Gender-specific cancer survivors and their labor market attachments: Evidence from 2008-2014 MEPS data

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ABSTRACT

Rising cancer survival rates and retirements at older ages improve the probability of labor market presence for US cancer survivors. This study utilizes the 2008-2014 nationally representative Medical Expenditure Panel Survey data, and the correlated random effects and over-dispersion models that address the potential endogeneity of cancer in the labor market outcome equations. Separate models are fitted using subsamples of those surviving gender-specific cancers. Substantial male-female differences are detected. Our robust estimates confirm that gender-specific cancers adversely affect the likelihood of employment for men and women. Conditional on employment, cancer survivors worked more than three hours weekly with no change in wages. Additionally, empirical results indicate that cancer significantly increases the working days lost for women but not for men. The total annual cost of workplace absenteeism for employed male and female cancer survivors is US$15.55bn. Policy implications are discussed in light of the rising survival among chronic disease sufferers.

JEL code: I1 (Health), J22 (Time allocation and Labor supply)

Keywords: cancer survivors; labor market presence; correlated random effects (CRE) model; over-dispersion model; longitudinal MEPS 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 *et al*., 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 *et al*., 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 *et al*., 2017).

The 2008 ADA exogenous policy shift provides a natural time break for assessing the job market outcomes of cancer survivors in the labor market. . Past studies report mixed effects of surviving cancer on the job market prospects. Moran *et al*. (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 *et al*. (2008) report a statistically significant result in short-run but indistinguishable from zero effects 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 effects for breast cancer. Akin to the Ganz *et al*., (2002), Bradley et al. (2005a) 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. Therefore, studies integrating health and labor economics would tend to yield richer insights (Hoynes *et al*., 2016).

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. Build upon economic models 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 2008-2014) datasets, we find that gender-specific cancer survivorship significantly reduces the likelihood of employment for both but with a larger magnitude for women. On the intensive margins, however, male-specific cancers have almost no effect but concurringly to the theoretical model of this paper, female-specific cancers increase hours of weekly working. On the working days aspect of job market, irrespective to genders, cancers significantly amplify lost working days but interestingly enough their effect is indistinguishable from zero for male-specific cancers but statistically negative for women-specific cancers. We also estimate the annual forgone productivity cost due to lost working days for the gender-specific cancers. As predicted, the monetary value of productivity loss is greater for women.

The contribution of this paper to the literature is threefold. First, to quantify the differential effects of cancer survivorship in the labor market, we bifurcate the data to estimate gender-specific models. This is because gender-specific cancers have different labor market consequence due to pathological uniqueness and course of disease development. Second, contrasted to other studies on labor markets effects of cancer, this study uses a large nationally representative data of cancer survivors and non-cancer comparison group in the US population with a broader age groups of 18-64 years old. This can be justified by the fact that akin to most developed economies, the US has a large and growing stock of ageing cancer survivors and they are increasingly present in the labor market for the economic reasons and in search for improved life quality (Korpi, 1997). This is in line with the health and labor economics literature regarding the overall impact of illness on the job market (Brajša-Žganec *et al*., 2011, Cai and Kalb, 2006, Lloyd and Auld, 2002, Okun, 2015). Third, although many papers exploit longitudinal data to study the labor market effects of cancer sufferers, their estimated econometric models plagued with unobserved heterogeneity. The CRE technique in our current study exploits the time dimension and richness of the panel data to obtain bias-corrected estimates of the effects of the presence of cancer survivors on labor market attachment. Similarly, we test for the endogeneity problem of cancer survivorship and the labor market outcomes in several different ways.

Sections 2 and 3 of this paper focus on the theoretical and empirical models, respectively. Section 4 discusses the dataset, and section 5 presents the empirical findings. Section 6 probes the robustness of our empirical model estimates, and Section 7 concludes.

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, 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, 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 are constrained to keep their jobs for employment-based health insurance coverage reasons or to secure more incomes to defray catastrophic medical costs. Third, changes in wages due to productivity loss induced by cancer. Finally, changes in the abilities of a survivor affect 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 fix ideas, consider a model of labor supply with health capital akin to Peng et al. (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 ρ is the discount rate and the function U_{it} can be expended as follows,

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

where 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

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

$$C_{it} = A_{it} + \mathrm{N}_{it}\omega_{it} \quad (4)$$

$$\Delta = \mathrm{N}_{it} + \Sigma_{it} + \mathrm{I}_{it} + L_{it} \quad (5)$$

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

$$\Sigma_{it} = \Sigma(H_{it}, \Pi_i, \mathrm{P}_{it}) \quad (7)$$

and Eqs. (3) - (7) formalize different constraints. Starting with health constraint, current health H_{it}, is determined by past health status $H_{i,t-1}$, time spent in health production I_{it}, and unobserved heterogeneity in health production, ζ_i. The resources available for consumption C_{it}, is equal to sum of non-labor income A_{it}, and labor income $\mathrm{N}_{it}\omega_{it}$. The time constraint assures that sum of hours worked in the market N_{it}, total sick time Σ_{it}, time spent on health production I_{it} and leisure time

L_{it} , is no more than available time Δ . The wage constraint ω_{it} , explains that wage is determined by current health stock H_{it} , exogenous determinants of wage Θ_{it} , observable characteristic of occupation and employer ξ_{it} and unobserved productivity Λ_i . Finally, the sick time constraint Σ_{it} , is determined by current health stock, survivor-specific propensity for relapse Π_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, $\mathrm{N}_{it} \geq 0$, optimal consumption, $C_{it} > 0$ and optimal time spent in health production, $\mathrm{I}_{it} \geq 0$ subject to constraints ((3)-(7)). The partial derivative with respect to weekly hours worked provides conditional labor supply in time t , as it follows

$$\frac{\partial U_2}{\partial L_{it}} \geq (1+\rho)^t \, \omega_{it}\sigma_{it}, \qquad t = 1,....,T \tag{8}$$

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

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

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 purpose, these unobserved factors constitute constant α_i , and time–varying κ_{it} , components. We write $\alpha_i = \zeta_i + \Phi_i + \Pi_i$. Then, Eq. (9) can take the form,

$$N_{it} = (H_{it}, \Theta_{it}, \xi_{it}, \mathrm{P}_{it}, \alpha_i, \kappa_{it}) \tag{10 }$$

This expression is 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, λ_0 is a constant, Θ_{it} is a vector of observed regressors, Z_{it} is an indicator variable denoting whether the respondent is a cancer survivor in time t, α_i is the fixed effects term capturing the unobservable measures of productivity, physical and mental health. Finally,κ_{it}, is the idiosyncratic error with the assumption of strict exogeneity.

The α_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 and 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 *et al*. (yyyy) crafted an empirical roadmap for this generalization in a three-period model context. In 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*.'s) three-period model, α_i is replaced by its linear projections as follows:

$$\alpha_i = \mu_0 + \mu_1 Z_{i1} + \mu_2 Z_{i2} + \varphi_i \tag{12}$$

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

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

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

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

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

Collapsing a three-period model (Cabanillas *et al*., yyyy) 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 π, by estimating the above structural equations, we instead estimate the following reduced form equations:

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

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

Further, the parameters of Eqs. (16) and (17) are organized in a column matrix $\mathrm{M}_{(4x1)}$ and their variance-covariance matrices are preserved in the symmetric matrix S_{4x4}. The assumed restrictions $(q_1 - q_2)$ on the parameters is $R = W_{(4x2)}V_{(2x1)}$, 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:

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

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). 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 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 $y_{it} \left| \lambda_{it} \sim Poisson(\lambda_{it}) \right.$, where $\lambda_{it} \left| \delta_i \sim gamma(\lambda_{it}, \delta_i) \right.$ and $\lambda_{it} = e^{(\Theta_{it}\beta + offset_{it})}$, δ_i is the model's dispersion parameter, as in Hausman, Hall & Griliches, (1984)

$$\Pr(y_{it} \left| Z_{it}, \Theta_{it}, \delta_{it} \right.) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \left(\frac{1}{1+\delta_i} \right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i} \right)^{y_{it}} \tag{18}$$

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

$$\Pr(y_{it} \left| Z_{it}, \Theta_{it} \right.) = \int_0^{\propto} \prod_{t=1}^{T} \Pr(y_{it} = Z_{it}, \Theta_{it}, \delta_i) f(\delta_i) \, d\delta_i \tag{19}$$

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

4. Data

The empirical data studied come from the 2008 - 2014 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 asked respondents whether a physician or other healthcare professional had ever told them that they had any type of cancer or a malignancy. Except non-melanoma skin cancers[1], we include all those responding, "Yes" to the above question. Then, it asked individuals about specific types of cancer in each reference period. MEPS began inclusion of cancer questions since 2008. Therefore, we utilize 2008 to 2014, which corresponds to panels 12-18[2] to construct our balanced panel sample. In total, there are 110,431 observations completed all the five rounds of each panel in waves 12-18. We limit our sample to prime age working adults (18-64 years old)[3], not self-employed, not full-time student, having positive survey weights. After several steps of data cleaning[4], the final estimation sample of 51,878

[1] Non-melanoma cancers are progressing latently in years with minimum impact on physical and mental activities of an individual.

[2] Given the overlapping design of the survey, we can only get the half of respondents for the panel 12 and 18. This means that panel 12 includes all those responded in(2007- 2008) and 18 includes respondents in (2014-2015). As a result, there is only one observation for the respondents in these two panels.

[3] Our sample exclude all retired and disabled cancer survivors on social security income.

[4] We exclude 11,123 respondents who were self-employed, as MEPS does not ask about their wage information. We further exclude 29, 372 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 6,333 observations with zero survey weight. Finally, we exclude 5,015 full- time students.

(23, 412 men and 28,466 women) comprises of 4,463 cancer and 47,415 non-cancer observations. We estimate gender-specific models as the prevalence of cancer and job market attachments differ substantially for male and female by splitting gender-specific cancers[5].

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 addition, conditional on employment, every individual provides detailed information on weekly hours of work[6] and hourly wage rate. Monetary values are adjusted for inflation using the urban consumer price index (CPI) for constant 2014 dollars.

To estimate cancer impact on absenteeism and workplace productivity loss, we use the MEPS variables on illness related absenteeism. It asks if the respondent misses a full working day due to illness, injury, and mental or emotional problems[7]. If the respondent indicates missing workdays, the next question identifies the exact number of lost working days. To adjust for the 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); Census regions (Northeast, Midwest, South, West); perceived health

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5 Breast, Ovaries, Cervix, uterus are women cancers while Prostate and Testis are men-specific cancers. Other types of cancer can be diagnosed regardless of the gender. For a detailed information, refer to table 2A in the appendix.

6 We exclude all 35 observations with more than 120 weekly hours of work as outliers in the data after looking at the upper fence of the data.

7 We exclude respondents with all other co-morbidities when estimating the monetary indirect cost associated with cancer as well as estimating impact of cancer on lost working days.

status (excellent, very good, good, fair, poor), number of co-morbidities[8]; labor union membership; employing firm size[9] (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 received by each family member normalized by family size, log of hourly wage and year dummies.

Table A1 presents descriptive statistics on the main variables included in the analysis. Approximately, 70% of all the survey respondents, aged 18-64 are actively employed and this percentage is higher for men. On average, men work 41 hours per week with an hourly wage rate of $23.15 while women work 36.47 hours with an average hourly wage of $18.58. 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 40.17 years and middle aged women in self-assessed good health.

5. Empirical Results

5.1 Employment status

Table I contains parameter estimates[10] for the CRE probit models of the impact of cancer survivorship on the likelihood of employment for the panels of male, female and the combined sample in the column (3), respectively. Cross-sectional and fixed-effects models results are given in columns (1) and (2), for comparative purposes.

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[8] Heart and pulmonary disease such as myocardial infarction, heart failure, ischemic heart disease, COPD, and other systemic diseases are among co-morbidities

[9] Number of employees in each firm is used to proxy for proxy the firm size.

[10] To save space, we only provide the estimated coefficients for the variable of interest, which is binary cancer status. However, the complete set of results separated for each gender-specific cancer as well as all cancers for each gender and the total sample estimates are available upon request.

Regardless of the model specification, as anticipated, we find statistically significant and negative effect of cancer on employment. Male-specific cancers reduce the likelihood of employment by 1.7 percentage points while female-specific cancers are associated with almost a 10-percentage point decrease in the likelihood of employment. This is quite similar to the effect estimated in past studies (Moran *et al*., 2011, Zajacova *et al*., 2015). While all cancer types lack statistically significant effect on men's employment status, they decrease the employment likelihood for women-only and the combined sample roughly 7.5 to 9 percentage points, respectively. In the CRE model of interest, the RE for capturing unobserved heterogeneities is correlated with educational attainment, marital status, perceived health status and family income. We detect an upward bias in the male-specific but a downward bias in female-specific estimates using cross-sectional and FE probit models. In these cases, the endogeneity problem likely results from failing to consider unobserved productivity and factors affecting the health stock of individuals beside cancer.

Table I. Marginal effects of cancer survivorship on employment [a]

	Probit model (Cross section)	Fixed-effect (Panel)	Correlated Random-effect model (Panel)
Panel 1: Male only			
Male-Specific cancers	-0.0697***	-0.0381*	-0.0170**
	(0.0232)	(0.0223)	(0.00654)
All cancers	-0.0582***	-0.0470***	-0.0392
	(0.0162)	(0.0148)	(0.0578)
Panel 2: Female only			
Female-Specific cancers	-0.0473**	-0.0458***	-0.102*
	(0.0194)	(0.0159)	(0.0537)
All cancers	-0.0514***	-0.0454***	-0.0915***
	(0.0161)	(0.0129)	(0.0275)
Panel 3: Common (male and female)			
Cancer	-0.0569***	-0.0476***	-0.0755**
	(0.0111)	(0.00971)	(0.0313)

[a] The control variables include: sex, race/ethnicity, age and its square; marital status, education attainment, census regions, health status, number of co-morbidities; log of family income normalized by family size (Adjusted for 2014 USD) and year dummies. Male-specific cancers are Prostate and Testis cancers while female-specific cancers include Breast, Ovary, Uterus and Cervix. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ show significance test levels.

5.2 Weekly hours of work and hourly wage

Table II contains the estimated marginal effect of cancers on the weekly hours worked conditional on employment. Column (3) provides estimates of CRE models for male, female and the entire sample, respectively. Even though estimated coefficient for male-specific cancers is marginally statistically significant, female-specific cancers increase hours worked by about 3 hours. Considering all the cancer types for each gender, however, cancer has no statistically significant effect for male but interestingly enough it does lessen the weekly hours worked by almost 1.5 hours. This might arise from the clinical peculiarities associated with gynecological cancers, better treatment outcomes and good prognosis of these cancers with minimum negative impact on daily activities including labor market hours of work (Ganz *et al*., 2002).

Table II. Marginal effect of cancer survivorship on weekly hours of work [b]

Work hours (Continuous variable)	OLS model (Cross section)	FE Model	CRE model
Panel 1: Male only			
Male-Specific cancers	3.260**	1.358*	3.072^{+}
	(1.376)	(0.715)	(1.899)
All cancers	1.091	0.208	1.925
	(0.801)	(0.479)	(1.672)
Panel 2: Female only			
Female-Specific cancers	-0.603	-0.749*	3.143**
	(0.514)	(0.423)	(1.586)
All cancers	-0.300	-0.0679	-1.697**
	(0.434)	(0.340)	(-0.742)
Panel 3: Common (Male and female)			
Cancer	0.161	-0.00580	1.739*
	(0.392)	(0.280)	(1.012)

[b] The control variables, are: sex; race/ethnicity, age and its square; marital status, educational attainment, Census regions, health status number of co-morbidities; log of family income normalized by family size (Adjusted for 2014 USD); type of organization (public, private); industry indicator, labor union status and year dummies. Male-specific cancers are Prostate and Testis cancers while female-specific cancers include Breast, Ovary, Uterus and Cervix. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey. *** p<0.01, ** p<0.05, * p<0.1 show significance test levels.

Parameter estimates of the CRE models for weekly hours of work indicate significant correlation between random effects and hourly wage rate as well as level of education. This could be the source of the established negative and lower positive values of coefficients in the gender-specific RE models. Unlike for the weekly hours of work model, the CRE models in Table III indicate lack of statistically significant relationship between log-wage and cancer survivorship. Nevertheless, The RE model estimates of log-hourly wage shows a small increase (US$1.06) of cancer survivor compared with non-cancer individuals.

Table III. Marginal effect of cancer survivorship on log-hourly wage [c]

Work hours (Continuous variable)	OLS model	FE Model	CRE model
Panel 1: Male only			
Male-Specific cancers	0.0997***	1.062*	0.981
	(0.0365)	(0.0330)	(0.0806)
All other cancers	0.0407	1.026	0.967
	(0.0279)	(0.0212)	(0.0705)
Panel 2: Female only			
Female-Specific cancers	-0.0152	1.011	1.075
	(0.0253)	(0.0184)	(0.0742)
All other cancers	-0.00592	1.009	1.082
	(0.0219)	(0.0148)	(0.0679)
Panel 3: Common (Male and Female)			
Cancer	0.00713	1.010	1.021
	(0.0174)	(00121)	(0.0487)

[c] The control variables, are: sex, race/ethnicity, age and its square; marital status, educational attainment, census regions, health status number of co-morbidities; log of family income normalized by family size (Adjusted for 2014 USD); type of organization (public, private); industry indicator; labor union status; and cancer treatment and year dummies. Male-specific cancers are Prostate and Testis cancers while female-specific cancers include Breast, Ovary, Uterus and Cervix. . Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ show significance test levels.

5.3 Absenteeism Among Employed Workers

Table IV reports the marginal effects of cancer on the likelihood that an employed worker misses working days and the lost working days. Columns (1) and (2) are the estimates for the cross-sectional probit and zero-truncated models while those in columns (3) and (4) are for the panel data structure. To obtain robust estimates of cancer-associated work absenteeism[11], we restricted our samples to individuals without co-morbidities. The results indicate that cancer survivorship increases the likelihood of missing working days by 14% for females when compared with non-cancer individuals; but it has no statistically significant effect on the probability of missing working day for males. Similarly, estimates from over-dispersion models suggest that

[11]To preserve statistical power and sufficient number of observations, we avoid estimating gender-specific models.

cancer survivorship increases the number of lost days worked by 1.33 days for females, and no statistically significant effect for males. Interestingly, using the full sample, we find a significant and positive effect on the probability of missing a working day and the number of working days.

Table IV. Marginal effect of cancer survivorship on employed workers Absenteeism [d]

Variable	Cross sectional models		Panel models	
	Probit model	ZTNH model	RE probit model	Over-dispersion RE
Panel 1: Male only				
All cancers	0.00476 (0.0144)	0.0896 (0.0861)	0.0205 (0.0253)	1.099 (0.136)
Panel 2: Female only				
All other cancers	0.0487*** (0.0129)	0.215** (0.105)	0.140* (0.0727)	1.334*** (0.0979)
Panel 3: Common (male and female)				
Cancer	0.0301*** (0.00936)	0.0900 (0.0672)	0.176*** (0.0676)	1.260*** (0.0790)

[d] The control variables, are: sex; race/ethnicity, age and its square; marital status, educational attainment, Census regions, health status, number of co-morbidities; the log of family income normalized by family size (Adjusted for 2014 USD); type of organization (public, private); industry indicator; labor union status; and cancer treatment and year dummies. Male-specific cancers are Prostate and Testis cancers while female-specific cancers include Breast, Ovary, Uterus and Cervix. Estimates of probit, zero-truncated negative binomial hurdle (ZTNH) for cross sectional data and RE probit and overdispersion RE models for the panel data are given. Standard errors are shown in parentheses and balanced repeated replication technique is used to adjust for MEPS complex survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ show significance test levels.

5.4 Total indirect productivity cost associated with cancer survivorship absenteeism

Table V reports the annual indirect productivity cost associated with missed working days for all employed cancer survivors. We estimate lost productivity by assessing employment health-related missed workdays because of ill health, stratified by gender. We estimated the monetary cost of missing workdays for each year based on the hourly rate of pay of individuals. 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. This finding is consistent with an earlier discussion in this paper on cancer survivorship raising the number of lost working days significantly for females but not for males. These losses translate to annual foregone earnings[12] of $2.5 billion for males and $13 billion for female cancer survivors.

Table V. Annual work absenteeism costs associated with cancer survivorship in the US for employed adult age 18-64

Year	Employed male survivor	Employed female survivor	Absenteeism cost for male (billion)	Absenteeism cost for female (billion)
2008	960,172	1,615,321	[2.107-2.211]	[10.896-11.001]
2009	1,141,450	2,191,232	[2.502-2.987]	[14.729-16.123]
2010	947,036.11	2,059,892	[2.173-3.020]	[13.853-13.987]
2011	1,220,015	1,784,042	[2.753-2.965]	[12.04-12.712]
2012	1,106,181	1,811,558	[2.42-3.117]	[12.276-13.541]
2013	1,176,227	2,116,928	[2.675-3.456]	[14.274-15.321
2014	1,261,346	1,961,040	[2.894-3.7650]	[13.269-14.761]

All costs are adjusted for 2014 US$ using the Consumer Price Index (CPI). The 95% confidence interval is given for the mean cost of absenteeism for both genders.

6. Endogeneity problems and robustness checks

The endogeneity problem is a prevalent 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[13]. 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

[12] We estimated the annual cost associated with lost working days for the non-cancer group. For male and female, cost of lost working days, are $598 and $1,176, respectively. For the cancer survivors it is $2,234 for the male and $6,736 for the female.

[13] Results are achievable upon request.

actively treated for cancer or disabled. The labor market consequence might be large for those who are actively treated for cancer or identified as disable by 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 individual fixed effect and 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[14] with interaction between cancer survivorship and age categories[15], 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 hourly wage rates for younger cancer survivors increased significantly (34% *P*<001). In the same line of reasoning, we tested 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[16], we estimated an alternative model using CRE ordered probit specification[17]. We could not a find a statistically significant relationship between

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[14] The result will be provided upon the request.
[15] Age categories are 18-39, 40- 59, 60-64.
[16] We created a categorical variable of weekly hours of work which includes: (1) <30 hours; (2) 30-40 hours; (3) >40 hours
[17] Authors if requested can provide the full set of results for this model.

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 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.

6. 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. The latest treatment technologies for improving cancer survival, include Janssen Biotech's Zytiga™ (for men with advanced prostate cancer), AstraZeneca's Lynparza™, a new type of drug called PARP inhibitor (for women inheriting BRCA gene mutations predisposing them to breast cancer), and Loxo Oncology Inc.'s Iarotrectinib™ (for many cancer types with a certain gene abnormality in both pediatric and adult cancer patients).[18]

This paper, by exploiting the panel dimensions of the MEPS, estimated the causal relationship between gender-specific cancers and certain job market attachments among prime age working adults. Given the challenges in estimating the negative effects of cancer survivorship on

[18] Source: The 2017 (Chicago, IL) meeting of the American Society of Clinical Oncology conference. *https://www.mdlinx.com/internal-medicine/top-medical-news/article/...*

the labor market outcomes by structural models, we proposed a sound empirical model that is tightly fitted with the theoretical model of the paper as well as accounts for the endogeneity problem of cancer through correlated random effects (CRE) model. Our robust estimates indicated that post-cancer likelihood of employment is negative for males and females but the magnitude is greater for the females. At the mean data values of all other covariates, the estimates suggest that female-specific cancers decrease the likelihood of working by 10 percentage points while male-specific cancers only drop the likelihood of employment by 1.7 percentage points. Are these differences really related to gender-specific cancer types or do they reflect differences in the labor supply behavior of males and females? Women's labor supply is more elastic because women are more likely to be secondary earners in the family, so we hypothesize that men and women may react differently to the same health shocks. To test this hypothesis, we run separate models of labor supply for those cancers that are common for males and females. The results reconfirm our earlier findings. The estimated male-female differential, consistent with some previous studies (Bradley et al., 2005b, Moran et al., 2011), could be tied to certain physiological and economic factors. For instance, breast cancer unlike other prevalent types of cancer, is usually diagnosed at a relatively younger age; on the other hand, most prostate cancer cases are diagnosed at an older age (Miller *et al*., 2016). On the economic side, women historically benefit from their spousal income or health insurance coverage and their motivation to attach to the labor market is comparatively lower (Bradley *et al*., 2002).

Furthermore, weekly hours worked is analyzed as another crucial labor market dimension for the cancer survivors conditional on employment. We observed an approximately three hours increase in the total number of weekly hours worked for gender-specific cancer survivors when compared with non-cancer individuals though the coefficient for male-specific is marginally significant. Interestingly enough, amplification in the weekly hours worked is diminished by half when the entire sample is considered in the analysis. Moreover, this positive effect alters to negative when all types of cancer examined. Moran *et al*. (2011), in contrast to our estimates, approximate an average 3.5 hours reduction in usual hours per week for male and female cancer survivors. We contemplate that the contradiction roots into the fact that we used a short panel data structure and thus our model captures a short-term relationship while studies based on a cross-individual long panel could provide estimates for long-term effect. In the same line of reasoning, in short-run, the substitution effect of cancer reduces the utility of leisure time and the survivor may attach more to labor market but in long- run the diminishing effect of cancer on the stock of health decline weekly hours of work. The heterogeneous nature of entire cancer survivor reverses the sign of the coefficient as one may expect.

Besides weekly hours worked, we inspected the impact of gender-specific cancer on hourly wage rate of employed survivors. Given that we used a short data panel, it is difficult to observe diminished health stock due to cancer in the short run, detection of negative effect of cancer as prior expected is not found based on the robust CRE model estimates. However, the income effect induced by high out-of-pocket health spending might be a reasonable justification for significant increase in hourly wage rate estimated using individual RE model. We assessed 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 \$2.107 to \$2.189 billion for male and \$10.90 to \$12 billion for the female. These result might be supported by the fact that women-specific cancers in relatively younger ages exhibit a severe clinical course (Narod, 2012) and require more aggressive treatment and lead to longer and more frequent lost working days. The total cost of lost working days for both employed male and female cancer survivors is US(real 2014)$15.55 billion annually.

According to American Cancer Society (ACS), approximately 1,688,780[19] new cancer cases are expected in the US for 2017. As this study sheds light on the impact of gender-specific cancer survivorship at the extensive and intensive margins of labor market outcomes, it has workplace implications for the growing population of cancer survivors. Equivalently, our estimates on the increasing economic loss from absenteeism associated with cancer motivate public policy debates on flextime work regimes for the economic well-being of millions of Americans increasingly living with chronic health conditions.

The findings in this paper yield some novel insights into the relationship between gender-specific cancer survivorship and labor market attachments, variously measured, not previously available. There may be some limitations, however. First, we assume that the main confounding factors in the CRE models are time-invariant unobserved productivity and health dimensions. Such may not be the case, however. Second, MEPS does not provide any information about timing of cancer diagnosis. Knowing the exact timing of cancer is essential for knowing pre-and post- cancer job market attachments associated with cancer. These issues are for future studies to explore.

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[19] This only includes cancers that are reported to cancer registries. Some benign types of cancer are not required to be reported.

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Table A1. Summary statistics of variables- MEPS (2008-2014)

	Male				Female			
	Non-cancer		Cancer		Non-cancer		Cancer	
Census regions	Row %	95% CI	Row %	95% CI	Row %	95% CI	Row %	95% CI
Northeast (n=8,314)	95.5	[94.5,96.4]	4.5	[3.6,5.5]	92.8	[91.8,93.7]	7.2	[6.3,8.2]
Midwest (n=9,956)	95.5	[94.6,96.2]	4.5	[3.8,5.4]	91.2	[90.3,92.0]	8.8	[8.0,9.7]
South (n=19,605)	94.8	[94.1,95.5]	5.2	[4.5,5.9]	91.9	[91.2,92.6]	8.1	[7.4,8.8]
West (n=14,003)	95.1	[94.2,95.8]	4.9	[4.2,5.8]	91.5	[90.4,92.5]	8.5	[7.5,9.6]
Total (n=51,878)	95.2	[94.8,95.5]	4.8	[4.5,5.2]	91.8	[91.4,92.2]	8.2	[7.8,8.6]
Marital Status								
Married (N=25,642)	93.8	[93.1,94.4]	6.2	[5.6,6.9]	90.9	[90.2,91.5]	9.1	[8.5,9.8]
Widowed (N=971)	86.5	[78.8,91.7]	13.5	[8.3,21.2]	88.9	[85.9,91.4]	11.1	[8.6,14.1]
Divorced (N=7,463)	92.8	[91.2,94.0]	7.2	[6.0,8.8]	87.6	[86.4,88.7]	12.4	[11.3,13.6]
Never Married (N=17,802)	98.1	[97.6,98.4]	1.9	[1.6,2.4]	96.2	[95.6,96.8]	3.8	[3.2,4.4]
Total (N=51,878)	95.2	[94.8,95.5]	4.8	[4.5,5.2]	91.8	[91.4,92.2]	8.2	[7.8,8.6]
Education attainment								
Some education (n=9,924)	96.8	[95.9,97.4]	3.2	[2.6,4.1]	93.4	[92.3,94.3]	6.6	[5.7,7.7]
GED and HS (n=20,665)	96.2	[95.7,96.7]	3.8	[3.3,4.3]	91.4	[90.7,92.0]	8.6	[8.0,9.3]
Bachelor (n=15,624)	94.2	[93.5,94.9]	5.8	[5.1,6.5]	92.1	[91.2,92.8]	7.9	[7.2,8.8]
Graduate (n=5,665)	92.7	[91.3,93.9]	7.3	[6.1,8.7]	91.2	[89.9,92.4]	8.8	[7.6,10.1]
Total (n=51,878)	95.2	[94.8,95.5]	4.8	[4.5,5.2]	91.8	[91.4,92.2]	8.2	[7.8,8.6]
Perceived Health Status								
Excellent (N=12,818)	97.3	[96.7,97.8]	2.7	[2.2,3.3]	94.6	[93.9,95.3]	5.4	[4.7,6.1]
Very Good (N=16,434)	95.9	[95.2,96.5]	4.1	[3.5,4.8]	93.0	[92.2,93.6]	7.0	[6.4,7.8]
Good (N=15,379)	94.3	[93.5,95.0]	5.7	[5.0,6.5]	91.0	[90.1,91.9]	9.0	[8.1,9.9]
Fair (N=5,643)	91.2	[89.5,92.7]	8.8	[7.3,10.5]	87.0	[85.3,88.5]	13.0	[11.5,14.7]
Poor (N=1,604)	83.3	[79.0,86.8]	16.7	[13.2,21.0]	79.5	[75.8,82.9]	20.5	[17.1,24.2]
Total (N=51,878)	95.2	[94.8,95.5]	4.8	[4.5,5.2]	91.8	[91.4,92.2]	8.2	[7.8,8.6]
Employment status								
Not Employed (n=16,285)	91.9	[90.9,92.8]	8.1	[7.2,9.1]	89.4	[88.5,90.4]	10.6	[9.6,11.5]
Employed (n=35,593)	96.1	[95.6,96.5]	3.9	[3.5,4.4]	92.9	[92.4,93.4]	7.1	[6.6,7.6]
Total (n=51,878)	95.2	[94.8,95.5]	4.8	[4.5,5.2]	91.8	[91.4,92.2]	8.2	[7.8,8.6]
Race/Ethnicity								
Non-Hispanic White (n=20,885)	93.5	[92.9,94.1]	6.5	[5.9,7.1]	89.5	[88.9,90.1]	10.5	[9.9,11.1]
Non-Hispanic Black (n=10,790)	97.2	[96.6,97.7]	2.8	[2.3,3.4]	95.6	[94.9,96.2]	4.4	[3.8,5.1]
Non-Hispanic others (n=5,304)	94.9	[88.1,97.9]	5.1	[2.1,11.9]	92.0	[84.8,96.0]	8.0	[4.0,15.2]
4 (n=14,899)	98.5	[98.0,98.8]	1.5	[1.2,2.0]	95.9	[95.3,96.4]	4.1	[3.6,4.7]
Total (n=51,878)	94.9	[94.4,95.3]	5.1	[4.7,5.6]	91.4	[91.0,91.9]	8.6	[8.1,9.0]
Labor Union Membership								
No (n=30,092)	96.1	[95.6,96.5]	3.9	[3.5,4.4]	92.9	[92.3,93.4]	7.1	[6.6,7.7]
Yes (n=3,976)	95.7	[94.1,96.8]	4.3	[3.2,5.9]	93.4	[92.1,94.6]	6.6	[5.4,7.9]
Total (n=34,068)	96.0	[95.6,96.4]	4.0	[3.6,4.4]	92.9	[92.4,93.4]	7.1	[6.6,7.6]
Organization type								
Public (n=5,967)	93.8	[92.5,94.9]	6.2	[5.1,7.5]	91.7	[90.7,92.6]	8.3	[7.4,9.3]
Private (n=28,432)	96.5	[96.0,96.9]	3.5	[3.1,4.0]	93.3	[92.6,93.9]	6.7	[6.1,7.4]
Total (n=34,399)	96.1	[95.6,96.5]	3.9	[3.5,4.4]	92.9	[92.4,93.4]	7.1	[6.6,7.6]

	Male						Female					
	Non-cancer			Cancer			Non-Cancer			Cancer		
	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max
Hourly wage	20.4 (13.1)	1	79.6	25.9 (12.1)	1	79.6	17.6 (11.3)	1	79.6	19.57 (12)	1.19	73.3
Log family income	9.94 (0.84)	5.4	12.7	10.31(0.79)	6.9	12.3	9.86 (088)	4.8	12.7	10.12 (0.87)	6.02	12.2
Weekly hours worked	40.5 (10.7)	1	119	41.5 (10.9)	1	96	36.17(10.55)	1	102	36.77	2	88
Annual work loss days	0.50 (3.1)	0	112	1.14 (7.0)	1	65	0.86 (5.3)	1	120	1.87(6.0)	1	153
Age	39.39 (13)	18	64	53 (10)	18	64	39.87 (12.9)	18	64	49.15 (11.2)	18	64
Number of co-morbidity	0.67 (1.05)	0	9	1.58 (1.66)	0	9	0.73(1.01)	0	9	1.41(1.5)	0	9

GED: General educational Development; HS: High school; MEPS: Medical Expenditure Panel Survey; Weighted means of continuous variables are represented for national representativeness