BCA yes/no, HRS	Years since diagnosis, HRS
Breast cancer (yes/no)	-.09**	---
	(.04)	
Two years or less since BCA diagnosis	---	-.13
		(.08)
Three years or more since BCA diagnosis	---	-.08*
		(.05)
Wealth	-.00004***	-.00004***
	(.00001)	(.00001)
Age	-.02***	-.02***
	(.001)	(.001)
Age 65 or older	-.20***	-.19***
	(.08)	(.08)
Never married	.12***	.12***
	(.03)	(.03)
Divorced, separated, or widowed	.12***	.12***
	(.01)	(.01)
High school diploma	.12***	.12***
	(.02)	(.02)
Some college	.17***	.17***
	(.02)	(.02)
College degree	.24***	.24***
	(.02)	(.02)
African-American	.04**	.04**
	(.02)	(.02)
Hispanic	-.06**	-.06**
	(.03)	(.03)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; ***$p \leq .01$. N=5974. Probit model. Partial derivatives of probability with respect to independent variables are reported with standard errors in parentheses. Omitted categories are no breast cancer, age less than 65, married, Caucasian/other, no high school diploma, New England region, and non-urban.

Table 3. Probability of Working—Married Women, Health and Retirement Study 1992

Independent variable	BCA yes/no, HRS	Years since diagnosis, HRS
Breast cancer (yes/no)	-.11***	---
	(.05)	
Two years or less since BCA diagnosis	---	-.15
		(.10)
Three years or more since BCA diagnosis	---	-.10**
		(.05)
Spouse has own employer-sponsored insured	-.10***	-.10***
	(.02)	(.02)
Wealth	-.00004***	-.00004***
	(.00001)	(.00001)
Age	-.02***	-.02***
	(.001)	(.002)
Age 65 or older	-.19**	-.19**
	(.08)	(.08)
High school diploma	.14***	.14***
	(.02)	(.02)
Some college	.19***	.19***
	(.02)	(.02)
College degree	.25***	.25***
	(.02)	(.02)
African-American	.06***	.06***
	(.02)	(.02)
Hispanic	-.05	-.05
	(.03)	(.03)

Notes: * Effect is significant at $p \le .10$; **$p \le .05$; *** $p \le .01$. N=4479. Probit model. Partial derivatives of probability with respect to independent variables are reported with standard errors in parentheses. Omitted categories are the same as those reported in Table 2.

Table 4. Average Weekly Hours Worked, Health and Retirement Study 1992

Independent variable	BCA yes/no, HRS (conditional model)	Years since diagnosis, HRS (conditional model)	BCA yes/no, HRS (unconditional model)	Years since diagnosis, HRS (unconditional model)
Breast cancer (yes/no)	3.24**	---	-1.51	---
	(1.38)		(1.75)	
Two years or less since BCA diagnosis	---	.75	---	-4.24
		(2.87)		(3.45)
Three years or more since BCA diagnosis	---	3.91***	---	-.69
		(1.56)		(2.01)
Wealth	-.001*	-.001*	-.002***	-.002***
	(.001)	(.001)	(.0006)	(.0006)
Age	-.30***	-.30***	-.83***	-.83***
	(.05)	(.05)	(.06)	(.06)
Age 65 or older	-2.08	-2.09	-5.70***	-5.66**
	(4.12)	(4.12)	(2.08)	(2.08)
Never married	1.88	1.88	5.68***	5.68***
	(1.19)	(1.19)	(1.51)	(1.51)
Divorced, separated, or widowed	3.66***	3.66***	7.05***	7.05***
	(.53)	(.53)	(.68)	(.68)
High school diploma	-.36	-.36	4.61***	4.60***
	(.63)	(.63)	(.72)	(.72)
Some college	1.30*	1.30*	7.76***	7.77***
	(.72)	(.72)	(.85)	(.85)
College degree	3.52***	3.53***	12.27***	12.27***
	(.76)	(.76)	(.92)	(.92)
African-American	-1.69***	-1.69***	.17	.17
	(.58)	(.58)	(.75)	(.75)
Hispanic	-.99	-.99	-2.67***	-2.66***
	(.92)	(.92)	(1.05)	(1.05)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; *** $p \leq .01$. N=3818 for conditional hours equation; N=5974 for the unconditional equation, 2156 for which 0 hours are observed, 3818 for which positive hours are observed. Standard errors are in parentheses. Omitted categories are the same as those reported in Table 2.

Table 5. Log Annual Earnings, Health and Retirement Study 1992

Independent variable	BCA yes/no, HRS (conditional model)	Years since diagnosis, HRS (conditional model)	BCA yes/no, HRS (unconditional model)	Years since diagnosis, HRS (unconditional model)
Breast cancer (yes/no)	.18**	---	-.30	--
	(.09)		(.36)	
Two or less years since BCA diagnosis	---	.08	--	-.09
		(.18)		(.73)
Three or more years since BCA diagnosis	---	.21**	--	-.36
		(.10)		(.42)
Wealth	.0000006	.0000006	-.001***	-.001***
	(.00004)	(.00004)	(.0001)	(.0001)
Age	-.01***	-.01***	-.13***	-.13***
	(.003)	(.003)	(.01)	(.01)
Age 65 or older	.007	.01	-1.27**	-1.27**
	(.23)	(.23)	(.55)	(.55)
Never married	.27***	.27***	1.32***	1.32***
	(.08)	(.08)	(.31)	(.31)
Divorced, separated, or widowed	.16***	.16***	1.33***	1.33***
	(.03)	(.03)	(.14)	(.14)
High school diploma	.29***	.29***	1.39***	1.39***
	(.04)	(.04)	(.15)	(.15)
Some college	.57***	.57***	2.18***	2.18***
	(.05)	(.05)	(.18)	(.18)
College degree	.93***	.93***	3.09***	3.09***
	(.05)	(.05)	(.19)	(.19)
African-American	-.02	-.02	.50***	.50***
	(.04)	(.04)	(.16)	(.16)
Hispanic	-.20***	-.20***	-.32	-.32
	(.06)	(.06)	(.22)	(.22)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; *** $p \leq .01$. N=3867 for conditional equation; N=5974 for the unconditional equation, 2107 for which 0 earnings are observed, and 3867 for which positive earnings are observed. Standard errors are in parentheses. Omitted categories are the same as those reported in Table 2. We add $1 to earnings.

Table 6. Log Hourly Wages—Conditional Model, Health and Retirement Study 1992

Independent variable	BCA yes/no, HRS (full sample)	Years since diagnosis, HRS (full sample)	BCA yes/no, HRS (cutoffs)	Years since diagnosis, HRS (cutoffs)	BCA yes/no, HRS (hourly increments reported)	Years since diagnosis, HRS (hourly increments reported)
Breast cancer (yes/no)	.13	---	.11**	--	.09	--
	(.08)		(.05)		(.06)	
Two years or less since BCA diagnosis	---	.23	---	.02	--	-.15
		(.29)		(.10)		(.10)
Three years or more since BCA diagnosis	---	.10*	---	.14***	--	.13**
		(.06)		(.06)		(.07)
Wealth	.0001***	.0001***	.0001***	.0001***	.0001***	.0001***
	(.00004)	(.00004)	(.00003)	(.00003)	(.00003)	(.00003)
Age	.002	.001	-.0005	-.0004	.002	.002
	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)
Age 65 or older	.23	.23	.05	.05	-.10	-.10
	(.42)	(.42)	(.15)	(.15)	(.15)	(.15)
Never married	.15*	.15*	.11**	.11**	.09	.09
	(.09)	(.09)	(.05)	(.05)	(.06)	(.06)
Divorced, separated or widowed	.02	.02	-.002	-.002	-.01	-.02
	(.03)	(.03)	(.02)	(.02)	(.02)	(.02)
High school diploma	.21***	.21***	.21***	.21***	.13***	.13***
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)
Some college	.44***	.44***	.43***	.43***	.36***	.37***
	(.04)	(.04)	(.02)	(.02)	(.03)	(.03)
College degree	.69***	.69***	.70***	.70***	.43***	.43***
	(.05)	(.05)	(.03)	(.03)	(.05)	(.05)
African-American	.04	.04	.0003	.0003	.04*	.04*
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)
Hispanic	-.09	-.09	-.12***	-.12***	-.11***	-.11***
	(.06)	(.06)	(.03)	(.03)	(.03)	(.03)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; *** $p \leq .01$. Sample sizes: columns 1 and 2, N=3502; columns 3 and 4, N=3381; and columns 5 and 6, N=1956. Standard errors are in parentheses. Omitted categories are the same as those reported in Table 2.

Table 7. Previous Models Excluding Wealth, Race, Age, and Education Controls, Health and Retirement Study 1992

Independent variable	Probability of working	Probability of working	Hours worked (conditional model)	Hours worked (conditional model)	Log annual earnings (conditional model)	Log annual earnings (conditional model)	Log hourly wage, with cutoffs (conditional model)	Log hourly wage, with cutoffs (conditional model)
Breast cancer (yes/no)	-.11***	--	2.91**	--	.18*	--	.11*	--
	(.04)		(1.42)		(.10)		(.06)	
Two years or less	--	-.15*	---	.29	--	.14	--	.05
since BCA diagnosis		(.08)		(3.02)		(.20)		(.13)
Three years or more	--	-.09**	---	3.62**	--	.19*	--	.12*
since BCA diagnosis		(.05)		(1.59)		(.11)		(.06)
Never married	.11***	.11***	1.59	1.60	.29***	.29***	.14***	.14***
	(.03)	(.03)	(1.17)	(1.17)	(.08)	(.08)	(.05)	(.05)
Divorced, separated,	.08***	.08***	2.64***	2.63***	.09**	.09**	-.03	-.03
or widowed	(.01)	(.01)	(.52)	(.52)	(.04)	(.04)	(.02)	(.02)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; *** $p \leq .01$. Sample sizes: columns 1 and 2, N=5974; columns 3 and 4, N=3818; columns 5 and 6, N=3867 and columns 7 and 8, N=3381 (cutoffs imposed). Standard errors are in parentheses. Control variables are the same as in Tables 2-5. The estimates should be compared with Table 2, Table 4 (columns 1 and 2), Table 5 (columns 1 and 2), and Table 6 (columns 3 and 4).

Table 8. Previous Models With and Without Tenure Control, Health and Retirement Study 1992

Independent variable	Probability of working	Probability of working	Hours worked (conditional model)	Hours worked (conditional model)	Log annual earnings (conditional model)	Log annual earnings (conditional model)	Log hourly wage, with cutoffs (conditional model)	Log hourly wage, with cutoffs (conditional model)	Log hourly wage (wage in hourly increments)	Log hourly wage (wage in hourly increments)
Breast cancer (yes/no)	-.09** (.04)	---	3.28** (1.38)	---	.17* (.09)	---	.11** (.05)	---	.09 (.06)	---
Two years or less since BCA diagnosis	---	-.16** (.09)	---	.78 (2.87)	---	.08 (.18)	---	.02 (.10)	---	-.15 (.10)
Three years or more since BCA diagnosis	---	-.07 (.05)	---	3.96*** (1.56)	---	.20** (.10)	---	.14*** (.06)	---	.13** (.07)

Independent variable	Probability of working	Probability of working	Hours worked (conditional model)	Hours worked (conditional model)	Log annual earnings (conditional model)	Log annual earnings (conditional model)	Log hourly wage, with cutoffs (conditional model)	Log hourly wage, with cutoffs (conditional model)	Log hourly wage (reported wage in hourly increments)	Log hourly wage (reported wage in hourly increments)
Breast cancer (yes/no)	-.09** (.04)	---	3.26** (1.40)	---	.15* (.09)	---	.11** (.05)	---	.07 (.05)	
Two years or less since BCA diagnosis	---	-.17** (.09)	---	1.24 (2.82)	---	.11 (.20)	---	.05 (.10)	---	-.07 (.08)
Three years or more since BCA diagnosis	---	-.07 (.05)	---	3.81** (1.59)	---	.17* (.10)	---	.12** (.05)	---	.10 (.06)
Years worked at current job	.01*** (.0007)	.01*** (.0007)	.16*** (.02)	.16*** (.02)	.03*** (.001)	.03*** (.001)	.02*** (.0008)	.02*** (.0008)	.02*** (.001)	.02*** (.001)

Notes: * Effect is significant at $p \leq .10$; **$p \leq .05$; *** $p \leq .01$. Sample sizes for both panels: columns 1 and 2, N=5578; columns 3 and 4, N=3808; columns 5 and 6, N=3845; columns 7 and 8, N=3375 (cutoffs imposed); and columns 9 and 10, N=1952. Standard errors are in parentheses. Control variables are the same as in Tables 2-5.

Table 9. Log Starting and Current Hourly Wages—Conditional Model with Cutoffs (Restricted to those Reporting Starting Wage in Hourly Increments), Health and Retirement Study 1992

Independent variable	Log start wage	Log current wage
Breast cancer (yes/no)	-.08	.0001
	(.08)	(.07)
Wealth	.0001*	.0001***
	(.00004)	(.00003)
Age	.001	-.002
	(.002)	(.002)
Age 65 or older	-.12	-.04
	(.16)	(.15)
Never married	.12	.04
	(.08)	(.06)
Divorced, separated, or	-.03	-.02
widowed	(.02)	(.02)
High school diploma	.08***	.13***
	(.02)	(.02)
Some college	.31***	.37***
	(.03)	(.03)
College degree	.44***	.44***
	(.05)	(.05)
African-American	.10***	-.008
	(.03)	(.03)
Hispanic	-.07**	-.08***
	(.03)	(.03)
Years worked at current job	---	.02***
		(.001)

Notes: * Effect is significant at $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$. N=1824 for conditional log starting wage and log current wage equations, with current wage cutoffs of $2.75-$200. Standard errors are in parentheses. Omitted categories the same as those in Table 2.

Table 10. Probability of Working Full Time and Average Weekly Hours Worked for Full-Time Workers and Part-Time Workers, Health and Retirement Study 1992

Independent Variable	Probability of full-time employment (conditional model)	Probability of full-time employment (conditional model)	Hours worked for full-time workers (conditional model)	Hours worked for full-time workers (conditional model)	Hours worked for part-time workers (conditional model)	Hours worked for part- time workers (conditional model)
Breast cancer	.02 (.05)	---	1.83 (1.51)	--	5.92*** (1.33)	--
Two years or less since BCA diagnosis	---	.03 (.10)	---	.45 (2.11)	--	-2.42 (3.37)
Three years or more since BCA diagnosis	---	.02 (.05)	---	2.23 (1.83)	--	7.90*** (.93)

Notes: *** Effect is significant at $p \leq .01$. In columns 1 and 2, N=3818. Probit model. Partial derivatives of probability with respect to independent variables are reported. In columns 3 and 4, N=2832, and in columns 5 and 6, N=986. Standard are in parentheses. Control variables are the same as in Table 2.

Table 11. Descriptive Statistics: Detroit Current Population Survey March 1999, and Detroit SEER Cancer Registry 1999

Variable	Detroit CPS & Detroit Cancer Registry (N=407)	Detroit CPS Female Respondents (N=342)	Detroit Cancer Registry, Breast Cancer (N=65)
Employment Characteristics			
Currently Employed	54.05%	55.85%*	44.62%
Mean Hours Worked Per Week (Workers Only)	38.10	37.79	40.14
	(11.38)	(11.39)	(11.27)
Currently Working 35+ hours per week	80.45%	80.10%	82.76%
Annual Earnings (Workers Only)	$26,998.73	$25,167.99**	$40,966.67
	($22,103.65)	($17,941.50)	($39,904.37)
Hourly Wage (Workers Only)	15.07	14.60	18.46
	(10.38)	(9.79)	(13.74)
Breast Cancer			
Mean Number of Years Since BCA Diagnosis	N/A	N/A	5.94
			(.90)
Age			
Age (Mean)	53.22	52.12***	59.03
	(9.14)	(8.87)	(8.35)
Age >65	16.22%	13.45%***	30.77%
Race/Ethnicity			
Caucasian, other	77.15%	76.02%	83.08%
African-American	19.90%	20.47%	16.92%
Hispanic	2.95%	3.51%***	0%
Marital Status			
Married	62.16%	61.99%	63.08%
Divorced, Separated or Widowed	28.50%	28.95%	26.15%
Never Married	9.34%	9.06%	10.77%
Education			
No High School Diploma	12.04%	13.16%**	6.15%
High School Diploma	41.52%	41.23%	43.08%
Some College	19.90%	18.42%	27.69%
College Degree	26.54%	27.19%	23.08%

Notes: Standard deviations are parentheses for continuous variables. * Significantly different from adjacent cell in next column at p≤.10; ** p≤.05; * p≤.01.

Table 12. Analysis of Detroit Sample

Independent variable	Probability of Working--All Women	Weekly Hours Worked (conditional model)	Log Annual Earnings (conditional model)	Log Hourly Wage
Breast cancer (yes/no)	.01	2.81	.37	.26**
	(.08)	(2.20)	(.25)	(.13)
Age	-.02***	-.12	-.01	-.005
	(.004)	(.13)	(.01)	(.01)
Age 65 or older	-.20*	-8.64**	-.30	.11
	(.10)	(4.26)	(.44)	(.27)
Never married	.15	4.44	.22	.17
	(.09)	(2.98)	(.22)	(.15)
Divorced, separated, or widowed	.17***	4.89***	.14	.10
	(.06)	(1.48)	(.17)	(.10)
High school diploma	.17*	4.05	.55**	.13
	(.09)	(3.43)	(.28)	(.28)
Some college	.33***	4.61	.64**	-.01
	(.08)	(3.61)	(.30)	(.28)
College degree	.29***	5.58*	.88***	.37
	(.08)	(3.39)	(.30)	(.29)
African-American	-.05	1.42	.02	-.09
	(.07)	(1.68)	(.18)	(.12)
Hispanic	-.02	4.50	.18	-.28
	(.16)	(3.39)	(.18)	(.18)

Notes: * Effect is significant at $p \leq .10$, **$p \leq .05$, ***$p \leq .01$. Sample sizes: column 1, N=407; column 2, N=220; column 3, N=233; and column 4, N=216. Probit model in column 1, linear regression in column 2, and log-linear models shown in columns 3 and 4. Standard errors in parentheses. Omitted categories are no breast cancer, age less than 65, married, Caucasian/other, and no high school diploma.

Appendix A

HRS Questions Addressing Cancer

B9. (Has a doctor ever told you that you have) Cancer or a malignant tumor of any kind except skin cancer?

1. YES 5. NO

B9a. How many such cancers have you had? # OF CANCERS

	ONLY OR MOST RECENT CANCER	SECOND MOST RECENT CANCER
B10. In what year was your (most recent/next most recent) cancer diagnosed?	____________ YEAR	____________ YEAR
B11. In which organ or part of your body did this cancer occur?	____________________ ORGAN/PART OF BODY	____________________ ORGAN/PART OF BODY
B13. During the last 12 months, what sort of treatments have you received for this cancer? [CHECK ALL THAT APPLY.]	A. CHEMOTHERAPY/ MEDICATION B. SURGERY OR BIOPSY C. RADIATION/ X-RAY D. OTHER (SPECIFY) ____________________ NONE	A.CHEMOTHERAPY/ MEDICATION B. SURGERY OR BIOPSY C. RADIATION/X-RAY D. OTHER (SPECIFY) ____________________ NONE
B14. INTERVIEWER CHECKPOINT	SEE B9a ☐ TWO OR MORE CANCERS—GO BACK TO B10, SECOND MOST RECENT CANCER ☐ ALL OTHERS -->NEXT PAGE, B15	