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Health and work in the family: Evidence from spouses' cancer diagnoses☆

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ABSTRACT

Using Canadian administrative data from multiple sources, we provide the first nationally representative estimates for the effect of spouses' cancer diagnoses on individuals' employment and earnings and on family income. Our identification strategy exploits unexpected health shocks and combines matching with individual fixed effects in a generalized difference-in-differences framework to control for observable and unobservable heterogeneity. While the effect of spousal health shocks on labor supply is theoretically ambiguous, we find strong evidence for a decline in employment and earnings of individuals whose spouses are diagnosed with cancer. We interpret this result as individuals reducing their labor supply to provide care to their sick spouses and to enjoy joint leisure. Family income substantially declines after spouses' cancer diagnoses, suggesting that the financial consequences of such health shocks are considerable.

1. Introduction

Changes in health status may affect not just the individuals who experience them but also their family members. For example, if the main earner of a family loses the ability to generate income due to a health shock, the financial situation of the spouse and other dependents is invariably affected. In addition, spouses and working-age children may themselves increase their labor supply to make up for lost income or reduce it to care for the sick family member. Since consumption smoothing and self-insurance occur at the household level, the financial effects of health shocks on other family members have important policy implications. To shed light on such effects, we analyze how one spouse's cancer diagnosis affects the employment and earnings of the other spouse and total family income, using administrative data from Canada.

As in other developed countries, cancer is one of the leading causes of mortality and morbidity in Canada. Almost 200,000 individuals were diagnosed with cancer in 2014. According to 2011 data, it is the leading cause of death, accounting for 30% of all deaths.[1] With recent medical advances, however, survival chances following a cancer diagnosis have improved. For instance, the average five-year survival rate for all cancers in Canada increased from 56% in 1993 to 63% in 2007. This shift to longer survival emphasizes the importance of considering the medium- and long-term effects of cancer on survivors' own and their family members' labor market outcomes and financial well-being. Bradley et al. (2002a,b, 2005, 2006, 2007a) find moderate negative effects on the labor supply of cancer survivors. For Canada, Jeon (2016) estimates that individuals with high-mortality cancer diagnoses reduce their employment by up to 20%, but decreases in labor supply at the intensive margin are smaller.

When an individual experiences a negative health shock, such as a cancer diagnosis, the labor supply of his or her spouse is subjected to two opposing forces. On the one hand, the spouse's labor

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[1] See https://www.cancer.ca/en/cancer-information/cancer-101/cancer-statistics-at-a-glance/.

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supply may increase to make up for the sick individual's lost income ("added worker effect"). On the other hand, family members, and spouses in particular, may reduce their labor supply in order to care for their sick partner following a health shock ("caregiver effect"). Healthy spouses may also reduce their labor supply if both spouses wish to spend more leisure time together after a severe health shock, reflecting the complementarity of leisure among couples. We provide a conceptual framework for these effects in Section 2. It is theoretically ambiguous which effect dominates, so we answer this question empirically in the context of spousal cancer diagnoses among working-age Canadian couples.

There are two main challenges to analyzing the effects of changes in one spouse's health status on the other spouse's labor supply decisions. The first one is data availability. Analyzing the effects of individuals' health shocks on their family members requires that families in the data be identified. This is relatively easy in household-level survey data. However, the number of individuals suffering from severe health problems that can change families' economic well-being is usually small in such surveys. A considerably larger number of individuals with severe health conditions can be observed in administrative data (such as hospital records), but information about family members in such data is usually unavailable. To deal with these problems, we use a unique data set linking data from several Canadian administrative sources. In addition to containing a large number of individuals suffering from a potentially severe health problem (specifically, those who were diagnosed with cancer), we are able to identify married couples and to track their labor market outcomes over time.

The second challenge arises because it is difficult to find causal links between one spouse's ill health on the other spouse's labor market outcomes. Family formation is not random; couples are matched based on observable and unobservable characteristics that also affect the health and labor supply of spouses later in life. Even conditional on individual fixed effects, changes in individuals' health status may be correlated with their own or their spouses' labor supply and income, i.e. they may not be strictly exogenous. To establish a causal link between spousal health and labor market outcomes, we use cancer diagnoses as a substantial and unanticipated, hence strictly exogenous, health shock. It is unlikely that one spouse's labor supply or work preferences directly or indirectly affect the other spouse's likelihood of a cancer diagnosis. Therefore, we can provide these findings with a causal interpretation.[2]

Given these challenges, only a small number of studies have investigated the effect of changes in one spouse's health status on the other spouse's labor supply, and the empirical evidence is mixed. For example, Parsons (1977) and Charles (1999) find that women increase their labor supply in response to their husband's health shock while men lower theirs when their wife becomes sick. In contrast, Berger and Fleisher (1984) and Haurin (1989) find small or insignificant effects. Hollenbeak et al. (2011) find a decrease in wives' employment but no effect for husbands, whereas Coile (2004) estimates a small added-worker effect for husbands but no significant impact for wives. While the above studies rely on self-reported health and labor supply measures derived from survey data, only two studies use administrative data in this context, to our knowledge. Nahum (2007) finds evidence for caregiver effects using Swedish administrative data on spouses' sickness absence with a more pronounced negative effect among wives. In contrast, Garcia Gomez et al. (2013) find no significant effects for wives and negative effects for husbands of sick individuals using administrative hospital data from the Netherlands. Overall, existing studies do not reach a clear consensus on the effect of spousal health shocks on labor supply.

We contribute to the literature by providing new evidence on the effect of severe health shocks on spousal employment and earnings and family income among working-age couples. In contrast to most of the existing literature, we combine objective health shock measures from the Canadian Cancer Registry with administrative and nationally representative earnings data from Canadian longitudinal income tax records (see Section 3). In particular, our health shock measure differs from what other studies have used. For example, Garcia Gomez et al. (2013) use acute hospitalizations as a measure for health shocks, but an individual could have experienced declining health prior to being hospitalized. Hence, it is not clear that a hospital admission constitutes an unanticipated shock. In contrast, we use an individual's cancer diagnosis to measure a sudden and unanticipated change in a person's health status. It is unlikely that an individual and his or her spouse adjust their labor market behavior because they are aware of the illness before the diagnosis. By quantifying the decline in earnings and family income after a health shock, we also contribute to the growing literature on the opportunity costs of informal caregiving (see, e.g., Skira, 2015).

Besides using this novel source of exogenous variation in individuals' health, we combine matching methods with a generalized difference-in-differences (DID) strategy to control for observed and unobserved heterogeneity. We first apply Coarsened Exact Matching (CEM) to the data to make the treatment group (individuals whose spouses have been diagnosed with cancer) and the control group (individuals whose spouses have never been diagnosed with cancer) observably similar (see Section 4.1 for details). To make the DID approach more robust, we include individual fixed effects (see Section 4.2). The study data and methods allow us to causally interpret the estimation results, which is essential for an informed policy discussion. By using Canadian instead of U.S. data, our results may shed light on the effect of cancer diagnoses on spousal labor market outcomes in other countries with similar universal health care systems.

The results in Section 5 show that both husbands and wives reduce their employment rates by about 2.4 percentage points on average in the five years following their spouses' cancer diagnoses. Since women have lower average employment rates, this decrease represents a larger relative decline for them. Furthermore, annual earnings decrease by about \$2000 among men and \$1500 among women, which corresponds to 3.5% and 6% for men and women, respectively. Finally, we estimate that family income decreases by up to 4.8% among men and by up to 8.5% among women. These declines are due to lower earnings among individuals diagnosed with cancer and an additional decline in earnings among their spouses.

2. Conceptual framework

In this section, we use a dynamic family labor supply model to provide a conceptual framework for the potential effects of one spouse's health shock on the other spouse's labor employment and earnings. Period-specific utility is a function of each household member's leisure and total household consumption (see Blundell et al., 2007, for a summary).[3] Following Blundell et al. (2016), we do not assume that the per-period utility function is separable in household consumption and each family member's leisure.

[2] Canada has a universal health care system, which limits selection bias due to health insurance choice. This reduces the correlation between health and labor market outcomes and makes a causal interpretation of our findings more plausible.

[3] We assume that household members maximize utility as if they were a single decision maker, i.e. we use a unitary family labor supply model. The literature has extended household models to collective and non-cooperative models (see Chiappori and Mazzocco, 2014, for an overview), but we limit our discussion to the unitary model for simplicity.

Non-separable utility implies that one spouse may enjoy leisure more when it is shared with the other partner (complementarity of leisure).

In the context of a dynamic labor supply model, a health shock, such as a cancer diagnosis, represents a permanent wage shock for the affected individual because his or her productivity permanently declines.[4] This negative wage shock reduces the family's permanent income. In a standard setting (e.g., Blundell et al., 2008, 2016), this decline in permanent income leads to increased labor supply of the other spouse to make up for lost income and to smooth consumption. This result is also known as the "added worker effect" in the literature (Lundberg, 1985; Stephens, 2002). In our context, it is therefore possible to find an increase in one spouse's labor supply following the other spouse's cancer diagnosis.[5]

In contrast to an economic shock, a health-related wage shock, such as a cancer diagnosis, has additional implications for spousal labor supply. First, a health shock reduces the life expectancy of the spouse experiencing the shock. Since the family maximizes its utility over its lifecycle, the expected death of one spouse may change the household's optimal consumption and leisure paths. It is possible, for example, that marginal utility of household consumption, especially of durable goods, declines. This change in the optimal consumption level implies that it may not be necessary for the unaffected spouse to increase his or her labor supply to smooth consumption.

Second, if utility is non-separable in each partner's leisure, we also expect a smaller increase or even a decrease in labor supply of the unaffected spouse. Non-separability or complementarity imply that one spouse's marginal utility of leisure is a function of the other partner's leisure time. Hence, the two partners prefer spending leisure time together, which in turn affects their labor supply decisions (see Michaud and Vermeulen, 2011, for a recent study). In this case, the household may opt to forgo even more of its income by also lowering the labor supply of the unaffected spouse. For a cancer diagnosis, this non-separability may also interact with the decline in life expectancy discussed above.

Finally, family members, and spouses in particular, may reduce their labor supply in order to care for their sick spouses following a health shock. Ettner (1995), Johnson and Lo Sasso (2006), Van Houtven et al. (2013), and Heger (2014) document such a "caregiver effect" in situations where one family member, typically an elderly parent, requires long-term care and another family member acts as an informal caregiver. While there is less evidence related to informal caregiving among spouses, it is likely that the labor supply effects of a spousal health shock are similar to that of an elderly parent. These three effects may outweigh the family's desire to smooth consumption, so the overall effect of a spousal cancer diagnosis on the partner's labor supply is likely negative.

A household's decision to reduce labor supply after one of the spouses experiences a health shock may lead to a permanent exit from the labor force. While the effect of health on own retirement has received some attention (see, e.g., Bound et al., 1999; French, 2005), we focus on labor supply changes at the extensive and intensive margins that are likely not permanent. The retirement decision has further implications for other decisions, such as saving decisions that are not the focus of this paper. Moreover, our data do not allow us to distinguish between a temporary decline in employment and permanent retirement.

The predicted impact of a health shock on spousal labor supply may be heterogeneous across families. Consumption smoothing is easier for households with high asset levels, so the decline in labor supply may be a function of wealth. Moreover, prior labor market attachment, time left until retirement, and number and ages of children affect the household's reaction to a member's health shock. While we cannot address all of these dimensions of heterogeneity due to data and statistical power issues, we control for a number of household characteristics when estimating the effect of one spouse's cancer diagnosis on the other spouse's labor supply.

3. Data and summary statistics

The data used in this paper come from five administrative sources: the Canadian 1991 Census of Population, the Canadian Cancer Database (CCDB), the Canadian Mortality Database (CMDB), the Longitudinal Worker File (LWF), and the T1 Family File (T1FF). The LWF and the T1FF are derived from individual tax returns.[6]

Statistics Canada linked these data sources in multiple steps. First, the *1991 Canadian Census Cohort: Mortality and Cancer Follow-Up* links selected personal information from the CMDB and CCDB (including death records up to 2006 and cancer records up to 2003) to individual records of those 25 and over in the 1991 Census file.[7] Second, the 1991 Census cohort was linked to the LWF, which is a random 10% sample of Canadian tax return files from 1983 onward, and the T1FF, which contains spousal and total family incomes. The linked data include demographic characteristics, cancer diagnoses and death records, as well as longitudinal profiles for individual, spousal, and family income from 1983 to 2010. In addition to death records from the CMDB, income tax files also provide information about individuals' years of death until 2010.[8] The final 1991 Census–LWF linkage data represent approximately 1.4% of the Canadian population aged 25 and over as of 1991.

We use the *1991 Canadian Census Cohort: Mortality and Cancer Follow-Up* to identify married couples in the 1991 Census–LWF and to track their cancer histories until 2003 and their death records until 2006. However, the marital status of individuals in the 1991 Census–LWF data can change over time. To study the impact of spouses' cancer diagnoses on individuals' labor market outcomes, we first verify that they were still married to the same person as in the 1991 Census at the time of the cancer diagnosis.

To construct the sample, we take the following steps. First, using 1991 Census data, we select all married individuals aged 59 and under in 1991 and retain only individuals never diagnosed with cancer up to that year. We refer to these people simply as "individuals," and those to whom they were married, we call "spouses."[9] We exclude individuals if their spouses were aged 60 or over in 1991 or if their spouses had been previously diagnosed with cancer.

Second, we construct individuals' marriage spells using family status information from the annual T1FF. In any year, individuals are treated as being continuously married to the same spouse if their marital status has not changed between any two consecutive years from 1991 to that year. If individuals separate, their marriage

[4] A less severe health shock, such as a temporary illness, may constitute a transitory wage shock, but for our purposes the assumption that a cancer diagnosis leads to a permanent wage shock is sensible.

[5] In the U.S., obtaining health insurance may be an additional reason to increase labor supply after a spousal health shock. Bradley et al. (2007b, 2013) consider the role of employer-provided health insurance after women's breast cancer diagnoses. Canada has a universal health care system, so this issue is not relevant in the context of our study.

[6] We provide a brief description of each data source in Online Appendix A. Further data development extending the information on the 1991 Census cohort to more recent years is currently in progress. Detailed information about the 1991 Census and both databases is available from the Statistic Canada website (www.statcan.gc.ca).

[7] Online Appendix A contains details on the match quality.

[8] Death records in the tax data capture about 80% of deaths.

[9] That is, for the terminology used in this study, "spouses" are persons who were diagnosed with cancer between 1992 and 2003, and "individuals" are persons whose labor market outcomes are considered.

spell ends.[10] However, in the event the spouse dies, the marriage spell is coded as continued until the individual is remarried, so widows and widowers are retained in the sample as long as they do not remarry.[11] Once all continuous spells from 1991 onward are identified, we track changes in individuals' marital status from 1991 back to 1983 in order to identify the starting year of these continuous marriage spells. Within the identified continuous marriage spells that span years before and after 1991, individuals are presumed to have been married to the person identified as their spouse in the 1991 Census.[12]

The marriage spell data contain 107,921 married couples, in which both spouses were aged 59 and under in 1991 and neither of whom had a cancer history prior to 1992. The average length of the marriage spells that cover part of or the whole period from 1983 to 2010 is 21.4 years, and 94% of the spells are 10 years or longer. The average age of the individuals is 39.7 years in 1991 and the average age of their spouses is 39.8 years. Spouses of 3665 individuals were diagnosed with cancer for the first time between 1992 and 2003. The age of these individuals at the time of the diagnoses ranges from 28 to 64 years.[13]

Finally, we impose further restrictions on the marriage spell data to obtain our treatment and control samples. In each year $t = 0$ from 1992 to 2003, we select individuals who had yet to reach the age of 60, so they are still of working age. We impose the same age restriction on the spouse. We impose the age restriction on individuals and their spouses to focus on couples where both partners are unlikely to be in retirement or early retirement (see Section 2 for a discussion). Individuals who have never been diagnosed with cancer up to the end of year $t = 0$ and who lived for at least five years following year $t = 0$ are kept regardless of the length of their marriage spells.[14] We restrict the sample to individuals whose employment status (working or not) can be determined in at least two years prior to year $t = 0$. Individuals are presumed to have worked in each year in which they had nonzero annual earnings.[15]

The treatment group that satisfies these restrictions consists of 2636 individuals (1501 men and 1135 women) whose spouses were diagnosed with cancer for the first time between 1992 and 2003.[16] The most common cancer sites for male spouses are prostate (16.7%) and lung and bronchus (12.7%), and the most common cancer sites for female spouses are breast (39.2%) and cervix uteri (11.8%), see Table 1. The control sample consists of individuals whose spouse was not diagnosed with cancer at any time from 1992 to 2003. In the control sample, individuals satisfying the above sample restrictions in each year $t = 0$ may appear more than once because we select a control sample for each year between 1992 and 2003. The total number of observations from 1992 to 2003 in the control sample is 932,970 (450,763 for men and 482,207 for women). This is the pooled number of observations for 100,449 individuals (48,583 men and 51,866 women).

We conduct the analysis separately for men and women because male and female age profiles of labor supply differ, and they may have different earnings processes. The sample is not restricted to individuals who worked prior to their spouse's cancer diagnosis to allow for the inclusion of all possible changes in employment due to a spousal health shock.

Table 2 shows differences in the characteristics of the treatment and control samples for men (columns (1) and (2)) and women (columns (6) and (7)). We observe the same patterns for both men and women. The most notable difference is in the average ages of the treatment and control samples.[17] Individuals in the treatment sample are older than those in the control sample. The age differences also seem to be associated with differences in other characteristics. Individuals in the treatment sample are less likely to work but, on average, their annual earnings and total family income are higher than those of their counterparts in the control sample. They have fewer children at home and the youngest child in the treatment sample is generally older than in the control sample. For both men and women, there are also fewer members of visible minorities among the treatment sample than among the control sample. Not surprisingly, individuals' age is positively correlated with the probability of their spouse's cancer diagnosis and their own labor supply. However, other differences in the characteristics of the treatment and control samples, such as the number of children and family income, may also be associated with individuals' labor supply decisions.

In order to balance the covariates shown in Table 2 between treatment and control samples, we first apply CEM to the data before estimating the effect of spousal cancer diagnoses on individuals' employment and earnings. The next section describes our matching and estimation approaches.

4. Empirical strategy

4.1. Coarsened exact matching

To balance treatment and control group covariates, we use CEM, a multidimensional exact matching algorithm applied to cells generated by dividing continuous variables into discrete intervals or by

[10] We cannot completely rule out that a divorce and a marriage happened in the same calendar year because the linked tax data have longitudinal identifiers only for tax filing individuals but not their spouses. However, it is highly unlikely that an individuals becomes divorced and remarries in the same year. Canadian tax laws recognize legal marriages and common-law unions. For an individual to be legally married to two spouses in the same year would imply that he or she divorces and remarries in the same calendar year. To be recognized as a common-law union by the Canadian tax system, couples must live in a conjugal relationship lasting at least 12 continuous months. This 12-month cohabitation period makes a separation and an entry into a common-law relationship in the same calendar year virtually impossible. Individuals can also enter a common-law union if they have a child together. However, the average age in our sample is 48, so this is also unlikely.

[11] We conduct robustness checks where widows and widowers are excluded from the estimation sample.

[12] At this stage, 112,410 continuous marriage spells were identified. 4489 individuals with earnings below 0.25% and above 99.75% of the earnings distribution in any year were dropped from the sample to remove the influence of positive and negative outliers (extreme earners) in the tax data. The bottom and top earnings cut-off points are –$8818.9 for 0.25% and $377,701 for 99.75%.

[13] One possible concern is that a cancer diagnosis may lead to marital dissolution, so marriage may be endogenous to health shocks. We cannot test this hypothesis directly in our sample because of data limitations. However, Syse and Kravdal (2007) find no significant effect of a cancer diagnosis on divorce using Norwegian data.

[14] This study's data allow for individuals in treatment and control samples to be diagnosed with cancer in later years. The number of individuals diagnosed with cancer within the spousal post-cancer study period in the final matched treatment sample is 34 (21 males and 13 females).

[15] Annual earnings are defined as the sum of all wages and salaries received in a given year plus the net self-employment income for that year. All monetary amounts are in 2010 dollars.

[16] Of the 3665 individuals initially identified as having spouses diagnosed with cancer for the first time from 1992 to 2003, 864 were dropped from the sample because of age restrictions in the year of the spouse's cancer diagnosis. While this number seems large, this is due to the non-linear relationship between age and cancer diagnoses. An additional 88 were dropped because their marriage spells ended in the year of the diagnosis; 43 were dropped because they were diagnosed with cancer before their spouse; 22 were dropped because they died within the next five years, and 12 were dropped because their work status could not be determined for the previous two years.

[17] Age is the only variable for which the normalized difference exceeds the rule-of-thumb value of 0.25 (Imbens and Rubin, 2015). The normalized difference for covariate X is defined as $(\bar{X}_t - \bar{X}_c)/\sqrt{S_t^2 + S_c^2}$, where $\bar{X}_t$ and $\bar{X}_c$ are the sample means and S_t^2 and S_c^2 are the sample variance for the treatment and control groups, respectively.

Table 1
Distribution of spousal cancer sites for men and women.

	Men (wives' diagnoses)		Women (husbands' diagnoses)	
	Pre-matched	Matched	Pre-matched	Matched
High survival category				
Thyroid	4.13	4.18	2.64	2.60
Prostate	0	0	16.65	17.21
Testis	0	0	2.47	2.60
Skin melanoma	4.13	4.44	5.99	6.28
Breast	39.17	39.41	–	–
Corpus uteri	4.4	3.85	0.00	0.00
Hodgkin lymphoma	0.67	0.84	1.23	1.41
Medium survival category				
Chronic lymphocytic leukemia	–	–	0.79	0.97
Cervix uteri	11.79	11.46	0.00	0.00
Bladder (including in situ)	1.07	1.09	5.20	5.74
Kidney and renal pelvis	1.4	1.51	3.96	4.44
Soft tissue	0.6	0.59	1.06	1.08
Larynx	–	–	1.06	0.97
Rectum	2.33	2.34	5.90	5.63
Colon	3.86	4.1	7.75	7.25
Non-Hodgkin lymphoma	3.13	3.01	6.26	6.28
Oral (buccal cavity and pharynx)	1.33	1.34	3.96	3.79
Low survival category				
Ovary	3.33	3.01	0.00	0.00
Multiple myeloma	0.87	0.67	1.67	1.62
Leukemia (excluding CLL)	1.33	1.26	1.50	1.30
Stomach	0.53	0.5	2.73	2.71
Brain	1.4	1.42	2.82	2.71
Liver	–	–	–	–
Lung and bronchus	5.86	6.69	12.69	12.45
Esophagus	–	–	1.06	1.08
Pancreas	–	–	1.41	1.62
Others	7.53	7.28	9.87	9.31
Total number of spousal cancer diagnoses	1501	1195	1135	924

Note: Distribution in percent of all spousal cancer diagnoses. –: frequency suppressed to comply with Statistics Canada data disclosure rules.

regrouping categorical variables into fewer coarsened categories.[18] The CEM algorithm creates a set of strata with the same coarsened values of matching variables; it also restricts the matched data to areas of common empirical support by trimming unmatched observations from both the treated and control samples. For each stratum j, the CEM algorithm returns weights $n_t^j/n_c^j \times N_c/N_t$ that can be used to reweight observations in the matched control sample and balance the empirical distributions of the matching variables between the two samples.[19] Later, we use these matching weights in the regression analysis of work status, annual earnings, and family income.[20] Since CEM sets the matching weight to 1 in the treatment group, our estimates are to be interpreted as average treatment effects on the treated (ATET).

Increasing the number of matching dimensions by adding extra matching variables decreases the probability of finding matches between the treatment and control because the CEM requires exact matching in all coarsened categories of the matching variables. Therefore, it is ideal to have a relatively small set of matching variables that is sufficient to control for observable differences between the treatment and control samples and, at the same time, small enough to reduce the number of unmatched individuals from the treatment sample. Here, the set of matching variables includes individuals' own and family characteristics, but spouses' characteristics are not included in the matching variables.[21] The personal and family characteristics of individuals chosen as matching variables are likely to be direct determinants of individuals' labor market outcomes before and after their spouses' cancer diagnoses. Matching on these variables, therefore, controls for selection on observables in the individuals' labor market outcomes.

Individuals in the treatment and control samples are matched using pooled data from 1992 to 2003, with calendar years used as one of the matching variables. The matching variables also include age (coarsened to five-year intervals), education (four categories), visible minority status (coarsened to three categories), and province of residence. Family characteristics included in the matching variables are the number of children in the family (coarsened to four categories), age of the youngest child (coarsened to three categories), and total family income in the previous year (coarsened

[18] The CEM method reduces all imbalances related to first and higher moments, nonlinearities, interactions, and other multidimensional distributional differences between the treated and control groups. See Iacus et al. (2011, 2012) for a detailed discussion of CEM properties and a comparison with other matching methods. We obtain similar results by applying propensity score weighting (see Online Appendix C).

[19] Weights assigned to the matched control sample will be equal to the ratio of the treatment sample size (n_t^j) to the control sample size (n_c^j) in each stratum j multiplied by the ratio of the total size of the control sample (N_c) to the total size of the treatment sample (N_t). The weights for the matched treatment sample are equal to 1. The weights for unmatched records are set to 0.

[20] Ho et al. (2007) demonstrate that preprocessing raw data using matching procedures turns parametric models into a much more reliable tool for the empirical analysis of causal effects; in particular, estimates of causal effects are less sensitive to the choice of model specification. One of the proven properties of the CEM is that it reduces the degree of model dependence (Iacus et al., 2012). Model dependence is defined by how much the predicted value of the outcome variable varies as a function of the statistical model for a given set of explanatory variables (Ho et al., 2007). One of the key reasons for matching is to eliminate model dependence; however, it has never been proven for any of the other matching methods commonly used in various analyses. For a detailed discussion, see Iacus et al. (2011).

[21] Spouses' observable characteristics associated with cancer incidence such as age, education and visible minority status are also correlated with those of individuals because of assortative mating. Individuals' own characteristics are more likely to be direct determinants of their labor market outcomes before and after their spouses' cancer diagnoses. In a robustness check in Online Appendix B, we also add spouses' pre-diagnosis employment status in the CEM weights.

Table 2
Summary statistics for pre-matched and matched samples.

	Men					Women				
	Pre-matched sample			Matched sample		Pre-matched sample			Matched sample	
	Treatment group (1)	Control group (2)	Normalized difference (3)	Treatment group (4)	Control group (5)	Treatment group (6)	Control group (7)	Normalized difference (8)	Treatment group (9)	Control group (10)
Age (mean) at $t = 0$	48.365	45.221	0.301	48.328	48.232	48.211	42.993	0.539	48.084	47.927
Coarsened age at $t = 0$										
25–29	–	–	0.053	–	–	–	–	0.114	–	–
30–34	–	–	0.094	–	–	–	–	0.242	–	–
35–39	0.091	0.166	0.159	0.085	0.085	0.076	0.209	0.274	0.079	0.079
40–44	0.153	0.218	0.119	0.155	0.155	0.160	0.236	0.135	0.160	0.160
45–49	0.211	0.216	0.008	0.222	0.222	0.256	0.208	0.080	0.262	0.262
50–54	0.256	0.182	0.127	0.259	0.259	0.300	0.149	0.259	0.300	0.300
55–59	0.241	0.133	0.197	0.232	0.232	0.178	0.063	0.253	0.168	0.168
Highest level of schooling										
No high school	0.243	0.238	0.007	0.239	0.239	0.280	0.225	0.090	0.273	0.273
hs-w/wo trades certificate	0.428	0.425	0.004	0.444	0.444	0.409	0.409	0.000	0.440	0.440
Postsecondary non-university	0.147	0.158	0.020	0.131	0.131	0.188	0.218	0.053	0.174	0.174
University degree	0.183	0.179	0.006	0.187	0.187	0.123	0.148	0.052	0.113	0.113
Visible minority										
No minority	0.928	0.914	0.036	0.967	0.967	0.940	0.919	0.058	0.974	0.974
Asian	0.049	0.060	0.036	0.027	0.027	0.042	0.060	0.056	0.022	0.022
Other	0.023	0.025	0.009	0.007	0.007	0.018	0.022	0.020	0.004	0.004
Province/territory at $t = 0$										
Newfoundland	0.022	0.023	0.003	0.009	0.009	0.026	0.031	0.018	0.022	0.022
Prince Edward Island	–	0.005	0.012	–	–	0.004	0.006	0.012	0.000	0.000
Nova Scotia	0.048	0.033	0.052	0.037	0.037	0.033	0.032	0.002	0.027	0.027
New Brunswick	0.029	0.027	0.008	0.022	0.022	0.026	0.026	0.003	–	–
Quebec	0.268	0.259	0.015	0.299	0.299	0.244	0.236	0.014	0.264	0.264
Ontario	0.303	0.355	0.078	0.340	0.340	0.353	0.352	0.002	0.392	0.392
Manitoba	0.031	0.042	0.039	0.024	0.024	0.043	0.042	0.004	0.038	0.038
Saskatchewan	0.037	0.037	0.000	0.028	0.028	0.028	0.036	0.032	0.025	0.025
Alberta	0.118	0.092	0.060	0.119	0.119	0.085	0.097	0.028	0.078	0.078
British Columbia	0.127	0.108	0.040	0.118	0.118	0.117	0.109	0.018	0.108	0.108
North West Territories	–	0.005	0.048	0.000	0.000	0.004	0.006	0.014	–	–
Yukon	–	0.002	0.022	0.000	0.000	0.000	0.001	0.036	0.000	0.000
Missing	0.009	0.012	0.024	–	–	0.034	0.027	0.032	0.027	0.027
Year at $t = 0$ (year of spousal cancer diagnosis)										
1992	0.088	0.105	0.041	0.090	0.090	0.067	0.105	0.095	0.071	0.071
1993	0.079	0.103	0.060	0.081	0.081	0.087	0.103	0.038	0.094	0.094
1994	0.078	0.098	0.051	0.080	0.080	0.083	0.098	0.038	0.082	0.082
1995	0.079	0.094	0.037	0.072	0.072	0.093	0.094	0.001	0.087	0.087
1996	0.089	0.089	0.001	0.089	0.089	0.076	0.089	0.035	0.070	0.070
1997	0.075	0.085	0.025	0.075	0.075	0.081	0.085	0.010	0.079	0.079
1998	0.095	0.081	0.036	0.101	0.101	0.103	0.081	0.054	0.091	0.091
1999	0.099	0.077	0.054	0.100	0.100	0.092	0.077	0.038	0.101	0.101
2000	0.091	0.073	0.046	0.088	0.088	0.080	0.073	0.019	0.089	0.089
2001	0.085	0.069	0.041	0.081	0.081	0.094	0.069	0.064	0.095	0.095
2002	0.073	0.065	0.022	0.074	0.074	0.065	0.065	0.001	0.060	0.060
2003	0.070	0.061	0.026	0.068	0.068	0.078	0.061	0.048	0.081	0.081

Table 2 (*Continued*)

	Men					Women				
	Pre-matched sample			Matched sample		Pre-matched sample			Matched sample	
	Treatment group (1)	Control group (2)	Normalized difference (3)	Treatment group (4)	Control group (5)	Treatment group (6)	Control group (7)	Normalized difference (8)	Treatment group (9)	Control group (10)
Number of children at $t=-1$										
No dependent	0.292	0.196	0.159	0.320	0.320	0.321	0.192	0.210	0.338	0.338
1	0.268	0.232	0.060	0.258	0.258	0.243	0.227	0.026	0.224	0.224
2	0.310	0.385	0.112	0.310	0.310	0.314	0.389	0.112	0.323	0.323
3+	0.129	0.187	0.113	0.112	0.112	0.122	0.191	0.134	0.116	0.116
Age of the youngest child at $t=-1$										
No dependent	0.292	0.196	0.159	0.320	0.320	0.321	0.192	0.210	0.338	0.338
Age 0–6	0.147	0.237	0.163	0.129	0.129	0.078	0.240	0.320	0.069	0.069
Age 7–17	0.331	0.411	0.117	0.325	0.325	0.338	0.414	0.110	0.338	0.338
Age 18+	0.230	0.157	0.132	0.227	0.227	0.263	0.154	0.191	0.255	0.255
Total family income at $t=-1$ (mean)	100,339.653	94,046.486	0.080	104,531.840	102,595.709	102,319.648	98,389.221	0.031	105,908.821	105,471.984
Quintiles of family income at $t=-1$										
Lowest	0.175	0.2	0.046	0.148	0.148	0.192	0.2	0.014	0.171	0.171
Second	0.175	0.2	0.046	0.176	0.176	0.189	0.2	0.019	0.184	0.184
Third	0.215	0.2	0.025	0.209	0.209	0.181	0.2	0.033	0.184	0.184
Fourth	0.205	0.2	0.009	0.213	0.213	0.204	0.2	0.008	0.208	0.208
Highest	0.231	0.2	0.054	0.254	0.254	0.233	0.2	0.056	0.253	0.253
Share of earnings in the total family income at $t=-1>50\%$	0.568	0.613	0.064	0.609	0.609	0.123	0.134	0.233	0.107	0.107
Working at $t=-1$	0.931	0.938	0.020	0.960	0.960	0.791	0.808	0.029	0.834	0.834
Working at $t=-2$	0.932	0.943	0.033	0.971	0.971	0.804	0.809	0.010	0.844	0.844
Earnings at $t=-1$ (mean)	54,664.764	53,125.769	0.028	59,118.388	57,347.030	26,442.540	26,255.395	0.005	28,612.150	27,883.037
Earnings at $t=-2$ (mean)	55,139.961	53,091.717	0.038	59,522.453	57,746.236	26,700.395	25,788.135	0.025	28,802.635	27,717.043
Spouse working at $t=-1$	0.813	0.803	0.019	0.827	0.820	0.907	0.933	0.068	0.921	0.930
Spouse working at $t=-2$	0.815	0.804	0.020	0.831	0.821	0.918	0.939	0.056	0.929	0.938
Spousal earnings at $t=-1$ (mean)	27,579.803	25,895.680	0.044	28,301.061	28,629.385	53,106.047	56,541.649	0.036	54,374.271	57,259.229
Spousal earnings at $t=-2$ (mean)	27,750.081	25,439.347	0.061	28,610.633	28,063.469	54,053.505	56,174.215	0.023	55,562.033	58,177.100
Total number of observations	1501	450,763		1195	14,365	1135	482,207		924	13,144

Note: Pre-matched sample consists of all individuals, matched sample consists of individuals for whom a match in the treatment or control group could be found. The sample averages for the matched sample are weighted by the CEM weights (see text for details). – indicates suppressed result due to Statistics Canada disclosure policies.

to quintiles). The share of the individual's earnings in total family income in the previous year (coarsened to two categories) is also included as a matching variable to account for the individual's earnings contribution to total family income prior to the spouse's cancer diagnosis. To account for individuals' attachment to the labor market prior to their spouse's cancer diagnosis, the first and second lags of their employment status (i.e. working or not working) are also included as matching variables.

Columns (4), (5), (9), and (10) in Table 2 show the characteristics of the matched samples for men and women in the treatment and control samples, respectively. Not all individuals in the treatment sample can be matched to comparable individuals in the control sample. For 306 men (20.4%) and 211 women (18.6%) in the treatment sample, no comparable matches can be found in the control sample. Those in the treatment sample who did not work in the two years prior to their spouse's cancer diagnosis have a smaller chance of being matched to someone in the control sample than those who worked in those two years. Consequently, the matched individuals in the treatment sample have higher average individual earnings and total family income than individuals in the pre-matched treatment sample as shown in columns (1) and (6) of Table 2. Individuals not identified as a visible minority in the treatment sample are more likely to be matched with someone from the control sample than those identified as a visible minority. However, other characteristics such as average age, education, and age of the youngest child, and types of spousal cancer are similar for the pre- and post-matched treatment samples (see Table 1 for the distributions of cancer sites).

Finally, comparing columns (4) and (5) for men and (9) and (10) for women, respectively, in Table 2 shows how similar the characteristics of the matched treatment and the matched CEM-weighted control samples are. There are virtually no differences in characteristics between the two matched samples when matching weights are applied.

As the final step, we construct a regression sample for the matched individuals in the treatment and control samples. We denote the year of the spouse's first cancer diagnosis by $\tau = \{1992, \ldots, 2003\}$ and the number of years elapsed from the year of the diagnosis by t, so $t = 0$ in year τ. In the matched control sample, t can be equal to 0 in any year from 1992 to 2003 depending on the τ in the matched treatment sample, so that $t = 0$ is the same year in both samples. Individuals' longitudinal profiles are constructed from $t = -5$ to $t = 5$ as long as these time periods fall within individuals' continuous marriage spells.[22]

4.2. Generalized difference-in-differences regressions with individual fixed effects

To control for time-invariant unobservable individual characteristics potentially correlated with individuals' labor market outcomes and their spouses' health, we apply a DID model with individual fixed effects.[23] The effects of one spouse's cancer diagnosis on the other spouse's labor market outcomes are allowed to vary over time (generalized DID). The results from these regressions can be interpreted as causal effects if the treatment variable, in this case cancer diagnoses, is a strictly exogenous health shock.

We combine matching and DID by estimating a fixed effects model with interactions between Treatment group (C_i) and time (T_{it}) dummies (Jacobson et al., 1993; Boden and Galizzi, 2003; Hijzen et al., 2010) and applying the CEM matching weights in the estimation as follows:

$$Y_{it} = \alpha_i + X'_{it}\beta + \sum_{k=-5}^{5} \gamma^k T^k_{it} + \sum_{k=-5}^{5} \delta^k C_i T^k_{it} + u_{it}, \tag{1}$$

where Y_{it} is the labor market outcome variable (work status, annual earnings or family income) for individual i in time period t. α_i is the time invariant individual fixed effect. Vector X_{it} consists of individuals' time-varying characteristics. Each T^k_{it} is a dummy variable equal to 1 if $t = k$ and 0 otherwise. C_i is a dummy equal to 1 if the individual's spouse was diagnosed with cancer and 0 otherwise (treatment indicator). The reference period is $t = -1$, which is the year prior to the year of the spouse's cancer diagnosis. Hence, δ^k is an estimate of the difference in Y_{it} between treatment and control groups in different time periods t relative to the difference in Y_{it} between the two groups at $t = -1$. In other words, δ^k is the generalized DID effect of spousal cancer on individuals' labor market outcomes for k years after the cancer diagnosis. Specifically, δ^k is an estimate for the ATET due to the CEM weights in regression (1).

In order for the DID parameters to have a causal interpretation, the pre-treatment trends of the outcome variables have to be similar between treatment and control groups. Hence, the δ^k have to be close to 0 and not significant for $k < -1$. Since data on individuals' labor market outcomes before the (placebo) cancer diagnosis are available, we can easily test this common trends assumption. See Section 5.1 for graphical evidence for this assumption.

Individual panels are unbalanced because the start and end years of the marriage spells can differ across individuals. However, all marriage spells are continuous due to the sample construction. The length of individual panels varies from 4 to 11 consecutive time periods. The sample restrictions described in Section 3 imply that the minimum number of time periods in individual panels is 4 since each panel includes at least the time periods $-2 \le t \le 1$. One male individual in the treatment group and five people (one male and four females) in the control group are present in the sample for only 4 time periods. Overall, we observe 83% of individuals in the treatment group (82% males, 86% females) and 92% in the control group (92% males, 93% females) for the maximum of 11 years.

In addition to the generalized DID regression (1), we also run basic DID regressions that restrict the effect of spousal cancer diagnoses to be constant over time:

$$Y_{it} = \alpha_i + X'_{it}\beta + \gamma P_{it} + \delta C_i P_{it} + u_{it}, \tag{2}$$

where δ is the coefficient of interest and P_{it} is a post-treatment dummy equal to 1 for $t \ge 0$ and 0 otherwise. We use regression (2) to estimate heterogeneous effects by severity of the diagnosis and by whether the cancer can be detected in routine screenings. Because of smaller sample sizes, there is not enough statistical power to estimate time-specific effects δ^k. As in regression (1), we apply CEM weights to regression (2). In combination with individual fixed effects, the coefficient δ can therefore be interpreted as a causal parameter and is an estimate for the ATET of spousal cancer diagnoses.

5. Results

5.1. Graphical evidence

Before discussing the regression results, we present graphs depicting annual averages of individuals' labor market outcomes and family income for the treatment group and the control group. These averages are plotted over time relative to the year when the (placebo) cancer diagnosis occurred ($t = 0$) and separately for

[22] These reconstructed panel data do not constitute a balanced panel. The lengths of the spells vary from 4 to 11 consecutive years. See Section 4.2 for more details.

[23] Couples' observable characteristics such as age, education and visible minority status can be correlated with each other (assortative mating). Furthermore, spouses' unobservable health behavior, such as smoking, diet and exercise, and health status may also be correlated.

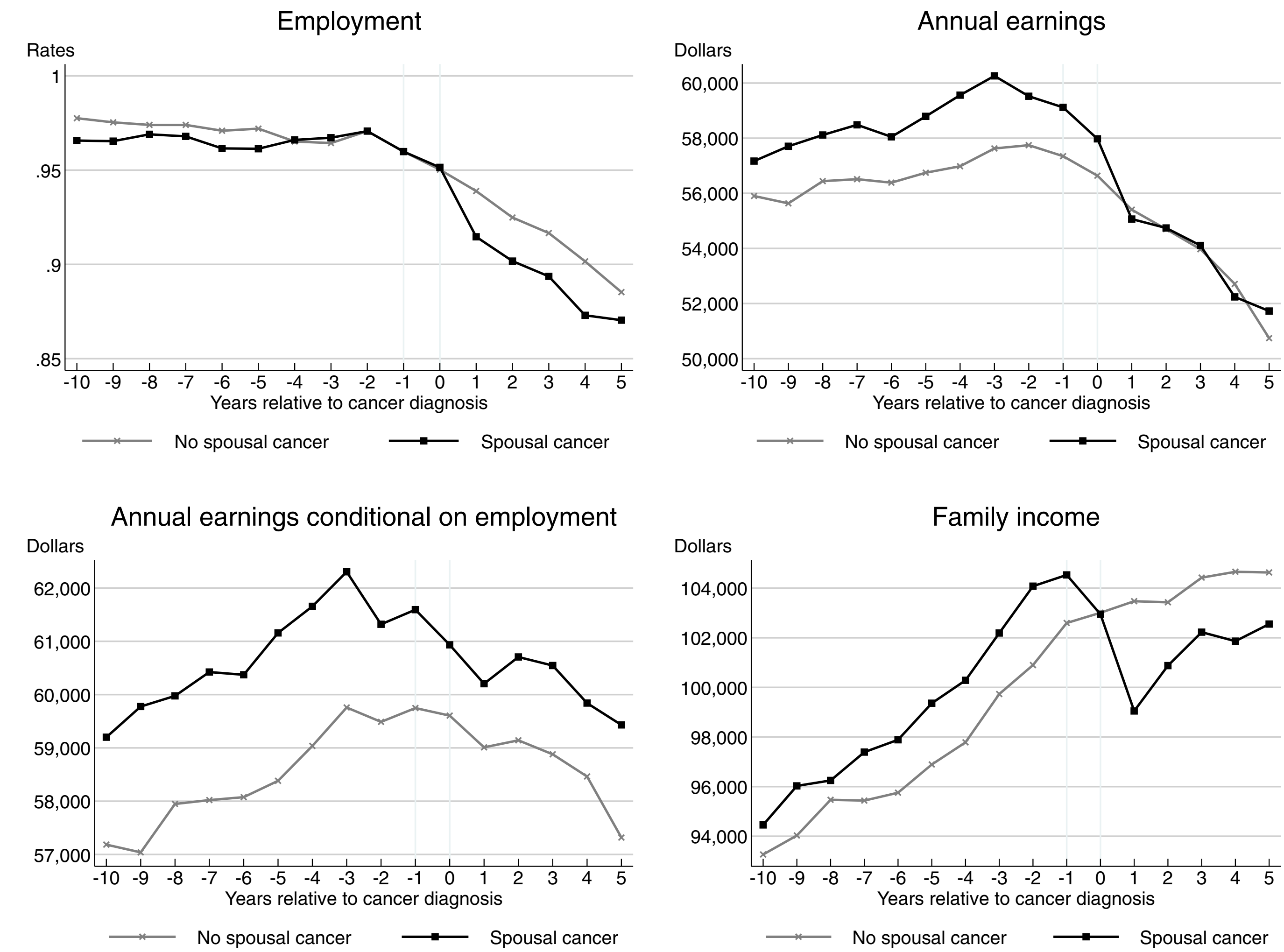

Fig. 1. Employment, earnings, and family income for men.

men and women.[24] We also assess the common trends assumption that is necessary for the causal interpretation of the DID estimator. We consider the following four outcomes: employment (defined by non-zero earnings in a given year), annual earnings, annual earnings conditional on employment, and total family income.[25] All outcome variables are weighted by the CEM weights.

The top left panel of Fig. 1 shows clear evidence for a decrease in men's employment after their wives are diagnosed with cancer. One year after the diagnosis, average employment is between two and three percentage points lower among the treatment group than the control group. This difference remains mostly stable during the five-year follow-up period. To assess the common trends assumption, we inspect employment rates across treatment and control groups before the cancer diagnosis. Weighted employment rates in the two years before the diagnosis are exactly equal because these two variables enter the CEM weights. Going back in time up to 10 years prior to the diagnosis also shows closely aligned trends. In particular, there is no evidence for a dip in employment among the treated, which may have indicated potential endogeneity of the wife's cancer diagnosis with respect to the husband's employment status in the pre-diagnosis period.

The top right panel of Fig. 1 shows unconditional annual earnings (i.e. they include men who were not employed in a given year). While earnings prior to the cancer diagnosis are higher among men whose wife is subsequently diagnosed with cancer, the trends are roughly similar, and slightly increasing, for both groups. Employment and earnings of men and women in both treatment and control groups follow an inverse U-shaped pattern. The observed pattern reflects the average age in our sample (the average age at the time of the diagnosis is 48) and the fact that hours worked and annual earnings generally start to decline when individuals enter their late 40s.[26] After the cancer diagnosis, earnings of the treated group decline relative to control-group earnings. Hence, the associated DID estimate is negative. With average annual earnings of around \$59,000 in the matched treatment group before the cancer diagnosis, this decline amounts to about 3% of annual earnings. Comparing this finding with the bottom left panel of Fig. 1 shows that a large part of the decline in earnings is due to a decrease in

[24] As in the remainder of this section, results for men are those where the wife was diagnosed with cancer, and results for women are those where the husband was diagnosed with cancer.

[25] Annual earnings and income variables are obtained from individuals' tax returns. Family income is total earned and unearned income of all family members before taxes, including government transfers. After-tax family income would be a better measure of the impact of spousal cancer diagnoses on families' financial well-being than before-tax family income. However, after-tax income is not available for all study periods in the data.

[26] Altonji (1986) estimates an inverse U-shaped pattern in a dynamic labor supply model.

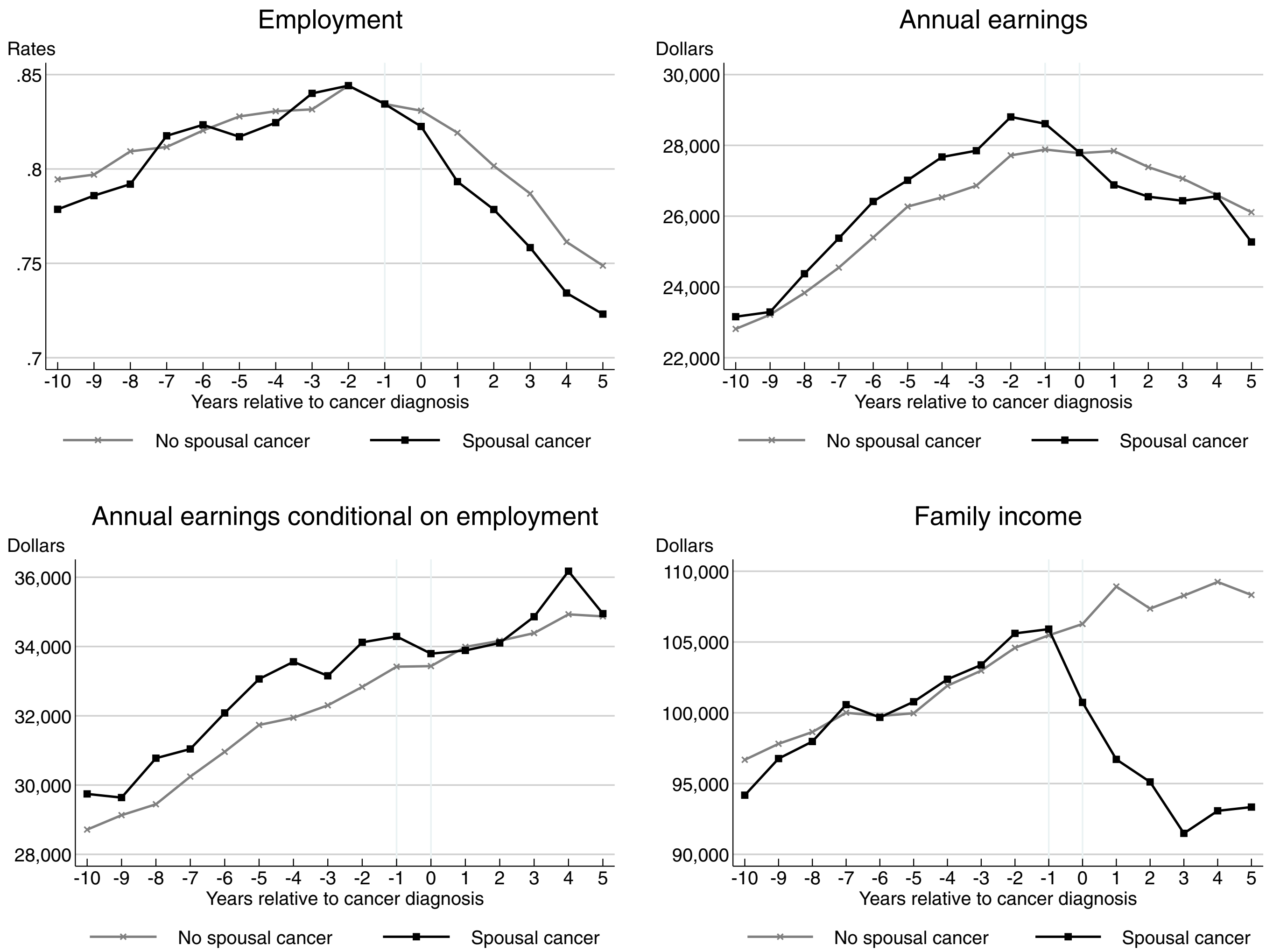

Fig. 2. Employment, earnings, and family income for women.

labor supply at the extensive margin. When only men who work are included, the DID estimate of the decline in annual earnings is about $1000. Again, men in the treatment group have higher conditional earnings before the diagnosis, but the pre-diagnosis trend is similar to control-group earnings. Hence, the graphical evidence implies that the caregiver effect dominates the added-worker effect among men whose wives were diagnosed with cancer.

Next, we consider total family income, i.e. the joint income of men, their wives who were diagnosed with cancer, and possibly other household members. We find a substantial drop in total income among the treatment group following the wife's cancer diagnosis. Two years after the diagnosis, this decline reverses slightly, but even five years after the cancer diagnosis, family income is about $4000 lower among the treated group compared with the control group relative to the pre-diagnosis income difference. Finally, we also verify the parallel trends assumption successfully for this outcome variable.

Fig. 2 contains the same set of results for women. The top left panel indicates that women reduce their employment by between two and three percentage points after their husbands are diagnosed with cancer. Annual earnings among women in the treatment group decrease by about $2000 compared with the control group. Given the lower earnings levels among women, this drop constitutes a larger relative earnings decline for women than for men. We find a smaller decrease for earnings conditional on employment than for unconditional earnings, implying that women reduce their labor supply mostly at the extensive margin. Overall, the graphical results show that the caregiver effect dominates among women as well as among men. Finally, family income drops substantially after husbands' cancer diagnoses (bottom right panel of Fig. 2). The negative effect on family income increases over time and reaches about $15,000 (15% of average annual family income) three years after husbands' cancer diagnoses. Hence, a husband's cancer diagnosis has substantial implications for the financial situation of affected families.

Using the graphs in Fig. 2, we assess the common trends assumption for women's labor market behavior. While the pre-diagnosis employment trend is noisier for the female treatment group than for the control group, this assumption appears to be valid. The two earnings measures also have parallel trends in the treatment and control groups before the (placebo) cancer diagnosis. For family income, annual averages are similar between treatment and control groups before $t = 0$. This result is remarkable since only family income in the year prior to the cancer diagnosis, along with number of children and the age of the youngest child, enters the CEM weights, but the pre-trends are very close for at least seven years before the diagnosis. Hence, for our sample, the variables that enter the CEM algorithm are sufficient to control for observable differences between the treatment and control groups for the extended pre-diagnosis period.

Table 3
Regression results for the effect of wives' cancer diagnoses on men's employment.

	(1)	(2)	(3)	(4)	(5)	(6)
δ: effects of spousal cancer – Eq. (1)						
$k = -5$	−0.011	−0.011	−0.011	−0.008	−0.006	−0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$k = -4$	0.000	0.000	0.000	−0.001	0.001	0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$k = -3$	0.002	0.002	0.002	0.002	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$k = -2$	0.000	0.000	0.000	0.000	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$k = -1$ (reference year)						
$k = 0$ (diagnosis year)	0.001	0.002	0.001	0.001	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$k = +1$	−0.024**	−0.023**	−0.021**	−0.025**	−0.024**	−0.020*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$k = +2$	−0.023**	−0.022*	−0.017^	−0.024**	−0.024**	−0.015^
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$k = +3$	−0.022*	−0.020*	−0.014	−0.022*	−0.022*	−0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$k = +4$	−0.030**	−0.028*	−0.022*	−0.031**	−0.030**	−0.018^
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$k = +5$	−0.017	−0.014	−0.008	−0.018	−0.018^	−0.007
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Additional cancer diagnosis		X				X
Lagged Widowhood			X			X
Non-labor income				X	X	X
Number of children					X	X
Self-employment in reference period					X	X
Disability benefits or tax credits					X	X
N	167,832	167,832	167,832	166,625	166,625	166,625

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
^ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

5.2. Regression results

In this section, we present the following sets of results for men's and women's employment (using a dummy variable that equals one if an individual has non-zero annual earnings during a given year), annual earnings, and family income: generalized DID regressions with time-varying effects (Tables 3–8 show the main results); robustness checks with samples that are restricted by the survival status of the spouse (Table 9); and DID results that allow for heterogeneity by severity of the cancer diagnosis (Table 10) and by whether the cancer could have been detected in a routine screening (Table 11).[27]

5.2.1. Main results

Here, we present the main results from estimating the generalized DID regression (1) separately for men and women.[28] Each regression is estimated first without additional controls and then again with different sets of controls. Table 3 contains the results for men's employment.[29] Column (1) shows that men whose wives were diagnosed with cancer are 2.2–2.4 percentage points less likely to work in the first three years after the diagnosis compared with men whose wives have never been diagnosed with cancer. In the fourth year, this negative effect increases to three percentage points, but no statistically significant effect is present in the fifth year. Overall, these results suggest that men significantly adjust their labor supply at the extensive margin for about the first four years after their wives' cancer diagnosis. After four years, cancer patients have likely recovered or may have passed away, so the need for caregiving is reduced and these husbands return to work.

The regressions in columns (2)–(6) in Table 3 contain results for men's employment with added control variables. Overall, the estimates are stable, but less precise. Column (2) adds an indicator for an additional cancer diagnoses during the five-year follow-up period. While an additional diagnosis has a large negative effect on husbands' employment, this effect is not statistically significant (coefficient not shown). Column (3) controls for lagged widowhood (i.e. an indicator that equals one if the individual's spouse passed away one year before or earlier).[30] Becoming a widower has a large negative but statistically insignificant effect on employment (coefficient not shown). In columns (4) and (5), controls are in place for non-labor income, number of children, and individuals receiving disability benefits.[31] Finally, when all of the above variables in column (6) are controlled for, we find smaller decreases

[27] We also estimate regression (2), i.e. DID regression with time-invariant effects, separately for men and women. The results are in Online Appendix B.

[28] These and all following regressions include individual fixed effects and use CEM weights. All standard errors are clustered at the individual level, which is equivalent to clustering on the family level because one observation is included for each couple and year.

[29] The regression tables only contain the estimates for the DID coefficients. Full regression results are available from the authors on request.

[30] Because of the annual frequency of our data, the lagged widow dummy is used to capture a full year of earnings and family income changes after becoming a widow(er). Widowhood includes all causes of death among spouses. That is, men in the control group (whose wives were not diagnosed with cancer) may become widowed too.

[31] Non-labor income equals total family income minus individual's own earnings. The number of children is categorized as no children, 1 child, 2–3 children, and 4 or more children. Self-employment status is based on having self-employment income from unincorporated businesses in a given year (income from incorporated businesses is reported on the tax form as wages and salaries). Disability benefits are measured by whether the individual received Canada Pension Plan disability benefits (CPPD) or disability tax credits in a given year. These benefits and tax credits

Table 4
Regression results for the effect of wives' cancer diagnoses on men's annual earnings.

	(1)	(2)	(3)	(4)	(5)	(6)
δ: *effects of spousal cancer – Eq. (1)*						
$k = -5$	178.136	174.990	172.416	364.814	254.955	243.834
	(926.765)	(926.766)	(926.850)	(966.038)	(951.490)	(951.473)
$k = -4$	647.903	646.134	645.584	621.085	630.142	625.362
	(800.363)	(800.386)	(800.369)	(804.458)	(794.450)	(794.509)
$k = -3$	849.855	849.277	848.997	795.221	733.322	731.397
	(825.931)	(825.937)	(825.943)	(840.021)	(826.557)	(826.619)
$k = -2$	4.859	4.859	4.859	141.140	−33.893	−33.295
	(596.819)	(596.820)	(596.822)	(602.412)	(601.292)	(601.337)
$k = -1$ (reference year)						
$k = 0$ (diagnosis year)	−435.020	−374.356	−435.020	−612.337	−550.489	−486.059
	(590.864)	(592.313)	(590.868)	(595.190)	(597.396)	(598.693)
$k = +1$	−2111.390*	−1990.062*	−1842.396*	−2594.977**	−2622.379**	−2170.408*
	(873.198)	(877.342)	(877.936)	(880.154)	(874.497)	(881.731)
$k = +2$	−1993.458*	−1825.611$^{\wedge}$	−1380.116	−2313.540*	−2384.956*	−1466.459
	(1005.925)	(1011.304)	(1022.897)	(991.473)	(991.437)	(1,007.228)
$k = +3$	−1831.738$^{\wedge}$	−1591.309	−1042.842	−2094.360$^{\wedge}$	−2207.291*	−998.357
	(1095.917)	(1103.611)	(1111.864)	(1074.480)	(1074.257)	(1,089.338)
$k = +4$	−2546.762*	−2274.372$^{\wedge}$	−1707.019	−2832.873*	−2946.032*	−1641.819
	(1228.601)	(1234.837)	(1252.031)	(1200.361)	(1206.337)	(1227.779)
$k = +5$	−672.939	−392.370	184.293	−1049.854	−1117.810	216.080
	(1334.154)	(1340.789)	(1369.751)	(1296.023)	(1307.527)	(1338.573)
Additional cancer diagnosis		X				X
Lagged widowhood			X			X
Non-labor income				X	X	X
Number of children					X	X
Self-employment in reference period					X	X
Disability benefits or tax credits					X	X
N	167,832	167,832	167,832	166,625	166,625	166,625

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
$^{\wedge}$ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 5
Regression results for the effect of wives' cancer diagnoses on men's family income.

	(1)	(2)	(3)	(4)
δ: *effects of spousal cancer – Eq. (1)*				
$k = -5$	−193.457	−195.411	−194.331	−110.765
	(1266.303)	(1266.423)	(1266.208)	(1265.661)
$k = -4$	290.143	289.950	290.391	376.218
	(1146.562)	(1146.644)	(1146.512)	(1145.729)
$k = -3$	263.614	263.045	263.828	313.989
	(1144.189)	(1144.221)	(1144.179)	(1142.642)
$k = -2$	879.818	878.922	880.401	909.003
	(950.035)	(950.065)	(950.019)	(949.623)
$k = -1$ (reference year)				
$k = 0$ (diagnosis year)	−1182.440	−1371.809	−1251.314	−923.442
	(958.691)	(956.684)	(958.344)	(960.026)
$k = +1$	−4408.536***	−4903.173***	−4328.716***	−3735.748**
	(1273.461)	(1267.230)	(1273.870)	(1281.596)
$k = +2$	−2380.738$^{\wedge}$	−3000.669*	−2000.923	−1790.669
	(1318.710)	(1328.243)	(1323.633)	(1321.976)
$k = +3$	−1645.935	−2267.298	−1119.145	−1065.668
	(1522.979)	(1532.048)	(1532.202)	(1522.170)
$k = +4$	−2463.894	−3072.066$^{\wedge}$	−1904.179	−1918.319
	(1602.354)	(1627.109)	(1627.503)	(1603.411)
$k = +5$	−856.109	−1409.221	−331.512	−471.001
	(1735.811)	(1763.498)	(1760.460)	(1734.978)
Widowhood		X		
Lagged widowhood			X	
Family size	X	X	X	X
Disability benefits or tax credits				X
N	166,625	166,625	166,625	166,625

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
$^{\wedge}$ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 6
Regression results for the effect of husbands' cancer diagnoses on women's employment.

	(1)	(2)	(3)	(4)	(5)	(6)
δ: effects of spousal cancer – Eq. (1)						
$k = -5$	−0.011	−0.011	−0.011	−0.015	−0.014	−0.014
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$k = -4$	−0.005	−0.005	−0.005	−0.005	−0.005	−0.005
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$k = -3$	0.009	0.009	0.009	0.009	0.007	0.007
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$k = -2$	0.000	0.000	0.000	0.000	−0.002	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$k = -1$ (reference)						
$k = 0$ (the year of diagnoses)	−0.008	−0.008	−0.008	−0.008	−0.007	−0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
$k = +1$	−0.026*	−0.025*	−0.024*	−0.025*	−0.024*	−0.024*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
$k = +2$	−0.023^	−0.022^	−0.019	−0.022^	−0.024^	−0.023^
	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
$k = +3$	−0.028^	−0.027^	−0.023	−0.027^	−0.028^	−0.027^
	(0.015)	(0.015)	(0.016)	(0.015)	(0.014)	(0.016)
$k = +4$	−0.025	−0.024	−0.020	−0.024	−0.025	−0.024
	(0.016)	(0.016)	(0.017)	(0.016)	(0.015)	(0.017)
$k = +5$	−0.023	−0.022	−0.017	−0.022	−0.021	−0.020
	(0.017)	(0.017)	(0.018)	(0.017)	(0.016)	(0.018)
Additional cancer diagnosis		X				X
Lagged widowhood			X			X
Non-labor income				X	X	X
Number of children					X	X
Self-employment in reference period					X	X
Disability benefits or tax credits					X	X
N	152,087	152,087	152,087	151,094	151,094	151,094

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
^ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

in employment after the cancer diagnosis, and they are also estimated less precisely. Overall, the estimates in column (1) are robust to including various control variables.

All regressions in Table 3 contain interactions between the treatment variable (the individual's wife was diagnosed with cancer in $t = 0$) and time periods before the diagnosis. The effects of these pre-treatment interactions on the outcome variable allow us to conduct placebo tests, i.e. we can formally assess the common trends assumption. None of these interactions have a statistically significant effect. Therefore, we can conclude that wives' cancer diagnoses do not affect husbands' employment before they occur. This finding supports our assumption that an initial cancer diagnosis changes a family's information set, and spousal employment does not change in anticipation of such a health shock.

Next, we explore the estimation results for men's earnings (reported in Table 4). The six regressions contain the same sets of control variables as the employment regressions described above. Starting in the year following their wives' cancer diagnoses, husbands earn about \$2000 less per year, which corresponds to a 3.4% reduction in earnings. This negative effect remains stable for the following three years and disappears in the fifth year after the cancer diagnosis. Hence, the pattern is the same as for the employment effects. Most of the decline in labor supply occurs at the extensive margin, so employment and annual earnings have similar patterns. The regression results including control variables, which are reported in columns (2)–(6) in Table 4, confirm the basic result on men's earnings. While the estimates become less precise as controls are added, the point estimates show a decrease in earnings of about \$2000 per year across specifications. The placebo tests also show that earnings do not change significantly in anticipation of a cancer diagnosis.

The third outcome considered is total family income before taxes. Table 5 contains the results for men. Changes in family income potentially operate through two channels. First, the sick wife may reduce her employment or hours worked and therefore have lower earnings. Second, the husband reduces his labor supply to act as a caregiver, which contributes to an overall decrease in family income. The results in Table 5 show the largest effect for the year immediately following the spousal cancer diagnosis. Depending on the specification, family income declines by between \$4000 and \$5000 (or 3.8–4.8%) for men whose wife was diagnosed with cancer.[32] This decline is very precisely estimated. In subsequent years, the reduction in family income becomes smaller and is not statistically significant.

Next, we report regression results for women. The treatment group consists of women whose husbands were diagnosed with cancer between 1992 and 2003, and the control group contains women whose husbands were never diagnosed with cancer. Table 6 displays the estimation results for women's employment using the same specifications in columns (1)–(6) as for men. Overall, women reduce their employment by about 2.5 percentage points during the five years after their husbands were diagnosed with cancer. In contrast to the results for men, women do not increase their

control for the individual's (not the spouse's) disability status. However, the CPPD recipient status of the spouse is also included as a control in the family income regressions below.

[32] For family income, we control for widowhood in two different ways: by including a lagged widow(er) dummy and by including a widow(er) dummy. Because of the annual frequency of family income data, the effect of spousal death on family income cannot be clearly determined with either of these two variables.

Table 7
Regression results for the effect of husbands' cancer diagnoses on women's annual earnings.

	(1)	(2)	(3)	(4)	(5)	(6)
δ: effects of spousal cancer – Eq. (1)						
$k = -5$	−1.770	−1.234	−2.913	176.024	198.545	199.468
	(592.460)	(592.431)	(592.448)	(611.951)	(612.374)	(612.233)
$k = -4$	502.356	502.675	502.691	551.513	593.883	594.318
	(535.227)	(535.228)	(535.216)	(539.514)	(535.973)	(535.954)
$k = -3$	231.106	230.943	231.745	265.694	291.073	291.273
	(500.865)	(500.864)	(500.883)	(502.288)	(504.384)	(504.380)
$k = -2$	356.480	356.480	356.480	362.589	347.064	347.133
	(389.058)	(389.059)	(389.061)	(385.399)	(389.793)	(389.813)
$k = -1$ (reference)						
$k = 0$ (the year of diagnoses)	−713.501*	−688.676$^{\wedge}$	−713.501*	−599.743$^{\wedge}$	−599.333$^{\wedge}$	−577.214
	(356.472)	(357.872)	(356.475)	(358.252)	(357.233)	(358.639)
$k = +1$	−1688.542***	−1654.408**	−1378.871**	−1477.700**	−1518.224**	−1301.039*
	(507.256)	(510.902)	(521.294)	(504.525)	(506.972)	(524.954)
$k = +2$	−1695.581**	−1656.692**	−1009.275	−1450.197*	−1578.169**	−1125.393$^{\wedge}$
	(591.058)	(595.304)	(638.239)	(589.520)	(587.643)	(650.246)
$k = +3$	−1388.761*	−1342.511*	−573.889	−1050.600	−1223.678$^{\wedge}$	−687.724
	(663.708)	(670.028)	(726.194)	(662.627)	(657.010)	(736.856)
$k = +4$	−834.180	−781.897	62.710	−509.541	−562.101	27.235
	(751.610)	(759.299)	(809.521)	(757.144)	(745.716)	(826.567)
$k = +5$	−1406.644$^{\wedge}$	−1351.243	−440.334	−1107.306	−1037.640	−406.044
	(845.863)	(855.317)	(918.192)	(848.025)	(839.187)	(930.974)
Additional cancer diagnosis		X				X
Lagged Widowhood			X			X
Non-labor income				X	X	X
Number of children					X	X
Self-employment in reference period					X	X
Disability benefits or tax credits					X	X
N	152,087	152,087	152,087	151,094	151,094	151,094

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
$^{\wedge}$ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 8
Regression results for the effect of husbands' cancer diagnoses on women's family income.

	(1)	(2)	(3)	(4)
δ: effects of spousal cancer – Eq. (1)				
$k = -5$	−241.034	−230.490	−220.087	−234.268
	(2,024.955)	(2,023.452)	(2,024.240)	(2,027.092)
$k = -4$	75.914	79.232	85.310	72.716
	(1815.672)	(1815.372)	(1815.525)	(1816.903)
$k = -3$	−622.249	−617.602	−610.365	−617.536
	(1748.643)	(1748.289)	(1748.448)	(1750.227)
$k = -2$	−113.448	−109.937	−105.883	−165.901
	(1794.005)	(1793.682)	(1793.823)	(1794.701)
$k = -1$ (reference year)				
$k = 0$ (diagnosis year)	−3667.799*	−3210.274*	−4233.406**	−2746.943$^{\wedge}$
	(1636.482)	(1615.914)	(1641.902)	(1643.149)
$k = +1$	−6566.490**	−5563.087**	−5768.479**	−5107.035*
	(2046.039)	(2010.836)	(2041.824)	(2051.005)
$k = +2$	−5713.904*	−4568.443*	−2403.819	−4730.918*
	(2292.549)	(2324.798)	(2308.929)	(2303.131)
$k = +3$	−9012.329***	−7797.006***	−5047.852*	−8129.335***
	(2081.860)	(2097.637)	(2097.974)	(2076.863)
$k = +4$	−7996.957**	−6800.037**	−3889.298	−7128.829**
	(2447.703)	(2487.625)	(2493.446)	(2443.529)
$k = +5$	−6745.085**	−5571.927*	−2309.191	−5991.915*
	(2488.816)	(2505.662)	(2528.706)	(2479.404)
Widowhood		X		
Lagged widowhood			X	
Family size	X	X	X	X
Disability benefits or tax credits				X
N	151,094	151,094	151,094	151,094

Note: All regressions are weighted by CEM weights and include individual fixed effects. Standard errors in parentheses are clustered on the individual level.
$^{\wedge}$ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 9
Regression results for the effect of spouses' cancer diagnoses on men's and women's employment, annual earnings, and family income (no-widow/er sample).

	Men (wives' diagnoses)			Women (husbands' diagnoses)		
	Employ. (1)	Earn. (2)	Family Inc. (3)	Employ. (4)	Earn. (5)	Family Inc. (6)
δ: effects of spousal cancer – Eq. (1)						
$k=-5$	−0.012	27.251	−8.941	−0.004	−77.103	−1040.817
	(0.008)	(1030.788)	(1399.350)	(0.017)	(743.686)	(2737.737)
$k=-4$	−0.003	505.023	437.622	−0.005	117.861	230.373
	(0.007)	(887.616)	(1272.034)	(0.015)	(676.527)	(2389.763)
$k=-3$	−0.004	533.862	620.184	0.011	122.954	−1477.958
	(0.007)	(935.293)	(1271.698)	(0.013)	(670.030)	(2268.303)
$k=-2$	0.000	6.411	1514.898	0.000	627.967	1208.016
	(0.005)	(680.333)	(1024.896)	(0.010)	(525.482)	(2595.155)
$k=-1$ (reference)						
$k=0$ (the year of diagnoses)	0.004	180.087	−622.458	−0.006	−440.876	−4881.442*
	(0.007)	(679.910)	(1016.761)	(0.011)	(481.243)	(2226.157)
$k=+1$	−0.024**	−2002.301*	−5285.241***	−0.019	−807.244	−8791.473***
	(0.009)	(997.630)	(1336.429)	(0.015)	(671.267)	(2453.317)
$k=+2$	−0.018^	−1591.957	−2380.740^	−0.003	−811.900	−710.596
	(0.010)	(1115.499)	(1378.831)	(0.016)	(755.776)	(2876.388)
$k=+3$	−0.010	−1627.775	−886.479	−0.031^	−352.582	−3855.757^
	(0.010)	(1190.142)	(1606.289)	(0.018)	(862.488)	(2290.112)
$k=+4$	−0.024*	−2284.623^	−2291.568	−0.037^	129.696	−4783.320
	(0.012)	(1345.708)	(1728.185)	(0.020)	(936.400)	(3058.972)
$k=+5$	−0.008	−61.128	−601.510	−0.023	−427.332	−953.379
	(0.012)	(1467.209)	(1863.448)	(0.020)	(1051.468)	(3042.091)
N	134,433	134,433	133,424	98,457	98,457	97,895

Note: Regressions corresponds to column (1) in Tables 5–10, respectively, but the sample is restricted to individuals whose spouse did survive at least five years after the cancer diagnosis. All regressions are weighted by CEM weights and include individual fixed effects. In (3) and (6) family size is controlled. Standard errors in parentheses are clustered on the individual level.
^ $p<0.1$.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

employment rates in the fifth year after the diagnosis. They either care for their husbands longer or do not return to the workforce for other reasons.[33] However, these effects are estimated less precisely than for men and are only statistically significant at the 5% level in the first year and at the 10% level in the second and third years. The point estimates do not change substantially when control variables are included. As for men, cancer diagnoses have no effect on women's employment in the pre-treatment periods; hence the common trends assumption is satisfied.

Table 7 contains results for women's annual earnings. The reduction in earnings amounts to between \$800 and \$1700 (2.7–5.9%) in the five years after the husband's cancer diagnosis in the baseline regression in column (1). The earnings loss is highest in the first two years and then becomes less significant in both economic and statistical terms. The effects of a cancer diagnosis become smaller in absolute value when control variables are added. The overall pattern persists, however, with negative point estimates in the first three years in all specifications. Lastly, we are able to verify the common trends assumption for this set of results.

Finally, we report regression results for family income when the husband was diagnosed with cancer in Table 8. The initial drop in family income is substantial, between \$5000 and \$6500 depending on the specification. In contrast to the results for men in Table 5, family income from the women's perspective drops further in subsequent years. The largest reductions amount to between \$8000 and \$9000 three years after the husband's cancer diagnosis. These large effects are due both to a reduction in employment and earnings of the husband who was diagnosed with cancer and the wife who works less in response. These results show the large negative effects of husbands' cancer diagnoses on the family's economic situation.

Overall, our regression results strongly suggest that both men and women reduce their employment and experience earrings losses after their spouses are diagnosed with cancer. Hence, the caregiver effect and leisure complementarities dominate the added-worker effect in the context of cancer diagnoses in Canada. The effects are larger for women than for men in relative terms, suggesting that women reduce their employment and earnings more than men in response to their spouse's cancer diagnosis.

5.2.2. Robustness and heterogeneity

In this section, we provide a robustness check and estimate heterogeneous effects based on cancer severity and screening status. Table 9 contains regression results for the same outcomes and specifications as in Tables 3–8, column (1), but the sample is restricted to individuals whose spouses survived for at least five years after their cancer diagnoses; hence, we exclude all individuals in the treatment and control groups who became widowed during the sample period.[34] Excluding window(er)s from the sample allows us to consider effects of spousal cancer that are not confounded by the spouse's death, although cancer types in such a sample are generally less severe than in the sample with widow(er)s included.

For men whose wives were diagnoses with cancer and survived for at least five years, the effects are similar to those reported

[33] The women's sample contains proportionally more spouses diagnosed with cancer types in the low-survival category than the men's sample (Table 1). Cancer types in the low-survival category (e.g., lung cancer) may be more severe and take longer time for recovery from cancer treatment than those in the high-survival category (e.g., breast cancer). We present regression results by survival category in Section 5.2.2.

[34] We recalculate the CEM weights for samples excluding widow(er)s. Here, only regression results for the baseline specification that corresponds to column (1) in Table 3–8 are displayed. The results with added controls are similar and are available from the authors on request.

Table 10
Difference-in-differences results for the effect of spouses' cancer diagnoses on men's and women's employment, annual earnings, and family income, by survival probability (samples pooled across genders).

	Employ. (1)	Earn. (2)	Family Inc. (3)
(A) High survival			
Post-diagnosis	−0.057***	−3736.372***	10,005.205***
	(0.004)	(458.987)	(905.348)
Spousal cancer × post-diagnosis	−0.017^	−1923.202^	−2650.326
	(0.009)	(1064.486)	(1756.122)
Constant	0.929***	51,292.037***	85,598.787***
	(0.002)	(213.401)	(1,219.858)
Family size controls			X
N	132,148	132,148	131,291
(B) Medium survival			
Post-diagnosis	−0.049***	−206.619	9986.803***
	(0.006)	(485.643)	(762.684)
Spousal cancer × post-diagnosis	−0.023^	−2284.390*	−5252.606**
	(0.012)	(1032.388)	(1661.249)
Constant	0.894***	39,651.452***	74,379.734***
	(0.003)	(225.524)	(1030.672)
Family size controls			X
N	87,788	87,788	87,034
(C) Low survival			
Post-diagnosis	−0.047***	−2350.591***	8301.568***
	(0.008)	(548.141)	(858.118)
Spousal cancer × post-diagnosis	−0.035*	−2619.977*	−9657.331***
	(0.017)	(1207.152)	(2813.860)
Constant	0.875***	36,468.741***	72,451.207***
	(0.004)	(254.312)	(1066.457)
Family size controls			X
N	54,431	54,431	54,027

Note: See Table 1 for a classification of cancer diagnoses into survival categories (high/medium/low). All regressions are weighted by CEM weights and include individual fixed effects. The CEM weights include gender in addition to the covariates used in the main results. The post-diagnosis period includes $k = \{1, \ldots, 5\}$ and observations for period $k = 0$ are excluded (see text for details). Standard errors in parentheses are clustered on the individual level.
^ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 11
Difference-in-differences results for the effect of spouses' cancer diagnoses on men's and women's employment, annual earnings, and family income, by screening and non-screening cancer diagnoses (samples pooled across genders).

	Employ. (1)	Earn. (2)	Family Inc. (3)
(A) Screening cancers			
Post-diagnosis	−0.053***	−2803.614***	9062.293***
	(0.004)	(437.757)	(695.226)
Spousal cancer × post-diagnosis	−0.027**	−2820.482**	−4060.291**
	(0.009)	(985.365)	(1,402.588)
Constant	0.922***	50,087.857***	84,165.507***
	(0.002)	(202.962)	(907.670)
Family size controls			X
N	129,349	129,349	128,492
(B) Non-screening cancers			
Post-diagnosis	−0.053***	−1779.713***	10,163.198***
	(0.004)	(343.832)	(709.317)
Spousal cancer × post-diagnosis	−0.017^	−1059.110	−5196.430**
	(0.010)	(782.291)	(1,647.213)
Constant	0.898***	39,359.941***	74,723.929***
	(0.002)	(159.935)	(960.600)
Family size controls			X
N	167,858	167,858	166,515

Note: Screening cancer sites include breast, cervix uteri, prostate, rectum, and colon. Non-screening cancers include all other sites listed in Table 1. All regressions are weighted by CEM weights and include individual fixed effects. The CEM weights include gender in addition to the covariates used in the main results. The post-diagnosis period includes $k = \{1, \ldots, 5\}$ and observations for period $k = 0$ are excluded (see text for details). Standard errors in parentheses are clustered on the individual level.
^ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

for the full sample in Tables 3–5. However, comparing the results for women with the main results in Tables 6–8, we find that the decrease in women's employment and earnings is less pronounced in sample that excludes widows. Also, the decline in the women's family income in the restricted sample is smaller than in Table 8 and not statistically significant.[35] The women's sample contains proportionally more spouses diagnosed with cancer types in the low-survival category than in the men's sample; therefore, excluding widows from the women's sample results in a smaller negative effect of cancer diagnoses on all outcomes. In other words, it appears that women whose husbands are diagnosed with cancer reduce employment and earnings mostly in cases where the diagnosis is particularly severe and their husbands die within five years from the year of the diagnosis. In these cases, women's family income loss is likely to be persistent and substantial.

We carry out two additional robustness checks in the Online Appendix. First, we restrict the sample to individuals and spouses younger than 55 to test if potential retirement plays an important role in individuals' labor supply decisions. Second, we include spousal pre-diagnosis employment status in the CEM weights to account for possible endogeneity. In both cases, the results do not differ significantly from our main results.

The results so far do not distinguish between different cancer sites or severity. It is likely, however, that individuals are more likely to reduce their labor supply in response to more severe type of cancer because the diagnosed spouse needs more intensive care or the individual wishes to spend more leisure time with the spouse if the sick spouse's life expectancy is low. To test this hypothesis, we classify cancer diagnoses into low, medium, and high survival categories (see Table 1) and pool data for men and women to gain more statistical power.[36]

[35] In contrast to the results in Table 7 and 8, where the declines in annual earnings and family income are statistically significant in most specifications, we find a significant decrease for family income but not women's earnings in Table 9. This difference is likely to suggest that men diagnosed with cancer who survive for at least five years reduce their own labor supply to the extend that family income immediately declines.

[36] We recalculate the CEM weights because the treatment groups now consist of different individuals. Since we pool men and women, we also include a gender dummy in the set of CEM covariates.

Table 10 displays the DID estimates by survival category based on the regression in Eq. (2).[37] The point estimates show a clear negative relationship between the severity of the spouse's cancer diagnosis and the individual's change in labor supply. For the high survival category, employment rates decline by 1.7 percentage points, for the medium survival category by 2.3 percentage points, and for the low survival category by 3.5 percentage points. Similarly, annual earnings decrease by $1900, $2300, and $2600, respectively, in post-diagnosis years. Finally, family income declines by $2700, $5300, and $9700, respectively. The estimated DID effects in panels (A), (B), and (C) of Table 10 are mostly not significantly different from each other (except for the difference in the family income decline between the high and low survival categories). We nevertheless find convincing evidence for our severity hypothesis since the point estimates for all three outcomes follow the same monotonic relationship between severity and reductions in labor supply.

Finally, we assess our identifying assumption that cancer diagnoses are unexpected and can therefore be interpreted as random health shocks. We exploit the fact that some cancer types are often detected during routine screenings while other cancer diagnoses are only made after a patient experiences certain symptoms.[38] The screening cancers include breast, cervix uteri, prostate, colon, and rectum cancer while all other cancer sites listed in Table 1 are classified as non-screening cancers. Spouses who are diagnosed with a screening cancer may be more likely to expect a diagnosis, so the non-screening cancers are more likely to be truly exogenous.[39] If this were the case, we would expect to find different results due to a bias in the screening cancer estimates.

Table 11 shows DID estimates for screening and non-screening cancers, again pooling data for men and women. We do not find a clear relationship between screening status and the size of the estimated effects. While employment rates (2.7 and 1.7 percentage points) and annual earnings ($2800 and $1100) decline more for screening than for non-screening cancers, we find the opposite for family income (a reduction of $4100 and $5200, respectively).[40] Moreover, none of these differences are statistically significant at any conventional level. Therefore, we cannot reject the hypothesis that health shocks are equally random in both cases. This result supports our assumption that cancer diagnoses represent exogenous health shocks.

6. Discussion and conclusion

We employ unique and nationally representative administrative data to estimate the effect of one spouse's cancer diagnosis on the other spouse's subsequent labor market outcomes. The results show that individuals reduce their employment and their earnings decline, in response to their spouse's health shock. We find negative effects that are both statistically and economically significant. Hence, our empirical results clearly reject the added-worker hypothesis in favor of the caregiver and complementarities-in-leisure hypotheses. In addition, we find that annual family income decreases by $2700 for men and by $6900 for women, which is substantial when compared with other types of costs incurred after a cancer diagnosis. For example, average out-of-pocket costs associated with cancer treatment amount to about $2900 per year in Ontario (Longo et al., 2006), and the average cost to the health care system is about $26,000 per cancer diagnosis in the year following such a diagnosis (de Oliveira et al., 2013).[41]

Our findings are partly in line with the existing literature. Garcia Gomez et al. (2013) estimate smaller negative effects, but this may be explained by the fact that they consider all types of hospitalizations whereas we consider only more severe health shocks associated with cancer diagnoses. Compared with Coile (2004), Hollenbeak et al. (2011), and Garcia Gomez et al. (2013), we find a smaller difference in labor market effects between husbands and wives. This discrepancy can likely be explained by country-specific differences in male and female labor supply profiles and caregiving options (Canada versus the U.S. and the Netherlands) and also the fact that Coile (2004) and Garcia Gomez et al. (2013) do not consider cancer diagnoses where leisure complementarities may play a particularly important role.

While the results are informative in their own right, we also contribute to the growing literature on the opportunity cost of care giving. We quantify the earnings losses that arise when individuals reduce their labor supply to act as caregivers for their spouses who were diagnosed with cancer. Existing studies exclusively focus on the labor market outcomes of adult children who act as caregivers for their elderly parents. For this population, Skira (2015) estimates opportunity costs in excess of $100,000 within a two-year window, and Arno et al. (1999) calculate that the total cost of informal caregiving exceeds spending on nursing homes and home health care in the U.S. Ettner (1996), Carmichael and Charles (1998), and Heitmueller and Inglis (2007) also find substantial costs of informal caregiving in terms of reduced labor supply. Because our population is different from those in other studies, our results are not directly comparable, but they nevertheless shed light on a dimension of informal caregiving – caring for sick spouses – that has been neglected in the literature thus far.

Overall, we provide novel and important evidence on the intra-family labor market effects of one family member's severe health shock. The magnitudes of these effects are substantial, suggesting that a cancer diagnosis has the potential to change labor supply substantially relative to when both spouses are healthy, and strongly affects a family's financial well-being, apart from the psychological costs of dealing with such a health shock.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhealeco.2016.12.008.

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[37] Due to the smaller sample sizes, we do not estimate generalized DID regressions for different survival categories.

[38] We are grateful to an anonymous referee for this suggestion.

[39] We do not observe if a cancer diagnosis resulted from a routine screening in the case of screening cancers or if the cancer was detected by other means. Moreover, we lack information on the cancer stage.

[40] The larger decline in family income for non-screening cancers could imply that the diagnosed spouses reduce their labor supply by more than they would if they were diagnosed with a screening cancer. However, non-screening cancers tend to be more severe, which may explain this difference.

[41] We are grateful to Sara Allin for pointing out these studies.

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