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## Cancer survivors in the labor market: Evidence from recent US micro-panel data

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## **Cancer survivors in the labor market: Evidence from recent US micro-panel data**

### ABSTRACT

Rising cancer survival rates and retiring at older ages improve the probability of labor market presence for cancer survivors. Yet, insufficient evidence exists on the labor market effects of male- and female- specific cancers. Therefore, using a theoretical construct of labor supply and health capital, this study exploits a nationally representative dataset, the 2008-2015 Medical Expenditure Panel Survey (MEPS), for estimating the correlated random effects (CRE) and over-dispersion empirical models to capture the job market effects for cancer survivors. After addressing the potential endogeneity of cancer and controlling for the number of years after cancer diagnoses, the estimated CRE model detect substantial male-female differences in the labor market outcomes for the survivors. Male and female cancer types adversely affect short- and long- run employment prospects, and male-specific cancers increase weekly hours of work and decrease short- and long-run annual labor incomes. Moreover, gender-specific cancers increasingly limit long run family incomes and raise total health expenditures in the short- and intermediate- runs but not in the long-run. Additionally, while the cancers increase the likelihood of missing a work day for both genders in the short-run the effect is larger for females. Finally, the total annual cost of workplace absenteeism for the employed male- and female- cancer survivors range from \$0.58bn to \$3.1 bn.

JEL code: C10, I1, J22, J29

Keywords: cancer survivors; labor market; correlated random effects (CRE) model; over-dispersion model; Medical Expenditure Panel Survey (MEPS) data, short and long-runs.

## **Cancer survivors in the labor market: Evidence from recent US micro-panel data**

### **1. Introduction**

The US population living with at least one type of cancer in 2017 was about 20 million, a number expected to grow rapidly within ten years (Siegiel, Miller, and Jemal, 2017). Recent diagnostics and treatment innovations in oncology are steadily transforming cancer disease mortality to chronic conditions with improved survival rates and quality of life improvements in the US and worldwide (Ganz et al., 2004). Cancer survivorship, differentially among working males and females, enhances physical, psychosocial, and economic outcomes. More specifically, job impairment is one of the stressful repercussions of cancer (Steiner, Cavender, Main, and Bradley, 2004). After enacting the Americans with Disabilities Act (ADA) in 1990, workers with cancer histories compared with other chronic diseases filed lawsuits against employers for unlawful terminations and other work-related discriminations. Consequently, the 2008 Amendments to the 1990 ADA took effect January 1, 2009. They protect employments of the disabled “... even when the impairment is in remission, or symptoms are managed through medications, making coverage more inclusive. [T]his way, the ADA Amendments Act improved coverage for individuals with cancer undergoing active treatment and expanded coverage to individuals ... denied in the past” (Feuerstein, Gehrke, McMahon, and McMahon, 2017). The 2008 ADA exogenous policy shift provides a natural time break for assessing the labor market consequences of chronic health conditions including cancers.

This study contributes to the growing body of work investigating the negative health shock effects on labor market outcomes (Acemoglu and Angrist, 2001; Artazcoz, Borrell, Benach, Cortès, and Rohlfs, 2004; Baldwin and Johnson, 2000; Dercon and Krishnan, 2000; Finkelstein, Luttmer, and Notowidigdo, 2009; McGarry, 2004; Wagstaff, 2007). Health stock is an essential

component of human capital with significant direct and indirect impacts on utility and well-being of individuals (Decker and Schmitz, 2016). Health shock refers to an unanticipated deterioration of person's health stock emanating from accidents or diseases. Negative health shocks could potentially affect socioeconomic activities in short- and long- runs as a result of diminished health stock. Mental health disorders, for instance, raise the likelihood of unemployment and work absenteeism, and atrophied productivity and earnings in long-run (Banerjee, Chatterji, and Lahiri, 2017). Reduced labor supply and job market exit are reported both in the short- and long- runs after stroke and heart attack (Jones, Rice, and Zantomio, 2016).

Past studies report mixed effects of surviving cancer on the job market prospects. Moran, Short, and Hollenbeak (2011), for instance, relying on a state-specific dataset, investigate the labor market consequences of cancer using cancer survivor and comparison groups. Their study which includes only survivors aged 28-54, finds lower employment rate of eight percentage points among cancer survivors. Adding a further sample inclusion criteria to the above dataset, Short, Vasey, and Belue (2008) report a statistically significant result in the short-run and an insignificant effect in the long-run. More recently, Jeon (2017), analyzing the labor market consequences of Canadian cancer survivors following diagnosis in the first three years, detects a moderate negative effect at the extensive and intensive margins. Although his study sample is representative of the Canadian population, he restricted the age groups included. Reaching a similar conclusion but using different data and context, Heinesen and Kolodziejczyk (2013) investigate the job market effects of breast and colorectal cancers. They find that cancer raises the likelihood of job market exit within the first 3 years of diagnosis among survivors 30-60 years old. The Ganz et al. (2002) study of breast cancer effects on the job market outcomes shows a twenty percent point reduction in the likelihood of employment among breast cancer survivors in the first five years post diagnosis. Absent a

comparison group of non-cancer survivors, their study could not find any long-term labor market effect for breast cancer. Similar to Ganz et al., (2002), Bradley, Neumark, Bednarek, and Schenk (2005) find a larger negative effect of breast cancer survivorship for African-American women compared with other ethnic groups.

Studies on the labor market attachments and gender-specific disease survival based on nationally representative sample of prime working age adults increasingly become important but are surprisingly rare in economics literature<sup>1</sup>. Therefore, studies integrating health and labor economics provide richer insights on the socioeconomic consequences of chronic health conditions (Hoynes, Simeonova, & Simonsen, 2016). Based on economic theory of labor supply and health capital (Currie and Madrian, 1999) and applying correlated random effects and random effects over-dispersion empirical modeling strategies using the Medical Expenditure Panel Survey (MEPS 2008-2015) dataset, this paper tests the hypothesis that surviving cancers affects the survivors' labor market outcomes, with a focus on gender-specific differences in how cancer survivors are treated in the labor market.

Our empirical estimates confirm that male- and female -specific cancers reduce the likelihood of employment by 2.7% and 3%, respectively, compared to cancer-free groups. These employment effects are larger in the first two years after cancer diagnosis but decline thereafter. Conditional on employment, weekly hours worked and the log-annual labor income differ between male and female survivors. While male-specific cancers induce the weekly hours worked by approximately 6 to 16 hours in the short- and long-runs, respectively, female-specific cancers lower weekly hours worked by 9 hours mostly in the long-run. Male cancers have no statistically significant effect on the log-annual income in the short-run, but they increasingly reduce income

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<sup>1</sup> Zajacova, Dowd, Schoeni, and Wallace (2015) also provide estimates on the labor market effects of male and female cancers.

by 16% to 27% in the intermediate and long runs. In contrast, female cancers increase income by 6.7% to 16.2% after the first five years following cancer diagnosis. The effect of male cancers on family income is stronger than female cancers both in the intermediate- and long- runs. Cancer as an acute health shock and a chronic health condition raise total health expenditure (THE) for both males and females. Similarly, cancers markedly increase the probability of missing a working day for both males and females, but the number of lost working days is significantly higher for females. Therefore, the annual cost of cancer related absenteeism is higher for females than males.

The following four unique dimensions set our work apart as a significant contribution to the previous literature. First, we tackle the unobserved heterogeneity associated with labor supply decisions of the cancer survivors by executing correlated random effects (CRE) empirical model. Specifically, our estimation strategy relaxes the past modeling constraints by explicitly allowing the correlation of socioeconomic factors with cancer incidence to disentangle the bias-corrected effects of cancer survivorship on both extensive and intensive margins of the labor market. Second, by exploiting the richness of a panel data, we capture the labor market effects of gender-specific cancers spanning different time periods after cancer diagnosis. In contrast to past work that only investigates the short- or long- run effects of cancers, we extend our analysis by providing estimation results on the immediate, intermediate and long term causal effects of cancers on the labor market attachments. Also, this study uses a large nationally representative data of cancer survivors and non-cancer comparison group in the US population encompassing individuals in the 18-64 years age group. This is justified by the fact that akin to most developed economies, the US has a large and growing stock of ageing cancer survivors that increasingly present in the labor market for economic reasons and search for improved life quality (Shapiro, 2006). Third, we estimate how cancer affects a survivor's work absenteeism to provide policy-relevant information

on how the cancers contribute to the growing burden of chronic diseases. Finally, this paper provides insights into the health expenditures of employed gender-specific cancer survivors. Cancer care as chronic health condition requires substantial financial resources in short- and long-runs with important implications for the labor market.

The rest of this work proceeds as follows. The theoretical model is laid out in section 2. The empirical approach and data structure are in sections 3 and 4, respectively. The research findings and robustness exercises are in sections 5 and 6. Finally, section 7 is on discussions and conclusion.

## **2. Cancer Survivorship and the Labor Market: Theory**

Cancer-associated morbidities negatively affect a host of physical and mental capabilities, which individuals deploy within the household and to the job market. Labor market attachments are affected by cancer survivorship in at least four different pathways (Wilson, 2001). First, there is reduction in the total available work and leisure hours for a cancer survivor due to more time deployed for health care. This change forces the agent to reallocate time for labor and leisure given the preferences and available resources. Second, the financial burden of cancer can be substantial for patients and their families. This causes a simple income effect induced by high out-of-pocket health spending. The survivors in turn could experience the job-lock phenomenon by remaining on their jobs for coverage in employment-based health insurance (Okunade and Wunnava, 2002) or to secure additional incomes to defray catastrophic medical costs. Third, there are changes in wages due to productivity loss induced by cancer (Grossman, 1972). Finally, there are changes in the abilities of a survivor which affects the marginal utilities of consumption and leisure. If cancer lowers the marginal utility of leisure time sufficiently, survivors may have stronger preference to the labor market attachments. On the other hand, employment probability decreases if the effect of leisure-work switch on the marginal utility of consumption is weak. To conceptualize the

underlying mechanisms, this paper considers a theoretical model of labor supply with health capital akin to Peng, Meyerhoefer, and Zuvekas (2016). The intertemporal utility maximization problem for a cancer survivor,  $i$ , is written as,

$$U_i = \sum_{t=1}^T \left( \frac{1}{1+\rho} \right)^t U_{it} \quad (1)$$

where,  $\rho$ , is the discount rate and the function  $U_{it}$ , can be expended as it follows:

$$U_{it} = U_1(C_{it}) + U_2(H_{it}, L_{it}) \quad (2)$$

in the above,  $C_{it}$  is a consumption good with price equal to 1,  $H_{it}$ , is the present health stock and finally  $L_{it}$ , indicates leisure time utilized by a cancer survivor in time,  $t$ . Eq. (2) is constrained by

$$H_{it} = H(H_{i,t-1}, I_{it}, \zeta_i) \quad (3)$$

$$C_{it} = A_{it} + N_{it}\omega_{it} \quad (4)$$

$$\Delta = N_{it} + \Sigma_{it} + I_{it} + L_{it} \quad (5)$$

$$\omega_{it} = \omega(H_{it}, \Theta_{it}, \xi_{it}, \Lambda_i) \quad (6)$$

$$\Sigma_{it} = \Sigma(H_{it}, \Pi_i, P_{it}) \quad (7)$$

and Eqs. (3) - (7) formalize different constraints. Starting with health constraint, current health,  $H_{it}$ , is determined by past health status,  $H_{i,t-1}$ , investment in health production,  $I_{it}$ , and unobserved heterogeneity in health production,  $\zeta_i$ . The resources available for consumption,  $C_{it}$ , is equal to sum of non-labor income,  $A_{it}$ , and labor income,  $N_{it}\omega_{it}$ . The time constraint assures that sum of hours worked in the market,  $N_{it}$ , total sick time,  $\Sigma_{it}$ , time spent on health production,  $I_{it}$ , and leisure time,  $L_{it}$ , is no more than available time,  $\Delta$ . The wage constraint,  $\omega_{it}$ , explains



that wage is determined by current health stock,  $H_{it}$ , exogenous determinants of wage,  $\Theta_{it}$ , observable characteristic of occupations and employers,  $\xi_{it}$ , and unobserved productivity,  $\Lambda_i$ . Finally, the sick time constraint,  $\Sigma_{it}$ , is determined by current health stock, survivor-specific propensity for relapse,  $\Pi_i$ , and a vector of exogenous determinant of sick time,  $P_{it}$ . In order to maximize lifetime utility (Eq. (2)), a cancer survivor chooses hours worked,  $N_{it} \geq 0$ , optimal consumption,  $C_{it} > 0$ , and optimal investment in health production,  $I_{it}$ , subject to constraints (3) - (7). The partial derivative of the second period (e.g., post-health shock) utility function with respect to weekly hours worked provides conditional labor supply in time,  $t$ , as it follows

$$\frac{\partial U_2}{\partial L_{it}} \geq (1 + \rho)^t \omega_{it} \sigma_{it} \quad (8)$$

in equation (8),  $\sigma_{it}$ , shows the marginal utility for keeping wealth in time,  $t$ . Then, supply of labor conditional on employment is shown

$$N_{it} = \left\{ \sigma_{it}, (1 + \rho)^t, H_{it}, \omega(H_{it}, \Theta_{it}, \xi_{it}, \Lambda_{it}) \right\} \quad (9)$$

Endogeneity of health is an important feature of the above quasi-reduced labor supply model. Surviving cancer could affect the current stock of health by varying time spent on health. From Eq. (9), many factors including unobservable determinants of health, sickness and productivity affects supply of work. For the simplicity, these unobserved factors constitute constant,  $\alpha_i$ , and time-varying,  $\kappa_{it}$ , components. We write  $\alpha_i = \zeta_i + \Phi_i + \Pi_i$ . Then, Eq. (9) can take the form

$$N_{it} = (H_{it}, \Theta_{it}, \xi_{it}, P_{it}, \alpha_i, \kappa_{it}) \quad (10)$$

Eq. (10) provides the foundation for the empirical analysis of this paper.

### 3. Empirical models

The choice of econometric method for modeling labor market attachments depends upon the underlying theoretical model and the data structure. The MEPS records employment status, weekly work hours, hourly rate of pay and total number of missed workdays due to illness during the reference period. Given each of these, we estimate the main equation (10) by

$$y_{it} = f(\lambda_0 + \Theta'_{it}\tau + Z_{it}\pi + \alpha_i + \kappa_{it}) \quad (11)$$

where,  $y_{it}$ , is the outcome variable for survivor,  $i$ , in time,  $t$ , and,  $\lambda_0$ , is a constant,  $\Theta_{it}$  is a vector of observed regressors,  $Z_{it}$ , is an indicator variable denoting whether the respondent is a cancer survivor in time,  $t$ , and time since cancer diagnosed, and,  $\alpha_i$ , is the fixed effects term capturing the unobservable measures of productivity, physical and mental health. Finally,  $\kappa_{it}$ , is the idiosyncratic error with the assumption of strict exogeneity.

Then,  $\alpha_i$ , in Eq. (11) can be modeled by estimating a fixed effects (FE) model. However, such a model does not yield consistent parameter estimates of non-linear specifications when the time dimension of the panel is fixed and short (Cameron & Trivedi, 2005). As an alternative, Chamberlain (1984) proposed the correlated random effects (CRE) estimation strategy for short panel data. Suri (2011) later suggested a generalization to the Chamberlain model and (Cabanillas, Davis, Michler, Michuda, and Tjernström, 2018) crafted an empirical roadmap for this generalization in a three-period model context. Either way, the minimum distance estimator (MDE) is implemented to recover the structural parameters from reduced form equations. In the context of histories on cancer survivorship in our paper and following (Cabanillas et al., 2018) three-period model,  $\alpha_i$  is replaced by its linear projections as it follows:

$$\alpha_i = \mu_0 + \mu_1 Z_{i1} + \mu_2 Z_{i2} + \varphi_i \quad (12)$$

and, by substituting Eq. (12) into Eq. (11), we have

$$y_{it} = \lambda_0 + \Theta'_{it} \tau + Z_{it} \pi + \mu_0 + \mu_1 Z_{i1} + \mu_2 Z_{i2} + \varphi_i + \kappa_{it} \quad (13)$$

by assuming strict exogeneity of  $\psi_{it} = \varphi_i + \kappa_{it}$  (Cabanillas et al., 2018; Suri, 2011), we have the following equations for each time period

$$y_{i1} = (\lambda_0 + \mu_0) + \Theta'_{it} \tau + (\pi + \mu_1) Z_{i1} + \mu_2 Z_{i2} + \psi_{i1}, \quad (14)$$

$$y_{i2} = (\lambda_0 + \mu_0) + \Theta'_{it} \tau + \mu_1 Z_{i1} + (\pi + \mu_2) Z_{i2} + \psi_{i2} \quad (15)$$

Collapsing a three-period model (Cabanillas et al., 2018) to that of two periods, Eqs. (14) and (15) are the structural equations for periods 1 and 2, respectively. Given that we cannot obtain the coefficient of interest,  $\pi$ , by estimating the above structural equations, we instead estimate the following reduced form equations

$$y_{i1} = p_1 + \Theta'_{it} \tau + q_1 Z_{i1} + q_2 Z_{i2} + e_{i1}, \quad (16)$$

$$y_{i2} = p_2 + \Theta'_{it} \tau + q_3 Z_{i1} + q_4 Z_{i2} + e_{i2}. \quad (17)$$

Further, the parameters of Eqs. (16) and (17) are organized in a column matrix,  $M_{(4 \times 1)}$ , and their variance-covariance matrices are preserved in the symmetric matrix,  $S_{(4 \times 4)}$ . The assumed restrictions  $(q_1 - q_2)$  on the parameters is  $R = W_{(4 \times 2)} V_{(2 \times 1)}$ , where  $W$  indicates restrictions on the reduced form equations and  $V$  is a vector of structural parameters. The MDE function (Chamberlain, 1984) is given by:

$$\min(V) = (M - R)' S^{-1} (M - R) \quad (18)$$

In the empirical result section, for each outcome of interest, we estimate structural and

reduced form equations and report the bias-corrected parameters of Eq. (13). Unlike previous research, our empirical model addresses certain shortcomings in the estimation of the labor market consequences of cancer. First, the model assumes that there is substantial heterogeneity in the effect of surviving cancer on job market outcomes. This is because cancer survival and recovery are not symmetric across groups. Second, the CRE model nests the fixed effects identification by accommodating heterogeneity (Elzinga and Gasperini, 2015). It explicitly allows for dependence between the regressors and the group heterogeneity by decomposing the OLS biases for each group of surviving cancers, separately. As a result, for each group of survivors, the CRE provides a parameter that indicates partial correlation between cancer effects and socio-economic factors. Finally, the CRE model is executed to circumvent the incidental parameter problems associated with other panel data models (Lancaster, 2000).

Next, we are interested in modeling absenteeism after surviving cancer. Given the right skewness of the zero-inflated count data on the missed working days variable, estimation using the ordinary Least Square (OLS) method would violate the underlying model assumptions (Wooldridge, 2012). Although the Tobit (Tobin, 1958) and Heckman (1977) sample selection models are alternatives, as they ‘correct’ for the zero-inflated data problem, (Grogan and Sadanand, 2013), they are incapable of correctly handling zero inflated data systems. The count and non-negativity of missed workdays might be tempting for the simple Poisson count model. However, the equality of conditional mean and variance assumption is unrealistic in observational data. Presence of overdispersion- the conditional variance larger the conditional mean in economic data which is associated with the heterogeneity and positive aspect in data (McCullagh and Nelder, 1989), requires modeling two separate decisions; whether or not to miss work due to illness and the days missed work. Therefore, we implement the CRE probit model in the first stage and RE

overdispersion model in the second stage. For the second stage, we begin the model with  $y_{it} | \lambda_{it} \sim \text{Poisson}(\lambda_{it})$ , where,  $\lambda_{it} | \delta_i \sim \text{gamma}(\lambda_{it}, \delta_i)$ , and  $\lambda_{it} = e^{(\Theta_{it}\tau + \text{offset})}$ , and  $\delta_i$  is the model's dispersion parameter. Akin to Hausman, Hall, and Griliches (1984), the probability of missing one working day is given

$$\Pr(y_{it} | Z_{it}, \Theta_{it}, \delta_i) = \left\{ \left( \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)} \right) \left( \frac{1}{1 + \delta_i} \right)^{\lambda_{it}} \left( \frac{\delta_i}{1 + \delta_i} \right)^{y_{it}} \right\} \quad (19)$$

This specification yields a negative binomial model with a dispersion factor,  $\delta_i + 1$ . Moreover, the dispersion factor is allowed to vary across groups. The joint probability of the counts for each group is shown

$$\Pr(y_{it} | Z_{it}, \Theta_{it}) = \int_0^\infty \prod_{t=1}^T \Pr(y_{it} = Z_{it}, \Theta_{it}, \delta_i) f(\delta_i) d\delta_i \quad (20)$$

In Eq. (19),  $f$ , is the probability density function. When explaining the empirical result, we provide estimates of cross-sectional models for the comparison purposes.

#### 4. Data

The empirical data studied come from the 2008 - 2015 waves of the nationally representative Medical Expenditure Panel Survey (MEPS), conducted by the US Agency for Healthcare Research and Quality (AHRQ) since 1996. The MEPS has two components, the household (HC) and the insurance (IC). The HC component collects nationally representative data at the individual and family levels. Specifically, MEPS collects detailed information on each household member's demographics, health and use of medical services, charges and payments for the service use, satisfaction and access to health care, income and work status.

Cancer status in MEPS is self-reported. The survey queried respondents on whether a doctor or other healthcare professional had ever informed them that they had any type of cancer or a malignancy. Except for non-melanoma skin cancers<sup>2</sup>, we include all those responding, “Yes”. Then, it asked individuals about age when the cancer was first diagnosed. By subtracting the age at which cancer was diagnosed from the current age, we obtain the years since cancer diagnosed. MEPS began inclusion of the cancer questions since 2008. Therefore, we utilize MEPS 2008 to 2012<sup>3</sup>, which corresponds to panels 12-16<sup>4</sup> to construct the panel sample. In total, there are 84,720 observations completed for all the five rounds of each panel in waves 12-16. We limit our sample to prime age working adults (18-64 years old)<sup>5</sup>, not self-employed, not full-time student, with positive survey weights. After many steps of data cleaning<sup>6</sup>, the final estimation sample of 45,321 (20,817 men and 24,504 women) comprises 3,745 cancer<sup>7</sup> and 41,576 non-cancer observations. We estimate gender-specific models, as the cancer prevalence and job market attachments differ markedly for males and females, by splitting the cancers into gender-specific types<sup>8</sup>.

MEPS asks employment questions on all individuals at each round of interviews. In the MEPS, employment variables consist of both person-level and job-related indicators, which refer to a person’s current main job. We created a binary variable indicating employment status. In

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<sup>2</sup>Non-melanoma cancers are progressing latently in years with minimum impact on physical and mental activities of an individual.

<sup>3</sup> We also constructed a balanced panel of 2008-2015 which corresponds to rounds 12-19. However, this sample does not include the time since cancer diagnosed. We provide all the results for the analysis of this sample in Appendix B.

<sup>4</sup>Given the overlapping design of the survey, we can only get the half of respondents for the panel 12 and 16. This means that panel 12 includes all those responded in (2007- 2008) and 16 includes respondents in (2012-2013). As a result, there is only one observation for the respondents in these two panels.

<sup>5</sup> Our sample data exclude all retired and disabled cancer survivors. Also, we exclude cancer survivors who are currently receiving social security income.

<sup>6</sup> We exclude 8,903 respondents who were self-employed, as MEPS does not ask about their wage information. We further exclude 22,671 individuals below 18 years old, as they were not asked the question on cancer, and above 64 years who are on social security income or retired. To obtain nationally representative estimates, we exclude 4315 observations with zero survey weight. Finally, we exclude 3510 full-time students.

<sup>7</sup> The few (42 observations) among the employed cancer survivors above the age of 64 were excluded from the main estimation sample. However, we retain them in the full sample (2008-2015).

<sup>8</sup> Breast, ovarian, cervical, and uterine are female cancers while cancers of the prostate and testes are male-specific. Common types of cancer can be diagnosed both in males and females.

addition, conditional on employment, every individual provides detailed information on weekly hours of work<sup>9</sup> and annual income. Monetary values are adjusted for inflation using the urban consumer price index (CPI) for constant 2012 and 2015<sup>10</sup> dollars.

To estimate cancer impact on absenteeism and workplace productivity loss, we use the MEPS variables on illness related absenteeism. It asks whether the respondent missed a full working day due to illness, injury, and mental or emotional problems. If the respondent indicates missing workdays, the next question identifies the exact number of lost working days. To adjust for variability across individuals for each reference period, we normalized lost working days for a 12- month period.

The estimated models in this study controls for many dimensions of the socio-demographic and labor market factors, including: the respondent's age (18-64) and its square; race/ethnicity (non-Hispanic White, non-Hispanic Black, non-Hispanic others, Hispanic); educational attainment (some education, GED or HS, bachelor's degree, graduate degree); marital status (married, widowed, divorced, single); health insurance coverage (public, private and uninsured); census regions (Northeast, Midwest, South, West); perceived health status (excellent, very good, good, fair, poor), number of co-morbidities<sup>11</sup>; sick pay dummy; labor union membership; employing firm size<sup>12</sup> (less than 25 workers, between 25 and 99 workers, between 100 and 500 workers, more than 500 workers); occupation (construction/mining/manufacturing, sales associate/transportation/ utilities, professional/education, public administration/military/ unclassified); and the log of income of each family member normalized by family size, log of hourly wage, and year dummies.

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<sup>9</sup> We exclude all 21 observations with more than 120 weekly hours of work as outliers in the data after looking at the upper fence of the data.

<sup>10</sup> We use CPI 2015 for inflation adjustment for the MEPS 2008-2015 sample.

<sup>11</sup> Heart and pulmonary disease such as myocardial infarction, heart failure, ischemic heart disease, COPD, and other systemic diseases are among the co-morbidities

<sup>12</sup> Number of employees in each firm is used to proxy for the firm size.

**Table 1 Characteristics of the respondents and summary statistics of the study sample**

Race/ethnicity	Male sample				Female sample			
	Cancer survivor (%)		Cancer-free (%)		Cancer survivor (%)		Cancer free (%)	
Non-Hispanic White	72.70		40.50		63.18		37.94	
Non-Hispanic Black	12.14		18.70		14.63		22.41	
Hispanic	10.49		30.38		16.96		29.63	
Non-Hispanic others	4.67		10.41		5.23		10.01	
Marital status								
Married	67.17		48.02		52.97		46.71	
Widowed	2.01		0.70		4.48		2.52	
Divorced/separated	16.52		10.46		26.69		15.03	
Never married	14.30		40.83		15.85		35.74	
Education								
Some education	12.86		21.82		13.98		19.91	
High School and General Equivalency Diploma	35.49		41.30		41.98		39.06	
Bachelor	33.19		26.66		30.30		29.23	
Graduate	18.46		10.21		13.74		11.81	
Regions								
Northeast	15.52		15.63		15.68		16.31	
Midwest	21.70		19.20		21.86		18.93	
South	39.58		36.92		38.17		38.04	
West	23.20		28.25		24.29		26.72	
Health status								
Excellent	16.31		30.62		14.97		26.11	
Very good	24.14		30.38		24.33		30.88	
Good	28.23		25.80		28.25		27.24	
Fair	18.39		10.11		19.70		12.19	
Poor	12.93		3.09		12.75		3.57	
Health insurance								
Private	74.43		62.09		64.02		59.20	
Public	17.96		12.90		24.44		20.93	
Uninsured	7.61		25.01		11.55		19.86	
Organization								
Public	23.92		13.21		25.49		19.83	
Private	76.08		86.79		74.51		80.17	
Occupation Type								
Construction/mining/manufacturing	10.61		16.06		0.52		0.44	
Sales/associate/transportation/utilities	26.64		28.87		16.16		18.67	
Professional/education	61.74		53.42		82.61		80.09	
administration/military/unclassified	1.01		1.65		0.71		0.80	
Labor union								
Membership	13.92		12.00		12.03		10.75	
No-membership	86.08		88.00		87.97		89.25	
Employment status								
Employed	58.62		73.51		56.18		62.59	
Unemployed	41.38		26.49		43.82		37.41	
Sick pay (Dummy)								
Yes	73.18		56.33		66.54		59.64	
No	26.82		43.67		33.46		40.36	
Continuous variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weekly hours worked	42.68	10.36	40.54	10.82	37.01	11.43	36.16	10.87
Log-hourly wage	3.12	0.60	2.85	0.58	2.83	0.59	2.71	0.58
Log-annual labor income	10.75	0.80	10.34	0.87	10.36	0.82	10.13	0.86
Log-Family income	10.40	0.79	9.92	0.88	10.09	0.91	9.84	0.91
Log-total health expenditure	7.96	1.70	6.67	1.62	7.88	1.63	7.07	1.51
Annual work loss days	7.91	14.94	4.55	9.97	7.30	13.95	4.84	9.77
Number of preconditions	1.52	1.51	0.62	1.01	1.41	1.49	0.68	1.05
Age	52.88	10.49	46.20	13.46	49.45	11.16	38.78	13.27

Table 1 presents characteristics of the survey respondents and summary statistics on the main variables included in the analysis. In the sample, approximately, 58% of male and 56% of female



cancer survivors aged 18-64 are actively employed. On average, male survivors work 42.68 hours per week with an hourly wage rate of \$26.98 while the females work 37.01 hours with an average hourly wage of \$20.14. Unlike annual income, on average, total health expenditure is higher for the females. Generally, this sample can be described as predominantly non-Hispanic white, South residents, married and privately insured, high income with high school and GED education, aged around 50 years and in self-assessed good health.

## **5. Empirical Results**

### ***5.1 Employment status and cancer***

Table 2 reports the marginal effects of male, female and common types of cancers on employment status. Coefficient estimates of cross-sectional Probit and panel CRE Probit models are shown in the columns (1) and (2), respectively. In comparison to cancer-free groups, male- and female- specific cancers lower the likelihood of employment by 2.7% and 3%, respectively. These effects increase by three and five percentage points for males and females, respectively, during the first two years of cancer diagnosis. While the negative effects of gender-specific cancers on employment remain statistically significant even after a decade post-diagnosis, female-specific cancers substantially reduce the likelihood of employment by 11.4% during the first 3-5 years of survival. Similarly, common types of cancer decrease the likelihood of employment for survivors by approximately 1.5% when compared with the cancer-free individuals. These effects fluctuate between 1.5% and 3.7% after controlling for years since cancer diagnosis. In the CRE Probit model of interest, the RE for capturing unobserved heterogeneities is correlated with educational attainment, marital status, perceived health status and family income. The correlation parameter estimates of male- and female- specific CRE Probit models are presented in Appendix A, Tables A1 and A2.

**Table 2. Marginal effects of cancer survivorship on employment status<sup>1</sup>**

	Probit model (cross-sectional)	CRE model (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.106*** (0.0190)	-0.0273* (0.0141)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0616* (0.0381)	-0.0579*** (0.00942)
Cancer (3-5 years)	-0.100** (0.0491)	-0.0164** (0.00807)
Cancer (6-10 years)	-0.0672 (0.0600)	-0.0158* (0.00806)
Cancer (10+ years)	-0.0974*** (0.0216)	-0.0285* (0.0152)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0355*** (0.0137)	-0.0303*** (0.00912)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.111*** (0.00937)	-0.0800* (0.0411)
Cancer (3-5 years)	-0.0644*** (0.00936)	-0.114** (0.0513)
Cancer (6-10 years)	0.0121 (0.0304)	-0.0293*** (0.00910)
Cancer (10+ years)	-0.0374** (0.0149)	-0.0332*** (0.00277)
<b>Panel 3. Common cancers (Male and Female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0203* (0.00277)	-0.0144* (0.00798)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0351** (0.00196)	-0.0370*** (0.00937)
Cancer (3-5 years)	-0.0392* (0.00647)	-0.0171* (0.00916)
Cancer (6-10 years)	-0.0418*** (0.00670)	-0.0274*** (0.00921)
Cancer (10+ years)	-0.0120 (0.00648)	-0.0155* (0.00917)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostate and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at 5% the level. \* Significant at the 10% level.

These results suggest that both the gender-specific and common cancers negatively affect

the employment prospects of survivors though the effects are stronger in the immediate years post-diagnosis. This finding is supported by previous studies on the labor market effects of cancer (Bradley et al., 2005; Heinesen and Kolodziejczyk, 2013; Jeon, 2017). However, the numerical magnitude of the cancer effects on the job market is comparatively smaller in our empirical model estimates when compared with past studies (Zajacova et al., 2015). There exists substantial heterogeneity in the effects of cancers on labor market (Lundborg, Nilsson, and Vikström, 2015) and the relatively smaller size of the effects might be an indication of bias-corrected estimate of CRE models (Wooldridge, 2010). What explains the difference between male and female employment response to cancer? Partly, this difference could be explained by differences in the male-female attributes of production and consumption time between men and women. For example, women participate significantly more in home production beside market work. This alternative could lower employment likelihood for women (Gronau, 1977). Further, since men earn a larger share of household income, women have lower propensity for labor market attachment after a health shock (García-Gómez, Van Kippersluis, O'Donnell, and Van Doorslaer, 2013).

## ***5.2 Weekly hours of work and cancer***

Table 3 presents the estimated marginal effect of gender-specific and common types of cancers on the weekly hours worked conditional on employment. Columns (2) and (3) provide parameter estimates of conditional OLS and CRE models, respectively. In contrast to female-specific cancers that lower weekly hours worked by 4.5 hours, male-specific cancers increase the weekly hours worked by 6.2 hours in comparison to cancer-free groups. Considering elapsed time since cancer

**Table 3. Marginal effects of cancer survivorship on weekly hours of work<sup>1</sup>**

	<b>Conditional OLS (Cross-sectional)</b>	<b>Conditional CRE (Panel)</b>
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.560 (0.683)	6.197** (2.925)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.527 (1.195)	5.752** (2.271)
Cancer (3-5 years)	-2.621* (1.428)	2.352 (2.169)
Cancer (6-10 years)	1.873 (3.033)	15.99*** (2.615)
Cancer (10+ years)	-0.463 (0.604)	-1.755 (2.641)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.213 (0.423)	-4.462* (2.463)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.228 (0.960)	0.814 (3.911)
Cancer (3-5 years)	-2.008 (1.312)	1.705 (4.154)
Cancer (6-10 years)	0.326 (1.056)	5.010 (4.362)
Cancer (10+ years)	0.0288 (0.456)	-9.310*** (3.033)
<b>Panel 3. Common Cancers (Male and Female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.654 (0.687)	1.125*** (0.296)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.782 (1.012)	0.458* (0.240)
Cancer (3-5 years)	1.065 (1.387)	1.169*** (0.296)
Cancer (6-10 years)	-0.323 (1.634)	-1.281*** (0.191)
Cancer (10+ years)	-0.108 (2.060)	-1.692*** (0.200)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostate and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

diagnosed, female-specific group of cancers has no statistically significant impact on weekly hours worked in short and intermediate runs but it reduces weekly hours worked by approximately 9

hours in the long-run. On the other hand, male-specific cancers induce weekly hours of work by 5.8 hours during the first two years after diagnoses and this effect rises to 16 hours per week in the intermediate term. Common types of cancer increase conditional weekly hours worked for the first five years post diagnosis but thereafter they negatively affect weekly hours of work.

For both genders, the parameter estimates of the CRE models on the effect of cancers on weekly hours worked indicate significant correlation between random effects and individuals as well as job-specific characteristics (see, Appendix A, Tables A3 and A4).

### ***5.3 Log-annual labor income and cancer***

Table 4 shows the marginal effects of gender-specific and common types of cancer on the log-annual income of survivors. Estimated coefficients of conditional OLS and CRE models of income equations are presented in the columns (2) and (3), respectively. The effect of male and female-specific cancers on the log-annual income is statistically insignificant when time since cancer diagnosed is not included in the model. However, male-specific cancers decrease the log-annual income at an increasing rate. Specifically, annual income, on average, declines by 16% during the first 3-5 years post-cancer diagnoses and the diminishing effect continues up to 27% a decade after living with cancer. In contrast, female-specific cancers have no statistically significant impact on log-annual income in short-run. However, female annual income increases by 6.7% to 16.2% in the intermediate- and long- runs. Not controlling for the years since diagnosed, surviving common types of cancer is linked to a 24% increase in annual income. However, the cancer effects are reversed when years since diagnosis are included as a control in the model estimation. Common cancers reduce the annual income by at most 65% within the first five years after being diagnosed.

**Table 4. Marginal effects of cancer survivorship on Log-annual labor income<sup>1</sup>**

	<b>Conditional OLS (Cross-sectional)</b>	<b>Conditional CRE (Panel)</b>
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0857** (0.0367)	0.222 (0.176)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.205*** (0.0635)	0.205 (0.183)
Cancer (3-5 years)	-0.0160 (0.0776)	-0.161* (0.0901)
Cancer (6-10 years)	0.267*** (0.0914)	-0.194** (0.108)
Cancer (10+ years)	0.0420 (0.0423)	-0.274*** (0.0905)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0245 (0.0221)	0.131 (0.125)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.0377 (0.0473)	-0.300 (0.218)
Cancer (3-5 years)	0.0446 (0.0669)	-0.346 (0.231)
Cancer (6-10 years)	0.0755 (0.0558)	0.067*** (0.028)
Cancer (10+ years)	-0.00384 (0.0246)	0.162*** (0.128)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.00367 (0.0247)	0.236* (0.126)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0218*** (0.00488)	-0.0900*** (0.0288)
Cancer (3-5 years)	-0.113* (0.0630)	-0.657** (0.295)
Cancer (6-10 years)	-0.0180* (0.0101)	-0.0416 (0.0634)
Cancer (10+ years)	-0.0622*** (0.0111)	-0.0570 (0.0633)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostate and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 5. Marginal effects of cancer survivorship on Log-family income<sup>1</sup>

	OLS (Cross-sectional)	CRE (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0217 (0.0323)	-0.0364 (0.185)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.0197 (0.0597)	-0.0891 (0.206)
Cancer (3-5 years)	-0.0374 (0.0878)	-0.0106 (0.0663)
Cancer (6-10 years)	0.123 (0.0777)	-0.0620*** (0.0146)
Cancer (10+ years)	0.0440 (0.0334)	-0.0895*** (0.0250)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.00857 (0.0196)	0.124 (0.115)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0235 (0.0431)	-0.0299* (0.0163)
Cancer (3-5 years)	-0.0294 (0.0651)	-0.0290*** (0.0110)
Cancer (6-10 years)	0.0293 (0.0469)	0.278 (0.397)
Cancer (10+ years)	-0.0804 (0.0490)	-0.0548*** (0.0127)
<b>Panel 3. Common Cancers (Male and Female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0434*** (0.0111)	0.0558 (0.0557)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0790* (0.0455)	-0.0901*** (0.00702)
Cancer (3-5 years)	-0.00405 (0.00658)	-0.0470 (0.0295)
Cancer (6-10 years)	-0.0804*** (0.00910)	-0.0900*** (0.0256)
Cancer (10+ years)	-0.286*** (0.00824)	-0.222*** (0.0391)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostate and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

## 5.4 Family income and cancer

Table 5 presents the estimated effects of gender-specific and common types of cancer on the log-family income. The CRE model estimates indicate that male- and female- specific cancers do not have statistically significant impacts on family income when years since cancer was diagnosed is not included as a control variable. Male-specific cancers constrain family income mainly in the intermediate- and long- terms after controlling for the number of years since cancer was first diagnosed. Specifically, from 6 to 10 years post male-specific cancer diagnosis, family income declines by 6.2% and the family loses about 9% of its income after a decade living with cancer.

The negative effects of female-specific cancers on the family income is comparatively smaller in magnitude but their impacts begin earlier than those for male cancers. Female cancers lower family income by approximately 3% during the first five years after cancer diagnosis. The effect increases by 2.5 percentage points a decade post cancer. Common type of cancers has both short- and long- term effect on family income. With a 9% decline in the family income in the short-run, this negative effect grows to 22% after a decade post-cancer diagnosis. This finding is consistent with past studies on the overall negative impacts of health shocks on family income and consumption (Coile, 2004; Smith, 2005).

### ***5.5 Health expenditures and cancer***

To examine the effects of gender-specific and common type of cancers on the total health expenditure (THE) of the employed cancer survivors, we empirically estimate the OLS and CRE models of THE and the estimated coefficients are provided in columns (2) and (3) of Table 6. The correlation parameter estimates in Appendix A, Tables A9 and A10, confirm the presence of potential heterogeneity when estimating the effects of living with the cancers on THE. The RE is correlated with marital status, type of health insurance, perceived health status, number of



preconditions and family income. Overall, gender-specific cancers raise THE for both males and females, but the effects are larger for males. Unlike the female-specific cancers with no statistically

**Table 6. Marginal effects of cancer survivorship on Log-total health expenditure<sup>1</sup>**

	<b>OLS (Cross-sectional)</b>	<b>CRE (Panel)</b>
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.694*** (0.113)	1.392*** (0.505)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	1.030*** (0.236)	0.693 (0.524)
Cancer (3-5 years)	0.245*** (0.0430)	0.476* (0.286)
Cancer (6-10 years)	0.0123 (0.277)	2.036*** (0.566)
Cancer (10+ years)	0.843*** (0.132)	1.256 (0.952)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.469*** (0.0584)	0.745** (0.359)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.918*** (0.147)	0.252 (0.439)
Cancer (3-5 years)	0.558*** (0.131)	1.339 (0.988)
Cancer (6-10 years)	0.392*** (0.146)	2.125*** (0.490)
Cancer (10+ years)	0.326*** (0.0632)	0.355 (0.411)
<b>Panel 3. Common Cancers (Male and Female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.612*** (0.0343)	0.617*** (0.146)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.404*** (0.0285)	0.419*** (0.142)
Cancer (3-5 years)	0.301*** (0.0208)	0.465*** (0.105)
Cancer (6-10 years)	0.157*** (0.0109)	0.139*** (0.0517)
Cancer (10+ years)	0.0134 (0.0220)	0.0343 (0.108)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostate and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

significant effect on THE, in the short run the male-specific cancers raise expenditures by 47% relative to the cancer free group. Surprisingly, however, the rise in THE converges for both genders in the intermediate run. Common types of cancer increase total health expenditures by 61% in the absence of controlling for time since diagnosis. The increased THE effects of these cancers diminish at increasing rates as the number of years living with the cancers lengthens.

### ***5.1 Absenteeism among employed cancer survivors***

Table 7 contains the marginal effects of cancers on the likelihood that an employed worker misses working days and the number of lost working days for the male and female panels, separately. Columns (1) and (2) are the estimates for the cross-sectional Probit and zero-truncated negative hurdle (ZTNH) models while those in columns (3) and (4) are the results of Probit CRE and random effects overdispersion models. In the panel models of interest, stage I-Probit CRE model captures the effect of cancer on the propensity to be sick enough to take days off, while stage II- RE overdispersion model provides estimate on the effect of cancers on the number of sick leave days.

Compared with cancer-free groups, the cancers increase the probability of missed working days by 6.9% and 3.9% for male and female survivors, respectively. In contrast, conditional on taking days off, on average, the effect of cancers on the number of missed working days is higher for females than males. The propensity to miss a working day is 11.8% during the first two years after cancer diagnosis but thereafter cancer has no statistically significant effect on probability of missing a working day and number of lost working days for men. For female survivors, cancers raise the likelihood of missing a work day by 6.1% and 7.9% during the immediate and intermediate time frames. On average, female survivors miss 3.12 working days during the first

two years following cancer diagnosis but this declines to 1.17 working days a decade after living with cancer. Our findings on the effect of cancer and work absenteeism is consistent with the past findings (Bradley, Oberst, and Schenk, 2006; Dahl, Cvancarova, Dahl, and Fossa, 2016; Sasser et al., 2005).

**Table 7. Marginal effects of cancer survivorship on absenteeism of employed workers<sup>1</sup>**

	Cross-sectional models		Panel models	
	Stage I-Probit model	Stage II- ZTNH model	Stage I- Probit CRE model	Stage II- RE overdispersion model
<b>Panel 1. Male Cancer survivors</b>				
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.410	0.00100	0.0689**	1.96**
	(0.231)	(0.00228)	(0.0331)	(0.796)
<i>Time dummies since cancer diagnosed</i>				
Cancer (0-2 years)	0.480	0.000458*	0.118**	0.382*
	(0.235)	(0.000255)	(0.0470)	(0.222)
Cancer (3-5 years)	0.459*	-7.397e+20	0.0131	-0.186
	(0.210)	(4.932e+20)	(0.0713)	(0.391)
Cancer (6-10 years)	0.762**	-9.06e-06	0.0538	-0.326
	(0.0992)	(6.99e-06)	(0.0771)	(0.400)
Cancer (10+ years)	0.550	-3.43e-10	0.0238	0.219
	(0.285)	(2.43e-09)	(0.0488)	(0.267)
<b>Panel 2. Female Cancer survivors</b>				
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0385*	1.753**	0.0385*	5.042***
	(0.0199)	(0.722)	(0.0199)	(0.769)
<i>Time dummies since cancer diagnosed</i>				
Cancer (0-2 years)	0.0617	0.352**	0.0617*	3.119**
	(0.0380)	(0.156)	(0.0375)	(1.428)
Cancer (3-5 years)	0.000956	-0.0819	0.000956	1.879**
	(0.0508)	(0.225)	(0.0509)	(0.871)
Cancer (6-10 years)	0.0785*	0.230	0.0785*	1.676
	(0.0418)	(0.157)	(0.0422)	(1.309)
Cancer (10+ years)	0.00925	0.280**	0.00925	1.171***
	(0.0271)	(0.115)	(0.0274)	(0.292)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization ownership type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostatic and testicular, while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

## 5.2 Total indirect productivity cost associated with cancer survivorship absenteeism

Table 8 presents the annual indirect productivity cost associated with missed working days for full-time employed cancer survivors. We compute lost productivity by assessing employment health-related missed workdays due to ill health, stratified by gender. We estimate the monetary cost of missing workdays,  $MW_t$ , for each year as it follows:

$$MW_t = A\omega_t * \beta * Nc_t \quad (21)$$

In Eq. (21),  $A\omega_t$ , is the average daily wage,  $\beta$ , is the marginal effect of cancer on the number of lost working days and,  $Nc_t$ , is the number of cancer survivor, all at time  $t$ . We calculate daily wage,  $\omega_t$ , using the equation:

$$\omega_t = \frac{(H\omega_t * WH_t)}{NDW} \quad (22)$$

In Eq. (22),  $H\omega_t$  is hourly wage rate,  $WH_t$  is the weekly hours worked, and  $NDW$  is the weekly days of work. We assume five and six days of weekly days work for those who work between 25-50 hours and above 50 hours, respectively. The lower and upper limits of our cost estimates refer to five and six days of weekly work, respectively. The associated cost of absenteeism is greater for females than males, perhaps because the number of survivors and the total number of missed working days are larger for women than men. These losses translate to annual foregone earnings of \$0.58 to \$0.83 billion for males. However, the annual earnings loss is much higher for females and varies between \$1.75 and \$3.1 billion.

**Table 8. Average Cost of labor productivity loss for full time employed cancer survivors in the US-MEPS 2008-2015**

	Population of cancer survivor full-time Employed	Average annual cost of absenteeism (US dollars)
<b>Panel A. Male cancer survivors</b>		
2008	148,707	[100,847,139-120,846,348]
2009	127,326	[53,655,176-71,623,421]
2010	168,936	[80,460,838-112,919,065]
2011	169,133	[73,924,651-102,102,209]
2012	155,805	[71,153,027-103,523,074]
2013	142,082	[57,923,989-90,505,234]
2014	143,922	[58,674,121-89,703,704]
2015	194,611	[86,204,888-112,142,643]
<b>Total</b>	1,250,522	[582,843,829- 803,365,698]
<b>Panel B. Female cancer survivors</b>		
2008	274,028	[216,061,076-385,771,822]
2009	242,048	[192,159,124-350,600,476]
2010	237,762	[194,842,749-403,721,064]
2011	270,423	[217,851,011-421,724,262]
2012	240,626	[223,436,882-470,477,369]
2013	257,040	[191,756,595-307,469,063]
2014	261,604	[220,862,316-331,659,196]
2015	320,331	[293,350,641-459,175,588]
<b>Total</b>	2,103,862	[1,750,320,394-3,130,598,845]

All costs are in 2015 US\$, based on the Consumer Price Index (CPI).

## 6. Endogeneity problems and robustness checks

The endogeneity problem is a critical issue in empirical studies of labor supply. For instance, do more working hours cause cancer, or is employment status associated with cancer survivorship? To address these questions appropriately, we estimate CRE models to test for the causal effects of employment and weekly hours worked on cancer survivorship. However, coefficients of interest are indistinguishable from zero when controlling for all other observables. The results are reported in the Tables 1C and 2C of Appendix C. Another equally important issue is the selection of cancer survivors. MEPS collects only job market variables for those survivors that are present in the labor market and they are not identified as disabled or dependent on social security income. Implicitly the study sample includes those who are not acutely treated for cancer or disabled. The labor market consequence might be large for those who are actively treated for cancer or identified as

disabled by the Social Security Administration. To further check presence of endogeneity in the models, we excluded a number of job market variables (type of occupation, firm size, labor union membership, type of organization). We hypothesize that these exclusions uncover the endogeneity problem if cancer survivors prefer to work in the jobs with specific attributes. The null hypothesis is rejected in CRE models, but cross-sectional models are highly sensitive to these exclusions. This also indicates the fitness of CRE models.

Although we estimate labor market effects of gender-specific cancers for male and female subsamples, other subgroups (e.g., age categories) with certain observable characteristics might respond differently to the cancer effects. Therefore, we re-estimated the models with interaction between cancer survivorship and age categories<sup>13</sup>, education, marital status, income and type of occupation. The revised estimates reinforce the depressing effect of survivorship on the job market attachments. Moreover, we find that annual labor income for younger cancer survivors increased significantly (7%  $P < 0.003$ ). In the same line of reasoning, we tested the hypothesis that employment and work hours differentials arise because a cancer survivor with a part-time job is unattached to the job market as a full-time employee.

Moreover, in attempting to test the impact of cancer survivorship on the weekly hours worked for part-time versus full-time employees<sup>14</sup>, we estimated an alternative model using CRE ordered probit specification<sup>15</sup>. We could not detect a statistically significant relationship between cancer survivorship and working part-time compared with full-time. Finally, to check whether the estimated differentials between the model results are due to functional form or unobserved

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<sup>13</sup> Age categories are 18-39, 40- 59, and 60-64.

<sup>14</sup> We created a categorical variable of weekly hours of work which, as follows: (1) <30 hours; (2) 30-40 hours; (3) >40 hours

<sup>15</sup> Complete results for this model are available from the authors on request.

characteristics, we estimate OLS models by including quadratic and cubic forms for the continuous variables (age, income, number of comorbidities), interactions and lags of variables. We observed a slight decrease in the parameter estimates of the CRE models for employment and work hour's equations.

## **7. Discussions and Conclusion**

The population of US cancer survivors is poised to rise significantly in the next decade, and as a result understanding the survivorship effects on the economic well-being of cancer survivors is timely and important. The 2008 Amendments to the 1990 ADA benefitting employments of cancer patients and significant improvements in the medical technologies of cancer care play major roles in the growing workplace presence of cancer survivors.

This paper, by exploiting the panel dimensions of the nationally representative MEPS dataset for the US, estimated the causal relationship between gender-specific cancers and certain job market attachments among prime age working adults. Given the challenges of estimating the negative effects of cancer survivorship on the labor market outcomes based on structural models, we proposed a sound empirical model that is tightly fitted with the theoretical model of the paper it also accounts for the endogeneity of the cancers through correlated random effects (CRE) model. Our robust estimates indicated that the post-cancer likelihood of employment is negative for males and females, but the magnitude is greater for females. When evaluated at the mean data values of all other covariates, the estimates suggest that female-specific cancers decrease the likelihood of working by 3% while male-specific cancers reduces it by 2.7%. Are these differences really related to gender-specific cancer types or do they reflect differences in the labor supply behaviors of males compared with females? Women's labor supply is more elastic because they are more likely to be

secondary earners in the family, so we hypothesize that men and women may react differently to identical health shocks. To test this hypothesis, we run separate models of labor supply for those cancers common to males and females. The results reconfirm our earlier findings. The estimated male-female differential, consistent with some previous studies (Bradley et al., 2002; Bradley et al., 2006; García-Gómez et al., 2013; Zajacova et al., 2015), could be tied to certain economic factors. Women historically benefit from their spousal income or health insurance coverage and their labor market attachment are not as strong compared with the males (Bradley et al., 2002). As a result, female employment response to a negative health shock is both large and more durable (Bradley, Neumark, Luo, and Bednarek, 2007). In a household setting, we hypothesize that married women may engage less in the job market if their spouses could compensate for their employment loss. To test this hypothesis, we estimate gender-specific cancer effects on employment status of married individuals who currently reside with their spouses. The estimates are presented in Table 3C (Appendix C). As we expected, the employment status of married survivors is significantly lower than cancer-free married women.

We analyze the effects of gender-specific cancers conditional on the weekly hours worked. Although male-specific cancers increase weekly hours worked in the short and intermediate runs by 5.8 to 16 hours, respectively, female-specific cancers reduce weekly hours worked in the long-run by 9 hours with no statistically significant short run impact. Our estimates on the effects of gender-specific cancers on weekly hours worked raise an important question. Why do the cancers increase labor supply for men but decrease it for women? A simple model of labor-leisure complementarity sheds light on the fact that men and women react differently to a health shock (Ashenfelter and Heckman, 1974; Gruber, 2000; Heckman and MaCurdy, 1980; Killingsworth and Heckman, 1986). If the shock increases the complementarity of leisure for women and reduces it



for men, one could expect women's weaker attachment to the labor market. In the context of a household, for instance, women's willingness to be responsible for in home production and market work lowers their supply. On the contrary, men in their traditional role as the main breadwinner in households attach more to the job market to offset the negative consequences of health shock, smooth consumption and provide spouse-base health insurance. Another explanation for the male's increased labor supply is the liquidity constraint especially if he is outside of the social security benefit eligibility age (Rossi and Trucchi, 2016).

Our robust estimates suggest that gender-specific cancers differently affect annual labor income. While male-specific cancers reduce annual labor income by 16% to 27% in the short- and long-runs, respectively, female-specific cancers with no statistically significant impact in the short-run, increase annual labor income by 6.7% to 16.2% in the intermediate- and long -runs. Findings on the effects of male- and female- specific cancers on the annual labor income agree with past studies (see, for example, Bailey, 2014; Bradley, Bednarek, and Neumark, 2002). These results lend support to the hypothesis that differences in how female and male earnings respond to a negative health shock could be attributed to the declining effects of cancers on productivity. Prostate cancer survivors, for instance, report challenges with mental and physical activities post cancer treatment (Kornblith, Herr, Ofman, Scher, and Holland, 1994). Although breast cancer survivors suffer from mild to moderate depressive and anxiety-related symptoms, the overall clinical prognosis of breast cancer is relatively better than prostate cancer (Bradley et al., 2007). Also, this result appears to be driven by the fact that the income effect of health shocks is larger for men than women (García-Gómez et al., 2013).

Furthermore, we analyze the impacts of gender-specific cancers on family income. The robust estimates consistently show the declining effect of cancers on household income. These impacts

on the family income raise an important debate on the importance of time-sensitive income response to a health shock. The overall reduction in family income indicates the short and long-term compromise in the income-generating capabilities of the household. We extend our analysis to investigate the effects of cancer on total health expenditures (THE). In general, male and female cancers increase THE, but the effects are larger for males. What accounts for this asymmetry? The direct medical cost of cancers could be large even among survivors with comprehensive health insurance coverage (Bradley et al., 2007). However, cancers with lower survival rates and poor outcomes cost more than the medically stable cancers (Gordon et al., 2005). Men are more likely to be diagnosed with cancers but women are more likely to be cancer survivors (Society, 2007). Cancer illness severity and less favorable clinical prognosis for male-specific cancers result in more frequent hospitalizations and higher medical costs (Sindelar, 1982).

Finally, we assess the indirect productivity costs from missed working days associated with cancer survivorship, separately for the male and female subsamples of employed cancer survivors. Compared to non-cancer samples, the annual cost associated with lost working days ranges from \$0.58 to \$0.83 billion for males and \$1.75 to \$3.1 billion for females. Rising incidence of female-specific cancers and increased presence of women in the job market amplify the economic burden of cancer survivorship.

In conclusion, according to the American Cancer Society (ACS), approximately 1.7 million<sup>16</sup> new cancer cases are expected in the US for 2018. Since this study sheds light on the impact of gender-specific cancer survivorship at the extensive and intensive margins of labor market outcomes, it has certain policy implications for the growing population of cancer survivors. First, knowledge of the heterogeneity on the effects of cancer on job market outcomes provides direction

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<sup>16</sup> This only includes cancers that are reported to cancer registries. Some benign types of cancer are not required to be reported.

on formulating targeted efforts toward specific cancer groups who suffer disproportionately from the disease. Second, understanding the gender-specific and time-dependent labor market consequences of cancer could motivate restructuring specific short, intermediate and long term strategic workplace reforms for reintegrating cancer survivors into the labor market. Third, the US national expenditure for cancer care is estimated to be around \$147 billion per year. The economic burden of cancer grows rapidly as the society ages and more advanced treatment options adopted. Therefore, lowering societal burden of cancer through offering labor market incentives such as flextime work regimes can be important policy tools.

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## Appendix A

Table 1A. Correlation parameter estimates of male-specific employment status: CRE models

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
<b>Educational attainment (Some education†)</b>					
HS and GED	0.0372*** (0.00651)	0.0364*** (0.00648)	0.0366*** (0.00649)	0.0364*** (0.00648)	0.0363*** (0.00649)
Bachelor	0.0361*** (0.00772)	0.0365*** (0.00769)	0.0366*** (0.00770)	0.0365*** (0.00769)	0.0357*** (0.00770)
Graduate	0.0679*** (0.0100)	0.0686*** (0.00997)	0.0682*** (0.01000)	0.0674*** (0.0100)	0.0685*** (0.00999)
<b>Marital status (Married†)</b>					
Widowed	-0.0936*** (0.0294)	-0.0850*** (0.0291)	-0.0885*** (0.0291)	-0.0852*** (0.0290)	-0.0918*** (0.0291)
Divorced/separated	-0.0803*** (0.00835)	-0.0826*** (0.00840)	-0.0838*** (0.00842)	-0.0833*** (0.00842)	-0.0825*** (0.00839)
Never married	-0.115*** (0.00666)	-0.116*** (0.00662)	-0.116*** (0.00662)	-0.116*** (0.00662)	-0.116*** (0.00663)
<b>Perceived health status (Excellent†)</b>					
Very good	0.0268*** (0.00583)	0.0270*** (0.00580)	0.0271*** (0.00580)	0.0272*** (0.00580)	0.0261*** (0.00581)
Good	0.00593 (0.00634)	0.00551 (0.00633)	0.00505 (0.00633)	0.00539 (0.00633)	0.00370 (0.00633)
Fair	-0.0834*** (0.00978)	-0.0824*** (0.00979)	-0.0825*** (0.00981)	-0.0833*** (0.00982)	-0.0843*** (0.00977)
Poor	-0.318*** (0.0190)	-0.320*** (0.0193)	-0.322*** (0.0194)	-0.320*** (0.0194)	-0.318*** (0.0191)
<b>Family income</b>	1.67e-06*** (8.85e-08)	1.66e-06*** (8.88e-08)	1.64e-06*** (8.87e-08)	1.65e- 06*** (8.89e-08)	1.64e-06*** (8.84e-08)

† Indicates the reference category.

Table 2A. Correlation parameter estimates of female-specific employment status: CRE models

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
Educational attainment (Some education†)					
HS and GED	0.107*** (0.00726)	0.109*** (0.00733)	0.108*** (0.00734)	0.109*** (0.00733)	0.106*** (0.00728)
Bachelor	0.135*** (0.00814)	0.136*** (0.00822)	0.135*** (0.00823)	0.136*** (0.00823)	0.135*** (0.00815)
Graduate	0.166	0.167	0.167***	0.166***	0.166***



	(0.0101)	(0.1143)	(0.0102)	(0.0102)	(0.0101)
<b>Marital status (Married†)</b>					
Widowed	0.087 (0.0165)	0.0856*** (0.0169)	0.0860*** (0.0169)	0.0863*** (0.0168)	0.0868*** (0.0166)
Divorced/separated	0.204*** (0.00710)	0.203*** (0.00723)	0.204*** (0.00724)	0.204*** (0.00723)	0.206*** (0.00712)
Never married	0.158 (0.00681)	0.156*** (0.00687)	0.157*** (0.00687)	0.157*** (0.00687)	0.158*** (0.00683)
<b>Perceived health status (Excellent†)</b>					
Very good	0.0439*** (0.00656)	0.0452*** (0.00659)	0.0445*** (0.00660)	0.0447*** (0.00659)	0.0434*** (0.00657)
Good	0.0192*** (0.00696)	0.0190*** (0.00702)	0.0189*** (0.00703)	0.0184*** (0.00703)	0.0185*** (0.00698)
Fair	-0.0614 (0.00947)	-0.0615*** (0.00963)	-0.0614*** (0.00965)	-0.0599*** (0.00964)	-0.0625*** (0.00951)
Poor	-0.264*** (0.0157)	-0.266*** (0.0163)	-0.268*** (0.0164)	-0.264*** (0.0164)	-0.265*** (0.0157)
<b>Family income</b>	-0.0397* (0.00297)	-0.0252*** (0.00932)	-0.0358*** (0.00969)	-0.0274*** (0.00933)	-0.0264*** (0.00931)

† Indicates the reference category.

Table 3A. Correlation parameter estimates of male-specific CRE models of weekly hours of work

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10 years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	-1.892** (0.890)	5.428** (2.387)	5.405** (2.426)	-1.877** (0.890)	4.931** (2.484)
Divorced/separated	-1.391*** (0.218)	0.580 (1.489)	0.531 (1.507)	-1.393*** (0.220)	0.344 (1.471)
Never married	-2.512*** (0.173)	-0.755 (1.016)	-0.782 (1.023)	-2.495*** (0.174)	-0.746 (1.003)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-5.484*** (0.392)	-5.424*** (0.393)	-1.961 (2.790)	-1.961 (2.790)	-1.877 (2.782)
Uninsured	-1.813*** (0.200)	-1.818*** (0.201)	-2.621* (1.428)	-2.621* (1.428)	-2.491* (1.415)
<b>Type of occupation (construction/mining/manufacturing†)</b>					
sales associate/transportation/ utilities	1.104*** (0.174)	-0.0408 (0.202)	-0.980*** (0.192)	-0.0357 (0.203)	-0.0484 (0.202)
professional/education	1.533*** (0.186)	-0.969*** (0.192)	-0.274 (0.766)	-0.976*** (0.192)	-0.998*** (0.191)
public administration/military/ unclassified	1.357*** (0.212)	-0.260 (0.761)	1.113*** (0.174)	-0.261 (0.766)	-0.299 (0.761)
Family income	5.18e-05*** (1.23e-01)	6.20e-05*** (1.68e-05)	6.04e-05*** (1.70e-05)	6.04e-05*** (1.70e-05)	6.13e-05*** (1.61e-05)

† Indicates the reference category.

Table 4A. Correlation parameter estimates of female-specific CRE models of weekly hours of work

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	1.263*** (0.416)	-2.697 (2.393)	-2.406 (2.391)	-2.971 (2.307)	-2.717 (2.382)
Divorced/separated	1.393*** (0.174)	2.931** (1.183)	3.020** (1.184)	3.093*** (1.182)	2.278** (1.154)
Never married	0.996*** (0.174)	3.224** (1.401)	3.363** (1.413)	3.269** (1.422)	2.931** (1.396)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-8.513*** (1.953)	-9.726*** (2.016)	-9.836*** (2.036)	-9.866*** (2.045)	-8.691*** (2.008)
Uninsured	-4.306*** (1.465)	-4.708*** (1.493)	-4.628*** (1.485)	-4.907*** (1.472)	-4.313*** (1.479)
<b>Employing firm size (less than 25 workers†)</b>					
Between 25-99 workers	2.522** (1.139)	2.436** (1.145)	2.392** (1.159)	2.316** (1.160)	2.928** (1.157)
Between 100-500 workers	4.546*** (1.316)	4.480*** (1.344)	4.250*** (1.351)	4.208*** (1.353)	5.148*** (1.322)
more than 500 workers	3.898*** (1.362)	3.622** (1.436)	3.683** (1.437)	3.673** (1.439)	4.136*** (1.415)
Family income	7.34e-05*** (1.93e-05)	7.33e-05*** (1.93e-05)	7.37e-05*** (1.92e-05)	7.32e-05*** (1.94e-05)	7.19e-05*** (1.92e-05)

† Indicates the reference category.

Table 5A. Correlation parameter estimates of male-specific CRE models of Log annual labor income

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	0.0261 (0.261)	0.0454 (0.262)	-0.134*** (0.0501)	-0.133*** (0.0501)	-0.153*** (0.0518)
Divorced/separated	-0.0161 (0.0772)	-0.0191 (0.0786)	-0.116*** (0.0123)	-0.115*** (0.0124)	-0.115*** (0.0123)
Never married	-0.174** (0.0693)	-0.168** (0.0699)	-0.232*** (0.0104)	-0.232*** (0.0104)	-0.234*** (0.0104)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-0.527*** (0.159)	-0.523*** (0.159)	-0.525*** (0.160)	-0.525*** (0.160)	-0.537*** (0.158)

Uninsured	-0.313*** (0.0899)	-0.314*** (0.0900)	-0.316*** (0.0912)	-0.316*** (0.0912)	-0.328*** (0.0903)
<b>Employing firm size (less than 25 workers†)</b>					
Between 25-99 workers	0.0359 (0.0673)	0.0349 (0.0684)	0.0327 (0.0691)	0.0781*** (0.0105)	0.0788*** (0.0105)
Between 100-500 workers	0.104 (0.0718)	0.105 (0.0719)	0.105 (0.0729)	0.142*** (0.0113)	0.143*** (0.0113)
more than 500 workers	0.156** (0.0763)	0.164** (0.0771)	0.170** (0.0777)	0.220*** (0.0127)	0.221*** (0.0127)
<b>Family income</b>	8.46e-06*** (3.37e-07)	9.90e-06*** (1.79e-06)	9.80e-06*** (1.81e-06)	9.80e-06*** (1.81e-06)	9.51e-06*** (1.67e-06)
<b>Occupation type (construction/mining/manufacturing†)</b>					
Sales/associate/transportation/utilities	-0.00530 (0.0864)	-0.00325 (0.0872)	-0.109*** (0.0124)	-0.108*** (0.0124)	-0.110*** (0.0123)
Professional/education	0.121 (0.0824)	0.120 (0.0826)	-0.0645*** (0.0119)	-0.0648*** (0.0119)	-0.0644*** (0.0119)
Public administration/military/unclassified	0.542 (0.621)	0.571 (0.615)	0.0143 (0.0551)	0.0141 (0.0551)	0.0133 (0.0547)

† Indicates the reference category.

Table 6A. Correlation parameter estimates of female-specific CRE models of Log-annual labor income

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	-0.0124 (0.128)	-0.0209 (0.125)	-0.0227 (0.124)	-0.0112 (0.122)	-0.0316 (0.120)
Divorced/separated	0.142** (0.0685)	0.142* (0.0724)	0.137* (0.0720)	0.148** (0.0725)	0.142** (0.0678)
Never married	0.164** (0.0686)	0.163** (0.0699)	0.170** (0.0705)	0.166** (0.0709)	0.189*** (0.0687)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-0.0314 (0.0648)	-0.417*** (0.118)	-0.401*** (0.119)	-0.413*** (0.120)	-0.385*** (0.115)
Uninsured	-0.0847 (0.0637)	-0.369*** (0.0831)	-0.365*** (0.0826)	-0.372*** (0.0824)	-0.394*** (0.0812)
<b>Employing firm size (less than 25 workers†)</b>					
Between 25-99 workers	0.0898 (0.0640)	0.107 (0.0655)	0.116* (0.0663)	0.110* (0.0665)	0.115* (0.0642)
Between 100-500 workers	0.209*** (0.0736)	0.205*** (0.0753)	0.200*** (0.0755)	0.203*** (0.0762)	0.229*** (0.0737)
more than 500 workers	0.272*** (0.0800)	0.285*** (0.0847)	0.289*** (0.0845)	0.291*** (0.0854)	0.287*** (0.0820)
<b>Family income</b>	1.07e-05*** (0.0286)	1.03e-05*** (2.18e-06)	1.05e-05*** (2.16e-06)	1.03e-05*** (2.18e-06)	1.04e-05*** (2.10e-06)
<b>Occupation type (construction/mining/manufacturing†)</b>					
Sales/associate/transportation/utilities	-0.681** (0.279)	-0.716** (0.293)	0.116* (0.0663)	-0.724** (0.296)	-0.703** (0.297)

Professional/education	-0.615** (0.270)	-0.650** (0.284)	0.200*** (0.0755)	-0.659** (0.288)	-0.617** (0.290)
Public administration/military/unclassified	-0.596 (0.430)	-0.635 (0.443)	0.289*** (0.0845)	-0.648 (0.447)	-0.631 (0.418)

† Indicates the reference category.

Table 7A. Correlation parameter estimates of male-specific CRE models of Log-family income

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6- 10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	-0.0649 (0.318)	-0.0812 (0.317)	-0.0828 (0.319)	-0.0828 (0.319)	-0.0903 (0.323)
Divorced/separated	0.293*** (0.0768)	0.296*** (0.0772)	0.301*** (0.0781)	0.301*** (0.0781)	0.297*** (0.0768)
Never married	0.276*** (0.0577)	0.271*** (0.0580)	0.268*** (0.0584)	0.268*** (0.0584)	0.265*** (0.0582)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-0.396*** (0.122)	-0.396*** (0.123)	-0.404*** (0.122)	-0.404*** (0.122)	-0.401*** (0.121)
Uninsured	-0.207*** (0.0782)	-0.197** (0.0786)	-0.204*** (0.0789)	-0.204*** (0.0789)	-0.212*** (0.0787)
<b>Health status (Excellent†)</b>					
Very good	-0.00604 (0.0526)	0.00895 (0.0524)	0.0172 (0.0527)	-0.0239*** (0.00887)	-0.0232*** (0.00885)
Good	0.0304 (0.0579)	0.0529 (0.0580)	0.0463 (0.0582)	-0.0704*** (0.00967)	-0.0700*** (0.00963)
Fair	-0.0562 (0.0917)	-0.0370 (0.0919)	-0.0406 (0.0936)	-0.0865*** (0.0151)	-0.0853*** (0.0150)
Poor	-0.00240 (0.193)	-0.00594 (0.199)	0.00751 (0.203)	-0.109*** (0.0340)	-0.112*** (0.0335)
Log-person's income	0.699*** (0.0384)	0.700*** (0.0387)	0.697*** (0.0388)	0.697*** (0.0388)	0.702*** (0.0242)

† Indicates the reference category.

Table 8A. Correlation parameter estimates of female-specific CRE models of Log-family income

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10years)	Cancer (10+ years)
Marital status (Married†)					
Widowed	-0.0293 (0.115)	-0.107 (0.114)	-0.101 (0.114)	-0.0598 (0.115)	-0.0396 (0.113)
Divorced/separated	-0.208*** (0.0592)	-0.228*** (0.0618)	-0.223*** (0.0614)	-0.222*** (0.0615)	-0.196*** (0.0602)
Never married	-0.0575	-0.0466	-0.0394	-0.0437	-0.0527

	(0.0643)	(0.0660)	(0.0659)	(0.0662)	(0.0643)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	-0.505*** (0.0937)	-0.525*** (0.0994)	-0.539*** (0.0986)	-0.537*** (0.0981)	-0.520*** (0.0940)
Uninsured	-0.165** (0.0747)	-0.139* (0.0768)	-0.142* (0.0763)	-0.141* (0.0762)	-0.150* (0.0771)
<b>Health status (Excellent†)</b>					
Very good	0.0625 (0.0549)	-0.0486*** (0.00912)	0.0548 (0.0561)	0.0715 (0.0566)	
Good	-0.0773 (0.0603)	-0.0901*** (0.0101)	-0.0832 (0.0621)	-0.0778 (0.0627)	0.0731 (0.0551)
Fair	-0.125 (0.0853)	-0.0854*** (0.0141)	-0.0999 (0.0868)	-0.0929 (0.0874)	-0.0670 (0.0610)
Poor	-0.219 (0.176)	-0.0700** (0.0308)	-0.261 (0.179)	-0.247 (0.179)	-0.114 (0.0867)
Log-person's income	0.702*** (0.0272)	0.683*** (0.0282)	0.684*** (0.0399)	0.688*** (0.0401)	0.694*** (0.0392)

† Indicates the reference category.

Table 9A. Correlation parameter estimates of male-specific CRE models of Log-total health expenditures

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	-0.261 (0.596)	-0.202 (0.591)	-0.164 (0.587)	-0.164 (0.587)	-0.159 (0.563)
Divorced/separated	-0.214 (0.248)	-0.222 (0.248)	-0.194 (0.251)	-0.194 (0.251)	-0.140 (0.249)
Never married	-0.124 (0.256)	-0.0993 (0.258)	-0.0967 (0.262)	-0.0967 (0.262)	-0.0742 (0.262)
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	0.0881 (0.0618)	0.0917 (0.0623)	-0.00763 (0.342)	0.0928 (0.0623)	0.0965 (0.0622)
Uninsured	-0.637*** 0.0881	-0.633*** (0.0386)	-0.0351 (0.199)	-0.632*** (0.0386)	-0.636*** (0.0385)
<b>Health status (Excellent†)</b>					
Very good	-0.00691 (0.191)	-0.00265 (0.195)	-0.0351 (0.199)	-0.0351 (0.199)	-0.0799 (0.199)
Good	0.525** (0.241)	0.544** (0.243)	0.519** (0.245)	0.519** (0.245)	0.457* (0.245)
Fair	0.886*** (0.326)	0.953*** (0.327)	0.890*** (0.338)	0.890*** (0.338)	0.793** (0.337)
Poor	0.931 (0.611)	0.907 (0.626)	1.079* (0.632)	1.079* (0.632)	1.227** (0.609)
Family income	0.235* (0.128)	0.215* (0.130)	0.216* (0.130)	0.216* (0.130)	0.263** (0.131)
Number of priority conditions	0.477*** (0.0984)	0.463*** (0.101)	0.462*** (0.103)	0.462*** (0.103)	0.442*** (0.101)

† Indicates the reference category.

Table 10A. Correlation parameter estimates of female-specific CRE models of Log-total health expenditures

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	0.0364 (0.0647)	0.0378 (0.0668)	0.0336 (0.0667)	-0.706 (0.437)	(0.215) -0.703*
Divorced/separated	-0.0202 (0.0282)	-0.0223 (0.0287)	-0.0227 (0.0287)	0.183 (0.198)	(0.427) 0.150
Never married	-0.158*** (0.0274)	-0.156*** (0.0277)	-0.156*** (0.0277)	-0.278 (0.195)	(0.193) -0.224
<b>Health insurance coverage (Private health insurance†)</b>					
Public insurance	0.120 (0.300)	0.0771 (0.316)	0.110 (0.321)	0.0670 (0.322)	0.0371 (0.297)
Uninsured	-1.026*** 0.120	-1.113*** (0.250)	-1.096*** (0.251)	-1.116*** (0.251)	-1.072*** (0.243)
<b>Health status (Excellent†)</b>					
Very good	0.149 (0.193)	0.160 (0.198)	0.170 (0.198)	0.155 (0.199)	0.157 (0.192)
Good	0.253 (0.195)	0.259 (0.205)	0.261 (0.206)	0.268 (0.208)	0.334* (0.201)
Fair	0.305 (0.295)	0.351 (0.301)	0.382 (0.311)	0.371 (0.311)	0.349 (0.306)
Poor	0.994* (0.557)	1.096* (0.615)	1.054* (0.638)	1.027 (0.634)	0.912 (0.565)
Family income	0.994* (0.557)	0.209** (0.100)	0.217** (0.102)	0.215** (0.102)	0.193** (0.0976)
Number of priority conditions	0.547*** (0.0831)	0.541*** (0.0863)	0.538*** (0.0876)	0.541*** (0.0875)	0.540*** (0.0863)

† Shows the reference category.

Table 11A. Correlation parameter estimates of male-specific Probit CRE models of lost work days

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10years)	Cancer (10+ years)
Marital status (Married†)					
Widowed	-0.0228 (0.0412)	-0.0227 (0.0411)	-0.0231 (0.0410)	-0.0230 (0.0410)	-0.0262 (0.0405)
Divorced/separated	0.0574*** (0.0117)	0.0589*** (0.0118)	0.0582*** (0.0118)	0.0578*** (0.0118)	0.0563*** (0.0117)
Never married	0.0384*** (0.00847)	0.0383*** (0.00847)	0.0385*** (0.00847)	0.0383*** (0.00847)	0.0377*** (0.00846)
Health insurance coverage (Private health insurance†)					

Public insurance	-0.0341*** (0.00901)	0.0187 (0.0187)	0.0192 (0.0187)	0.0184 (0.0187)	0.0212 (0.0188)
Uninsured	0.0457*** (0.00383)	-0.0343*** (0.00901)	-0.0340*** (0.00901)	-0.0341*** (0.00901)	-0.0339*** (0.00901)
<b>Health status (Excellent†)</b>					
Very good	0.0256*** (0.00967)	0.0253*** (0.00969)	0.0257*** (0.00968)	0.0254*** (0.00968)	0.0258*** (0.00966)
Good	0.0261** (0.0119)	0.0260** (0.0119)	0.0272** (0.0119)	0.0269** (0.0119)	0.0277** (0.0119)
Fair	0.0289** (0.0130)	0.0274** (0.0130)	0.0284** (0.0130)	0.0290** (0.0130)	0.0305** (0.0130)
Poor	0.00821 (0.0107)	0.00728 (0.0108)	0.0104 (0.0108)	0.00961 (0.0108)	0.00998 (0.0108)
Family income	-0.00960** (0.00449)	-0.00932** (0.00450)	-0.00969** (0.00450)	-0.00955** (0.00450)	-0.00925** (0.00450)
Number of priority conditions	0.0457*** (0.00383)	0.0454*** (0.00384)	0.0453*** (0.00384)	0.0451*** (0.00384)	0.0457*** (0.00383)
<b>Occupation type (construction/mining/manufacturing†)</b>					
Sales/associate/transportation/utilities	-0.0260** (0.0101)	-0.0261*** (0.0101)	-0.0252** (0.0101)	-0.0257** (0.0101)	-0.0251** (0.0101)
Professional/education	-0.00923 (0.00970)	-0.00929 (0.00971)	-0.00887 (0.00970)	-0.00887 (0.00971)	-0.00789 (0.00969)
Public administration/military/unclassified	-0.0147 (0.0286)	-0.0152 (0.0285)	-0.0127 (0.0108)	-0.0130 (0.0287)	-0.0134 (0.0286)

† Indicates the reference category.

Table 12A. Correlation parameter estimates of female-specific Probit CRE models of lost work days

Correlated Variables	Cancer (1 if diagnosed with cancer, 0 otherwise)	Time dummies since cancer diagnosed			
		Cancer (0-2 years)	Cancer (3-5 years)	Cancer (6-10years)	Cancer (10+ years)
<b>Marital status (Married†)</b>					
Widowed	0.0235 (0.0254)	0.0421 (0.0267)	0.0327 (0.0264)	0.0341 (0.0264)	0.0295 (0.0259)
Divorced/separated	0.0573*** (0.0103)	0.0573*** (0.0105)	0.0541*** (0.0105)	0.0552*** (0.0105)	0.0569*** (0.0104)
Never married	0.00104 (0.00885)	0.00622 (0.00918)	0.000803 (0.00894)	-5.98e-06 (0.00894)	0.00276 (0.00890)
<b>Education (Some education†)</b>					
HS and GED	0.0425*** (0.0113)	0.0275** (0.0120)	0.0421*** (0.0114)	0.0417*** (0.0115)	0.0439*** (0.0114)
Bachelor	0.0331** (0.0129)	0.0362*** (0.0140)	0.0346*** (0.0130)	0.0346*** (0.0130)	0.0360*** (0.0129)
Graduate	0.0473*** (0.0139)	0.0342** (0.0146)	0.0488*** (0.0140)	0.0482*** (0.0140)	0.0480*** (0.0139)
<b>Health insurance (Private insurance†)</b>					
Public	0.0435*** (0.0148)	0.0505*** (0.0153)	0.0429*** (0.0150)	0.0440*** (0.0150)	0.0440*** (0.0150)
Uninsured	-0.0281** (0.0109)	-0.0181 (0.0113)	-0.0302*** (0.0110)	-0.0305*** (0.0110)	-0.0290*** (0.0110)
<b>Family income</b>	0.00376 (0.00499)	-0.00304 (0.00515)	0.00400 (0.00504)	0.00486 (0.00505)	0.00470 (0.00502)

<b>Number of priority conditions</b>	0.0721*** (0.00417)	0.0700*** (0.00429)	0.0725*** (0.00426)	0.0727*** (0.00425)	0.0731*** (0.00421)
<b>Paid sick leave</b>	0.0684*** (0.00837)	0.0670*** (0.00857)	0.0667*** (0.00848)	0.0658*** (0.00848)	0.0660*** (0.00842)

† Indicates the reference category.

## Appendix B

Table 1B. Marginal effects of cancer survivorship on employment status- MEPS 2008-2015

	Probit model (cross-sectional)	CRE model (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0761*** (0.0122)	-0.0305*** (0.00914)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0504*** (0.00724)	-0.0942*** (0.0286)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0292*** (0.0104)	-0.0617*** (0.00924)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (Adjusted for 2012 USD), employment organization type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 2B. Marginal effects of cancer survivorship on weekly hours of work- MEPS 2008-15<sup>1</sup>

	Conditional OLS (cross-sectional)	Conditional CRE (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.626* (0.374)	6.528*** (2.001)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0120 (0.301)	-4.171** (1.955)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.564*** (0.129)	1.240* (0.644)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (Adjusted for 2012 USD), employment organization type (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine



and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 3B. Marginal effects of cancer survivorship on Log annual labor income- MEPS 2008-15<sup>1</sup>

	Conditional OLS (cross-sectional)	Conditional CRE (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0415* (0.0224)	-0.0438 (0.0960)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0378** (0.0162)	0.0966 (0.0955)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0756*** (0.0129)	-0.159* (0.0841)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2015 USD), type of organization (public, private), industry indicator, labor union status and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 4B. Marginal effects of cancer survivorship on Log-family income - MEPS 2008-15<sup>1</sup>

	OLS (cross-sectional)	CRE (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0333* (0.0173)	-0.00285 (0.121)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0117 (0.0140)	-0.0322 (0.106)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0469*** (0.00938)	-0.0652 (0.0627)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2015 USD), type of organization (public, private) and year dummies. Male-specific cancers are prostatic and testicular cancers while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 5B. Marginal effects of cancer survivorship on Log-total health expenditure –  
MEPS 2008-15<sup>1</sup>

	OLS (cross-sectional)	CRE (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.303*** (0.0474)	0.870*** (0.290)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	1.088*** (0.0797)	1.073** (0.508)
<b>Panel 3. Common cancers (male and female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.147*** (0.0149)	0.205** (0.0916)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (Adjusted for 2015 USD), type of organization (public, private), industry indicator and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 6B. Marginal effects of cancer survivorship on employed workers Absenteeism -MEPS  
2008-15<sup>1</sup>

	Cross-sectional models		Panel models	
	Stage I-Probit model	Stage II- ZTNH model	Stage I- Probit CRE model	Stage II- RE overdispersion model
<b>Panel 1. Male Cancer survivors</b>				
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0414** (0.0170)	0.206** (0.0815)	0.0414** (0.0170)	1.384** (0.583)
<b>Panel 2. Female Cancer survivors</b>				
Cancer (1 if diagnosed with cancer, 0 otherwise)	0.0394*** (0.0131)	0.155*** (0.0525)	0.0394*** (0.0143)	3.407*** (0.477)

<sup>1</sup>The control variables are: sex, race/ethnicity, age, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (Adjusted for 2012 USD), employment organization type (public, private), firm size, the industry indicator, paid sick leave and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

## Appendix C

Table 1C. Marginal effects of employment on cancer incidence- MEPS 2008-12<sup>1</sup>

	Probit model (cross-sectional)	CRE model (Panel)
<b>Panel 1. Male employment</b>		
Employed (1 if employed, 0 otherwise)	0.00235 (0.00504)	0.00166 (0.00162)
<b>Panel 2. Female employment</b>		
Employed (1 if employed, 0 otherwise)	-0.00326 (0.00211)	-0.00529 (0.00404)

<sup>1</sup>The control variables include: sex, race/ethnicity, age and its square, marital status, education attainment, census regions, health status, number of co-morbidities, health insurance coverage, log of family income normalized by family size (in real 2012 USD) and year dummies. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

Table 2C. Marginal effects of weekly hours worked on cancer incidence- MEPS 2008-12<sup>1</sup>

	Probit model (cross-sectional)	CRE model (Panel)
<b>Panel 1. Male labor supply</b>		
Weekly hours worked	-0.000660 (0.00631)	-0.00468 (0.00459)
<b>Panel 2. Female labor supply</b>		
Weekly hours worked	0.00203 (0.00319)	0.00488 (0.00328)

<sup>1</sup>The control variables are: sex, race/ethnicity, age and its square, marital status, educational attainment, Census regions, health status, number of co-morbidities, health insurance coverage (private, public, uninsured), log of family income normalized by family size (in real 2012 USD), employment organization type (public, private), industry indicator, labor union status and year dummies. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.

**Table 3C.** Marginal effects of cancer survivorship on employment status of married couples<sup>1</sup>

	Probit model (cross-sectional)	CRE model (Panel)
<b>Panel 1. Male-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.066*** (0.0165)	-0.0671*** (0.0175)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0238** (0.00863)	-0.0733*** (0.0311)
Cancer (3-5 years)	-0.0729*** (0.0108)	-0.0562*** (0.0123)
Cancer (6-10 years)	-0.281*** (0.0254)	-0.0372* (0.0194)
Cancer (10+ years)	-0.229*** (0.00248)	0.0405*** (0.00246)
<b>Panel 2. Female-Specific Cancers</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0331*** (0.0118)	-0.0642*** (0.0143)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	0.0218** (0.0102)	-0.233*** (0.0253)
Cancer (3-5 years)	0.0218** (0.0102)	-0.130*** (0.00673)
Cancer (6-10 years)	-0.0283*** (0.00421)	-0.185*** (0.0137)
Cancer (10+ years)	-0.0172 (0.0113)	-0.248*** (0.00869)
<b>Panel 3. Common Cancers (Male and Female)</b>		
Cancer (1 if diagnosed with cancer, 0 otherwise)	-0.0153 (0.0111)	-0.0573*** (0.0122)
<i>Time dummies since cancer diagnosed</i>		
Cancer (0-2 years)	-0.0292** (0.0117)	-0.345*** (0.0131)
Cancer (3-5 years)	-0.345*** (0.0125)	-0.274*** (0.0111)
Cancer (6-10 years)	-0.274*** (0.0107)	-0.236*** (0.0243)
Cancer (10+ years)	0.0414*** (0.00941)	-0.0288*** (0.00424)

<sup>1</sup>The control variables include: sex, race/ethnicity, age and its square, education attainment, census regions, health status, number of co-morbidities, health insurance coverage, log of family income normalized by family size (in real 2012 USD) and year dummies. Male-specific cancers are prostatic and testicular while female-specific cancers include breast, ovarian, uterine and cervical. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey design.

\*\*\* Significant at the 1% level. \*\* Significant at the 5% level. \* Significant at the 10% level.