Journal of Population Economics (2025) 38:19
https://doi.org/10.1007/s00148-025-01070-x

ORIGINAL PAPER

A family affair? Long-term economic and mental health effects of spousal cancer

Petri Böckerman[1,2,3] · **Mika Kortelainen**[4,5] · **Henri Salokangas**[5] · **Maria Vaalavuo**[5]

Received: 19 March 2023 / Accepted: 2 January 2025

Abstract
Research on the family spillover effects of health shocks, which has focused mainly on labor market outcomes, has yielded inconclusive results, with limited insight into long-term consequences or underlying mechanisms. We analyze the short- and long-term impacts of cancer on the unaffected spouse's labor supply and mental health as well as marital stability, considering gender and relative income status within the households. Using population-based register data from Finland (1995–2019) and a dynamic difference-in-differences design, we observe two key findings. First, a cancer diagnosis leads to very modest changes in a spouse's labor supply but significant increases in the likelihood of psychotropic drug use and psychiatric outpatient visits. Second, the main results mask considerable heterogeneity regarding relative income within the household. Secondary earners increase their labor supply in response to fatal cancers but decrease it in non-fatal cases, while breadwinners show small negative responses in both. Bereaved women with lower income share experience more psychiatric symptoms, a trend not observed in men. Our findings reveal the importance of pre-shock breadwinner status in family responses to health shocks, suggesting the need for targeted support for caregiving and bereaved spouses.

Keywords Health shock · Cancer · Family spillover effects · Household division of labor · Event study · Difference-in-differences · Mental health · Marital stability

JEL Classification I10 · J12 · J17 · J22

1 Introduction

There is a growing body of research on the indirect effects of severe health shocks within the family (e.g., García-Gómez et al. 2013; Jeon and Pohl 2017; Fadlon and Nielsen 2021; Vaalavuo et al. 2023). Indirect effects pertain to family members other

Responsible editor: Xi Chen

Extended author information available on the last page of the article

than the person who falls ill. Accurately quantifying such effects, which have been largely neglected in the evaluation of the cost-effectiveness of healthcare services, can provide novel insights for designing health interventions and deepen our understanding of the interconnections between health and labor market outcomes (Böckerman and Ilmakunnas 2009; Picchio and Ubaldi 2024). This perspective is particularly relevant for cancers, which are a major contributor to the global disease burden, with their impact expected to increase in the coming decades due to aging populations (Global Burden of Disease 2019 Cancer Collaboration 2022). Therefore, the well-being impacts of cancer are policy-relevant globally.

There are many possible reasons for indirect effects. First, the health shock may cause the person falling ill to reduce their effective labor supply or even withdraw completely from the labor market. It has previously been demonstrated that a cancer diagnosis can lead to significant economic losses in households across various institutional contexts (Bradley et al. 2005; Jeon 2017; Vaalavuo 2021). This can disturb the pre-existing arrangement on the joint labor supply of spouses, especially when the person falling ill is the main breadwinner in the family.[1] Consequently, the unaffected spouse may react to this by increasing her/his labor supply to maintain the family's income level and material well-being, in the spirit of what has often been called the "added worker hypothesis" (Mincer 1962) or "added worker effect" (Lundberg 1985). Limited social security, substantial debt, restricted access to credit, and high healthcare costs can significantly exacerbate this effect. The second potential driver of the indirect labor market effects leads to the opposite consequences. The healthy spouse might reduce her/his labor supply due to the provision of care (known as the "caregiver effect") or concerns for the physical/mental well-being of a close family member and a desire for more shared leisure time (the "family effect").[2]

Beyond affecting labor supply, a cancer diagnosis can cause psychological distress among family members. The uncertainty about recurrence, survival, and returning to work can significantly impact not just the patient but also their loved ones, leading to lasting effects on their lives (Mellon et al. 2007; Guan et al. 2021). This distress may extend to healthy spouses as well, as some evidence suggests (Hu et al. 2023; Angelini and Costa-Font 2023). Moreover, cancer, as a sudden, severe, and unexpected shock to the family, can significantly affect the marital stability of couples navigating this difficult situation (Syse 2008).

While family spillover effects have recently attracted increased interest among researchers and policy advocates in the field, empirical evidence on the topic remains inconclusive. The divergent results of existing research are likely explained, in part, by differences in institutional contexts, data characteristics, empirical methods applied, and the specific health shocks examined. To further complicate the picture, existing patterns in the division of household labor supply may substantially affect the response of the unaffected spouse (see also Riekhoff and Vaalavuo 2021; Vaalavuo et al. 2023). The couple's joint pattern of labor supply prior to the health shock affects the need, opportunities, and obstacles to adjusting labor market participation. In addition to labor

[1] Throughout the paper "spouse" refers to a significant other in a marriage or cohabitation.

[2] For a detailed discussion of the relevant terminology, see Bobinac et al. (2010).

market responses, these features may also influence other dimensions of well-being, including psychological health and marital stability.

In this article, our principal research question is how a spouse's cancer affects the labor market outcomes and mental health of the healthy spouse and the couple's marital stability. Furthermore, while labor market responses have been reported in the prior literature, we contribute by investigating the heterogeneous responses by relative income position within the household. Identifying the causal effects of a spouse's cancer diagnosis is challenging. Our identification strategy relies on quasi-random variation in the timing of the cancer diagnoses within the estimation window, using a dynamic difference-in-differences or event study design, as outlined by Fadlon and Nielsen (2019, 2021). This approach also enables us to assess the key identification assumptions of the empirical specification.

Our study advances the understanding of cancer's broader impacts on well-being in three important ways. First, we integrate theories and concepts of household division of labor into the empirical models. We examine the heterogeneous impacts by the relative income status of the spouses prior to the cancer diagnosis separately for men and women. Relative income is relevant because it entails information on the potential financial losses for the surviving spouse caused by cancer, and signals potential economic independence within the household. While some previous studies have examined gender differences in the spillover effects, they have not considered the effect of relative income status separately (independently of gender) or focused on long-term impacts. Second, our study focuses on the psychological spillover effects of cancer and the impacts on marital stability. These two dimensions of well-being have been only rarely examined in the literature, especially in connection to relative income status. Third, in contrast to many other studies, we use particularly long follow-up time as some attributes associated with cancer, e.g., uncertainty about recurrence, years of survival, and return to work, may have a prolonged effect on the cancer patients' lives but also on the lives of their loved ones. Using the panel structure of our data from Finland over the years 1995–2019, we follow couples 5 years before and 10 years after the initial cancer diagnosis.

While there exists only a nascent body of quasi-experimental research on the indirect effects of health shocks on the spouse's labor market outcomes, the connection between health and labor supply within the family is not new to the field of economics. Already in the 1970s, Parsons (1977) analyzed the impact of family structure on men's health, work hours, and earnings and observed that poor health significantly reduced men's work hours and earnings but did not notably increase work hours among other family members. Berger (1983) and Berger and Fleisher (1984) also found only small increases in wives' work hours and no substantial impact on labor force participation in response to husbands' poor health.

In a more recent and more closely related study, Jeon and Pohl (2017) examined the effect of different cancer diagnoses on the spouse's employment and earnings trajectories based on Canadian register data. We complement their study by analyzing the role of relative income within the household and by examining a wider set of outcomes, including psychotropic drug use. We are not aware of any previous quasi-experimental studies analyzing the spillover effects of a health shock on mental health.

While some studies (e.g., Bom et al. 2019; Stöckel and Bom 2022; Angelini and Costa-Font 2023) have examined mental health outcomes among spouses, they have not employed dynamic difference-in-differences or similar identification strategies to tease out causal effects.

Methodologically, the closest to our study is Fadlon and Nielsen (2021), who investigated households' labor supply responses to fatal and severe non-fatal health shocks using Danish data. While using a similar identification strategy, we concentrate on a different health shock (i.e., cancer) and provide evidence also on the psychological well-being effects. Moreover, we analyze the heterogeneity of labor supply responses based on the relative income position of couples and evaluate spillover effects both in the short and long run.

Our study is also related to concurrent work by Arrieta and Li (2023) that focuses on the effect of emergency department visits (i.e., acute health shocks requiring urgent care but with a potentially short duration) on intra-family adjustment of labor supply and care in the U.S. context. Overall, we contribute to the emerging literature on the topic by investigating longer-term impacts on labor supply and mental well-being as well as the potential mechanisms behind the spousal effects in more detail.

Our findings from Finland, a comprehensive Nordic welfare state, are likely to illuminate the institutional differences that drive labor supply responses in various country contexts. Additionally, the Finnish context holds broader interest for two other reasons. First, we examine the effects of cancer on total family income, including received social transfers. This issue is highly policy-relevant in other high-income countries as they develop more comprehensive social safety nets for families to tackle the financial burden caused by chronic illnesses. Second, Finland's cancer survival rates are among the world's highest, which highlights the importance of understanding the indirect effects of a health shock at the family level. In the near future, the indirect labor market effects of poor health might become particularly salient in aging societies that aim to prolong working careers while reconciling informal care and paid work among older employees.

We observe that female spouses increase their employment for some years after a severe health shock, which is consistent with the added worker effect. However, the magnitude of the impact on annual earnings is negligible. Among men, we observe the opposite: male spouses' earnings decrease once their partner falls ill. Overall, cancer diagnosis causes rather small changes in the labor supply of spouses but relatively large increases in the use of psychotropic medication and psychiatric outpatient visits.

More importantly, our results shed light on labor supply responses within families, considering both the breadwinner status and the survival of the cancer patient. We observe that both men and women experience decreasing earnings in cases of non-fatal cancers, with greater deficits for secondary earners. However, responses in the extensive margin are negligible. Both women and men moderately increase their psychotropic medication, with the most significant rise observed among secondary-earner women. Notably, secondary-earner women also experience a positive effect on marital stability, while men and breadwinner women remain unaffected. In fatal cancers, a clearer relationship emerges between relative income and labor supply decisions. The earnings responses are linearly related to the pre-cancer income share within

the household, indicating that the greater the income share of the deceased spouse, the greater the increase in the labor supply at the intensive margin of the surviving spouse. In the long-term, secondary-earner women also demonstrate increased labor supply at an extensive margin. This implies that the surviving spouse compensates for the economic loss by adding labor supply. At the same time, this group shows the most substantial increase in psychotropic medication use, suggesting a connection between the markedly increased labor supply and psychiatric symptoms from bereavement. Overall, the adverse mental health effects are substantial both among men and women, in both the short- and long-term. These findings highlight the importance of the follow-up duration, the survival status of the ill spouse, and the breadwinner status within the household in influencing the results. Consequently, they may help to resolve some inconsistencies present in the existing evidence on the topic.

The article is structured as follows. Section 2 offers an overview of the relevant literature. Section 3 describes the Finnish register data and the empirical framework. Section 4 presents the estimation results. The final section offers a comprehensive discussion of the key findings.

2 Conceptual framework

Individuals consider the well-being and economic prospects of their entire household, not just their own, when making labor supply decisions (Mincer 1962; Blundell and Walker 1982; Becker 1991). Early in their relationship, spouses often negotiate the division of household labor, where traditionally, the husband specializes in paid work outside the home, and the wife, in unpaid household work at home (Becker 1991; Leira 1992).

The household operates as an economic unit, sharing resources and risks. A health shock, like cancer, can significantly change the household's economic situation, impacting labor supply, marital stability, and mental health, all crucial for assessing family well-being. Existing research on the spillover effects of health shocks on spouses has primarily studied labor market impacts, yielding inconclusive results. Notably, Coile (2004) examined heart attacks and new cancer diagnoses among older adults in the U.S., revealing only a small added worker effect for men and none for women. On the other hand, Jeon and Pohl (2017) observed a significant decrease in labor supply among Canadians whose spouses were diagnosed with cancer, particularly among men at the intensive margin. The authors interpret this finding as individuals reducing effective labor supply to provide care for their sick spouses and to share leisure time. Similarly, Anand et al. (2022) found a reduction in labor force participation among potential caregivers following a spouse's health shock. In contrast, studies like Giaquinto et al. (2022) using UK data and Jolly and Theodoropoulos (2023) with SHARE data from Europe, show minimal changes in labor supply but highlight an increased focus on caregiving and a higher likelihood of retirement.

Evidence on the long-term spillover effects of health shocks on psychological well-being is sparse, and dynamic difference-in-differences designs have been rarely utilized in this research. Recent studies using survival analysis and register data from

Denmark and Sweden indicate that a spouse's cancer diagnosis increases the risk of receiving a psychiatric diagnosis in hospital-based inpatient or outpatient care compared to matched controls (Hu et al. 2023). Survey evidence also supports the view that cancer elevates the psychological distress of spouses. This increased distress may stem from a greater caregiving burden, impacting the spouse's mental health in a dose-response manner (Bom et al. 2019; Stöckel and Bom 2022), but also because the lives of spouses are intimately linked in terms of emotional well-being and family responsibilities (Northouse and McCorkle 2015).

In a recent study closely related to ours, Angelini and Costa-Font (2023) use a cross-sectional survey data from Europe (SHARE) and find that fatal cancer is significantly associated with the surviving partner's well-being, leading to increased depression, loneliness, and sleep problems. While being an important addition to the health spillover literature, their study departs from the conventional approach by using baseline characteristics and a first differences specification that may not fully account for unobserved factors influencing changes over time. Our article contributes to previous research by using more comprehensive register data on health-related consumption of psychotropic medicine and public psychiatric services within a dynamic difference-in-differences framework.

Gender differences in spousal responses to health shocks, particularly cancer, are shaped by survival rates and the role of the primary breadwinner, often the male. The relative income of each spouse has a significant impact on how households respond to such shocks. If the primary breadwinner falls ill, significant labor adjustments may be needed, potentially leading to increased psychological stress and changes in family dynamics (Becker et al. 1977). However, when the secondary-earner spouse is affected, labor adjustments might be smaller. Consistent with this view, Fadlon and Nielsen (2021) found that surviving widows, but not widowers, increased their labor supply following fatal events, linking financial loss to labor force participation. This finding indicates that self-insurance might play a crucial role in how families adjust their labor in response to health shocks.

Health shocks can affect marital stability, especially against the backdrop of changing gender norms in Nordic countries, where women increasingly academically outperform men, challenging the traditional male breadwinner model. Studies like Bertrand et al. (2015) show that female breadwinning can influence marital satisfaction and stability, a trend noted in the U.S. in the 1960s and 1970s but less so in the 1990s (Schwartz and Gonalons-Pons 2016), and is associated with increased marital dissolution (Foster and Stratton 2021). This highlights the need to explore how gender roles and relative household income influence marital stability following health shocks.

Contrary to Becker et al. (1977), who suggested that health issues could negatively impact marital stability by affecting traits like income potential and health, recent studies offer different views. For example, Bünnings et al. (2021), analyzing German data, discovered that a spouse's health decline does not necessarily lead to marital instability and may even strengthen the relationship. Moreover, Ehlert (2021) examined how a health shock's impact on marital stability varies depending on the expected survivor's pension, revealing a positive correlation between potential survivor benefits and the

likelihood of staying married after a health shock for female partners. This result suggests that higher economic dependency on the affected spouse might enhance marital stability, as the unaffected partner may have fewer alternatives outside the marriage. Conversely, lower economic dependence could have the opposite effect.

The existing literature provides insights into how the economic contributions of a partner, relative to those of the affected spouse, influence adjustments in labor supply and marital stability. However, the effects on mental health remain unexplored. Our study is the first to examine the role of relative income in moderating the mental health effects of a spouse's health shock. We examine two hypotheses: First, in households where the unaffected spouse contributes less economically, they may face greater mental health challenges due to financial stress. Second, if the unaffected spouse is the primary earner, they might encounter less financial stress but more emotional and caregiving burdens, impacting their mental health differently.

3 Empirical approach

3.1 Research design and identification

Our empirical approach employs the dynamic difference-in-differences design, similar to Fadlon and Nielsen (2019, 2021), hereafter referred to as FN DiD. By utilizing this identification strategy, we created counterfactual scenarios for couples in which one spouse received a cancer diagnosis. These were derived from among couples who were diagnosed Δ years later. Employing households affected by cancer as the control group is designed to reduce the selection bias encountered in straightforward case-control comparisons.

Figure 1 illustrates our research design using examples where the treatment groups consist of individuals whose spouses were diagnosed with cancer in the year 2000. In Panel A, we plot the yearly indicator for any psychotropic drug purchase for this treatment group and compare it to the trajectory of the same outcome in individuals whose spouses were diagnosed with a cancer diagnosis 11 years later ($\Delta = 11$). The follow-up continues until the last year when the control group has not yet been treated, i.e., year 2010. Although the pre-event levels of the two groups are very similar, direct comparison may not be appropriate due to differences in age and sex distributions between the groups. To ensure a valid comparison, we weighted the outcomes in the control groups according to the age-sex distribution of the treatment group, effectively mimicking matching along these dimensions. Panel B demonstrates that weighting slightly alters the outcome level for the control group once age and sex are adjusted. Both Panels A and B indicate that the likelihood of psychotropic drug purchases significantly increases for individuals once their spouse is diagnosed with cancer, compared to the control group.

In Panel C, we supplement the comparison with two alternative control groups: those affected by a spouse's cancer diagnosis in 2006 ($\Delta = 6$) and those whose spouse have not been diagnosed with cancer. The outcome dynamics and levels in these alternative control groups are very similar until 2006. Afterward, the group diagnosed with cancer

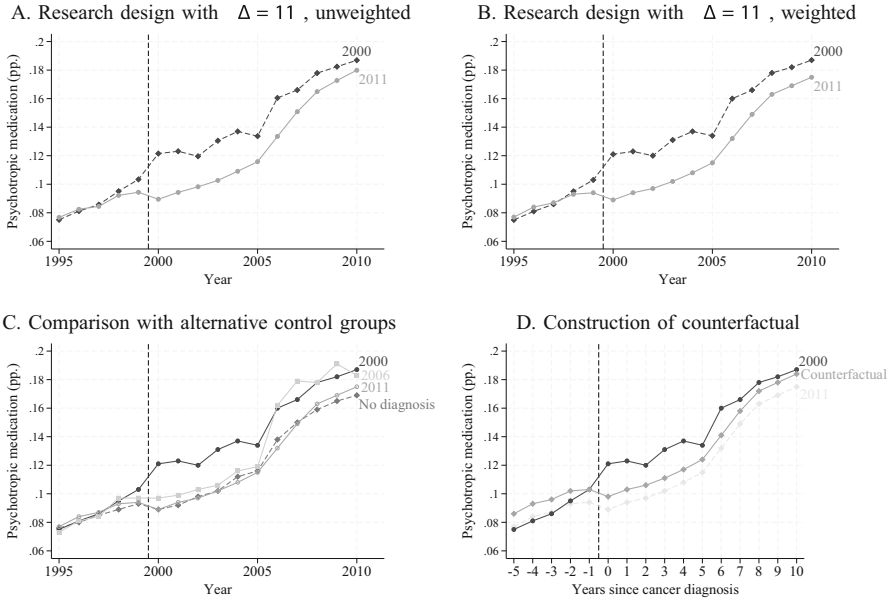

Fig. 1 Illustrations of the FN DiD design with psychotropic medication purchases. Panel A compares the treatment group with cohorts that received a cancer diagnosis 11 years later. Panel B includes the responses of households that underwent the same shock in different years, alongside matched controls that have no history of cancer diagnosis. Panel C demonstrates the construction of the counterfactual, based on the pre-cancer difference in outcomes. The outcomes for potential control groups are adjusted based on the age and sex distribution of the treatment group

in 2006 becomes "treated" and is no longer viable as a control group for studying the longer-term impacts of cancer.

The focus on the economic impacts of cancer typically spans 3–5 years in related studies (e.g., Jeon 2017; Jeon and Pohl 2017, 2019; Vaalavuo 2021). However, Tai et al. (2005) argue that for certain cancers, like pancreatic and stomach cancers, a plateau in statistical cure rates is observed within 10 years. Yet, for slower proliferating cancers, such as thyroid and early breast cancers, reaching this plateau might take even decades.

We argue that a timeframe shorter than 10 years might overlook significant long-term impacts of cancer within the family. The course of the illness, late treatment effects, and possible recurrence can have enduring emotional impacts on family members (Mellon et al. 2007; Guan et al. 2021). Additionally, the effects of health shocks on families often persist beyond 4 or 5 years after the event.[3] Therefore, a 10-year post-cancer follow-up period is justified.

This decision rules out the control group diagnosed with cancer in 2006 as a potential control group, leaving $\Delta = 11$ and unaffected matched control group as potential candidates for constructing the counterfactual. We opted for FN DiD following recent

[3] For example, Fadlon and Nielsen (2019) demonstrate that a health shock in one family member affects the health behaviors of others for more than 4 years post-shock, and Vaalavuo et al. (2023) find that the adverse impact of child cancer on a mother's earnings does not dissipate within 5 years post-shock.

trends in health shock literature using this method (e.g., Fadlon and Nielsen 2019, 2021; Vaalavuo 2021; Kvaerner 2022; Bonekamp and Wouterse 2023).

Panel D illustrates how the counterfactual is constructed using FN DiD with $\Delta = 11$ within the event study framework. The outcome's evolution is depicted relative to the years surrounding the cancer diagnosis, with period 0 denoting the diagnosis year. In the treatment group, cancer diagnosis occurs in period 0, and for the control group in period 11. Period 0 serves as the placebo shock period for the control group.

Following Fadlon and Nielsen (2021), we construct the "counterfactual" (solid gray line, diamonds) based on the pre-event difference in outcomes between the treatment (solid black line and circles) and control groups (light gray, dashed line). Specifically, the "counterfactual" reflects the outcome trajectory in the control group plus the difference in outcomes in the period between the treatment and control groups at period –1. Analyzing the differences in outcomes between the counterfactual and treatment groups during the post-cancer periods provides insights into the impact of cancer on the spouse's psychotropic medication purchases. The differences in psychotropic medication purchases in the pre-cancer periods are modest, paralleling what we observe for the participation rates (Appendix A1)

Overall, the visual evidence presented in these panels indicates parallel trends between the treatment and control groups prior to period 0. This observation supports our identification strategy, suggesting that the two groups are largely similar in terms of observed and unobserved characteristics, with the primary distinction being the timing of the cancer diagnosis. Consequently, the key to our identification hinges on the quasi-random variation in the precise timing of the health shock. Within the 11-year interval, this variation is presumed to be plausibly exogenous. Our analysis begins with the estimation of the following non-parametric event study specification:

$$\mathbf{Y_{i,r,t}} = \sum_{r\neq -1, r=-5}^{10} \gamma_r I_r + \sum_{r\neq -1, r=-5}^{10} \delta_r I_r C_{i,t} + \boldsymbol{X'_{i,t}\beta_t} + \pi_t + \theta_i + \epsilon_{i,r,t}. \quad (1)$$

where $Y_{i,r,t}$ represents the outcome of interest (e.g., employment, earnings, and psychotropic drug prescription purchases) for individual i observed in year t and r years after the index cancer diagnosis year. I_r represents the indicators relative to the index diagnosis year. The estimates produced by the event study framework presented in Eq. 1 allow us to examine dynamic patterns in outcomes in the year leading up to the cancer diagnosis.

The treatment variable, C_i, is an indicator variable set to one for an individual i whose spouse is diagnosed with cancer at period $r = 0$, and zero for an individual i whose spouse is diagnosed with cancer 11 years later. To facilitate the interpretation of the income-related estimates (in euros), we scale the absolute estimates with the predicted outcome from the group of the later-treated group ($\hat{Y}_{r0}$) for each r to construct

the estimates for the relative effect, $\delta_r^{rel} = \frac{\delta_r}{\hat{Y}_{r0}}$, representing the percentage change in the outcome.[4]

To account for the fact that the treatment and control groups differ somewhat in terms of their background characteristics, we also include individual fixed effects (θ_i). Using individual fixed effects brings out the within-group variation in both the treatment and the control group. Having a well-defined control group is advantageous because, in the canonical event study specification (employing both unit and time-fixed effects with a sample of treated units at varying treatment timing), heterogenous treatment effects could produce bias (Goodman-Bacon 2021; Callaway and Sant'Anna 2021; Borusyak et al. 2024). By contrasting the within-individual effects of those receiving the treatment with those in an explicitly defined group treated after the end of the follow-up period, we address this concern. $\boldsymbol{X}'_{i,t}$ represent time-varying control variables for the spouse, including age and year-fixed effects. These account for between-individual differences in labor market outcomes and mental health-related outcomes across ages and periods.

The primary parameter of interest is δ_r, which represents the differences in changes in outcomes between the treatment and the control group relative to the difference in the years preceding the index diagnosis ($r = -1$). Parameter γ_r represents the changes in the outcome in the control group. Assuming the control group forms a valid counterfactual for the treatment group, δ_r, represents the causal effect of cancer diagnosis when $r \geq 0$. To assess the parallel trends assumption, we focus on periods $-5 \leq r \leq -2$, which represent pre-cancer periods. If the parallel trends assumption holds, we expect the estimated effects to be statistically not significantly different from zero ($\delta_r = 0$) for $r \leq -2$.

A potential source of bias that threatens the causal interpretation of the estimates arises from the possibly divergent trends in counterfactual earnings between the treatment and the control groups. If the (unobserved) differences between the groups are significant, the earnings growth rates may vary. These baseline differences could challenge the validity of using the control group as the counterfactual for the treatment group. This concern becomes more pronounced when the differences in background characteristics between the two groups are substantial at period $r = -1$. For example, educational disparities between the groups may lead to substantially different (un)employment trajectories during economic downturns. Constructing counterfactuals from within the later-affected group is used to address this concern.

To investigate the heterogeneity in terms of breadwinner status and the survival of the affected spouse, we employed the triple difference estimator to evaluate the statistical significance in heterogeneity. For easier interpretation and to detect subtle responses, we categorized the relative time variable into three groups. Our moderation

[4] We adhere the recommendations outlined by Chen and Roth (2024). Traditional Average Treatment Effects (ATEs) using log transformations, which offer percentage interpretations, become ill-defined when outcomes include zero values. Consequently, ATEs for log-like transformations should not be construed as approximating percentage effects, as their scale and interpretation depend strongly on the units of the outcome. This issue becomes particularly salient when the treatment impacts the extensive margin (i.e., the likelihood of the outcome transitioning from zero to a non-zero value).

model, which analyzes relative income heterogeneity, is structured as follows:

$$\mathbf{Y_{i,r,t}} = \gamma_r P_r + \pi_r P_r C_{i,t} + \delta_r P_r C_{i,t} B_{i,r=-1} + \boldsymbol{X'_{i,t}\beta_t} + \pi_t + \theta_i + \epsilon_{i,r,t}. \quad (2)$$

where P_r represents an indicator for years after post-cancer diagnosis including the year of diagnosis. When separating the dynamic effects, this indicator is used as a categorical variable based on relative time r. It takes a value of 0 in the years before the index diagnosis ($r < 0$), a value of 1 during relative time periods 0 to 2 (short-term effect), a value of 2 during relative periods 3–5 (medium-term effect), and a value of 3 during relative periods 6–10 (long-term effect). $B_{r=-1}$ stands for breadwinner status.

The relative time r represents the actual cancer diagnosis for the treatment group and placebo diagnosis for the control group. In the empirical approach proposed by Fadlon and Nielsen (2021), this implies that the relative time for the treatment group is constructed by normalizing the time relative to the year of the actual cancer diagnosis and for the control group according to the time relative to the year of actual cancer diagnosis minus 11 years.

To study the heterogeneity in terms of breadwinner status and survival of the affected spouse, we used the triple difference estimator to conduct tests on the statistical significance of heterogeneity. We analyze the potential heterogeneity in terms of breadwinner status and the 10-year survival status of the affected spouse. Finally, we combine these two potential sources of heterogeneity in an additional analysis.

There are potential concerns related to the choice of this empirical strategy. First, using FN DiD strategy generally induces a trade-off with the length of follow-up and proximity of the treatment and control group in terms of baseline characteristics. For instance, households experiencing cancer 6 years, rather than 11 years, later are potentially less dissimilar to the treatment group both in terms of income and health, making them more compelling control group for causal interpretations. Moreover, it is not straightforward whether the FN DiD approach is an improvement over standard matching methods (e.g., Jeon and Pohl 2017) or up-to-date event study approaches such as stacked event study design (e.g., Cengiz et al. 2019). To provide a better idea to which extent our choice of event study method performs in relation to these three other strategies, we visualize the differences in the baseline labor market and health characteristics between the treatment and the control group in the Appendix Fig. A2. Importantly, after adjusting for birth year and sex, we generally we find that the differences in baseline characteristics are relatively similar among all the event study methods, with none of the methods consistently outperforming the others.

3.2 Data

Linked administrative data Our empirical analyses are based on nationwide linked individual-level register data that cover the population of Finland over the period 1995–2019. We linked three primary datasets: (i) the Care Register for Health Care maintained by the Finnish Institute for Health and Welfare (THL), (ii) register-based

information from FOLK data[5] on income and labor market outcomes, sociodemographic characteristics, and linkages between family members by Statistics Finland, and (iii) information on the filled psychotropic medications dispensed at Finnish pharmacies, which are reimbursed and recorded by the Social Insurance Institution. Because the data are routinely collected from nationwide administrative sources, the only sources of attrition are emigration and mortality. The data have been pseudonymized and analyzed using Statistics Finland's remote access system.

Study population Information on cancer diagnosis is based on the Care Register for Health Care. It includes all inpatient stays in public specialized healthcare for the years 1971–2019 as well as all outpatient visits to hospitals since 1998. The standard ICD-9 and ICD-10 codes for diagnoses were used to identify individuals with cancer and the timing of the first cancer diagnosis. We used only data on inpatient care because practically all cancer diagnoses that require medical treatment lead to hospital stays, and a cancer diagnosis detected only in outpatient care is likely to be a false positive diagnosis in the Finnish context.[6]

We limited the study population to couples where the affected person received their first cancer diagnosis between the ages of 28–64. We restricted the cases to this age range to analyze labor market consequences before the statutory retirement age in Finland. Moreover, to compare our findings to the earlier results, we used the same age restriction as Jeon and Pohl (2017). The identical restriction was used for spouses as well.

Using personal identifiers, we linked those affected with a cancer diagnosis to their cohabiting partners (i.e., non-affected spouses). We identified the spousal effects only in stable relationships. We therefore imposed a restriction of cohabitation of 2 years before the index cancer diagnosis. Appendix Fig. A3 clarifies our empirical approach and the spousal sample criteria.

Observation period We used a balanced panel in the analysis. We followed individuals 5 years before and 10 years after the initial cancer diagnosis. The diagnosed spouse may pass away during the 10-year post-diagnosis follow-up but this does not affect the sample. However, we only studied those spouses of the affected cancer patients who were present and alive in Finland for the full 16 years of follow-up. This led to a reduction of 8.2% in men and a 4.0% reduction in women in the analytic sample, which consisted solely of spouses of individuals with a cancer diagnosis.

Outcomes Register-based information on the individual-level characteristics was obtained from the FOLK data of Statistics Finland. These data were used to construct the labor market outcome variables and covariates. Our main outcomes for studying spousal labor market responses were the employment status and annual earnings. We used a binary variable indicating whether the person was employed or not based on

[5] "FOLK" is not an abbreviation; rather, it refers to the content of the datasets, which consists of population-based data.

[6] In a preliminary analysis, we cross-checked Care Register for Health Care data with Cancer Registry data for breast cancer, noting discrepancies and false positives. We assessed outpatient care diagnoses to minimize bias in our results and determined that due to a higher false positive rate in outpatient data since 1998, we would use only inpatient data from the Care Register for Health Care in cancer diagnoses.

the main activity in the last week of each calendar year. We also analyzed the effects on retirement, based on the same information as employment.

Information on annual earnings before taxes was obtained from state-run pension and tax registers that cover all legal employment contracts in Finland. Earnings refer to the sum of labor market income and entrepreneurial income. We imputed missing income information as zero for individuals who were alive and residing in Finland at the end of the calendar year. Labor market income overwhelmingly dominates the earnings measure. The share of self-employed individuals among all employed persons is approximately 13% in Finland.

At the household level, we utilized information on the total household income, which accounts for the pooling of economic resources within the household level and includes social transfers provided by the Finnish welfare state. It includes all taxable income without capital income, and social transfers such as pensions, sickness allowance, and unemployment benefits. Disposable household income refers to the total household income after taxes and other deductions. Equivalised household disposable income further divides the disposable household income by the number of household members, taking into account economies of scale within the household. We have used the modified OECD equivalence scale for this purpose.

Finally, we used information on the filled psychotropic medications dispensed at Finnish pharmacies, which are reimbursed.[7] These data are provided by the Social Insurance Institution of Finland. We used an indicator for the purchase of prescribed reimbursable psychotropic drugs as an indicator for psychological well-being at the yearly level. Since all permanent residents of Finland are covered under the Finnish National Health Insurance (NHI) system and are eligible for reimbursements for prescribed medicines by a doctor or dentist, the vast majority of psychotropic medication prescriptions are recorded in this register. As a result, there is a high concordance between self-reported medication use and official prescription database information on psychotropic medicine purchases (Haukka et al. 2007).[8]

As an auxiliary outcome for studying mental health effects, we utilized specialized psychiatric outpatient visits derived from the Care Register for Health Care. We employed ICD-10 codes in F-class, excluding dementia and mental retardation, identifying individuals attending specialized psychiatric care. These visits typically indicate more severe psychiatric symptoms and therefore complement the psychotropic medication purchases, which cover a broader range of psychiatric symptoms.

Heterogeneity analysis by breadwinner status To identify the role of the household division of labor and specialization, we investigated the heterogeneity of indirect effects on the spouse, focusing on gender and the household income share of the

[7] Self-medication using alcohol is a potential outcome in the Finnish context. We do have access to nationwide alcohol-related and drug-related hospitalization data. However, instances of alcohol-related and drug-related hospitalizations are infrequent in the data, leading to estimated effects that are very close to zero and not statistically significant (not reported). There is no population-based survey information on alcohol consumption in Finland that could be linked to our register data. The use of illicit drugs or legal pain medication is generally not particularly relevant in the current Finnish context. For example, in Finland, opioids are mostly prescribed by specialists or pain clinics and are more tightly regulated and monitored than in the U.S. Thus, opioids are considered only as the last-line treatment for severe chronic pain.

[8] The NHI reimbursements do not include prescriptions given in hospitals and nursing homes.

Table 1 Descriptive statistics of analytical sample

Variable	Men (wife has cancer)				Women (husband has cancer)			
	Control group	Treatment group	Adj. Difference	P	Control group	Treatment group	Adj. Difference	P
Birth year	1952.7	1951.5	NA	NA	1952.5	1951.3	NA	NA
Year of spousal cancer	2014.9	2004.5	NA	NA	2014.9	2004.7	NA	NA
Age 28–44	0.256	0.170	NA	NA	0.215	0.154	NA	NA
Age 45–54	0.385	0.388	NA	NA	0.435	0.373	NA	NA
Age 55–64	0.359	0.442	NA	NA	0.350	0.473	NA	NA
Number of children	0.991	0.851	−0.012	0.153	0.858	0.666	−0.039	< 0.001
Education: Primary	0.278	0.288	−0.003	0.504	0.285	0.305	0.003	0.458
Education: Secondary	0.534	0.514	−0.009	0.043	0.589	0.568	−0.007	0.133
Education: Tertiary	0.188	0.197	0.011	0.001	0.126	0.127	0.004	0.220
Apartment/house owner	0.849	0.860	0.000	0.990	0.847	0.854	−0.002	0.499
Lives in capital region	0.245	0.271	0.038	< 0.001	0.239	0.257	0.023	< 0.001
Breadwinner	0.721	0.716	0.003	0.379	0.302	0.321	0.014	0.001
Earnings	34572.2	34372.8	568.7	0.011	22736.3	22125.2	−20.4	0.900
HH earnings	62850.4	62963.0	594.9	0.069	59634.2	56545.4	−1451.4	< 0.001
Eq. disposable income	29899.2	31150.9	359.0	0.005	29734.3	30812.1	205.7	0.117
Employed	0.785	0.763	0.004	0.220	0.753	0.713	−0.009	0.013
Work experience (years)	25.92	27.09	−0.07	0.175	23.90	24.92	−0.02	0.730
On pension	0.128	0.149	−0.005	0.064	0.111	0.153	0.008	0.003
Taxable income	42688.8	43369.9	634.8	0.010	28339.9	28533.0	150.5	0.350
Psychiatric inpatient stay	0.003	0.003	0.000	0.999	0.003	0.004	0.002	0.003

Table 1 continued

Variable	Men (wife has cancer)				Women (husband has cancer)			
	Control group	Treatment group	Adj. Difference	P	Control group	Treatment group	Adj. Difference	P
Psychiatric outpatient visits	0.008	0.009	0.001	0.254	0.013	0.014	0.002	0.127
Psychotropic medication	0.085	0.093	0.000	0.871	0.136	0.156	0.007	0.018
Antipsychotic medication	0.009	0.010	0.000	0.938	0.013	0.016	0.002	0.077
Anxiolytic medication	0.022	0.025	0.001	0.631	0.035	0.038	0.000	0.902
Hypnotic/sedative medication	0.027	0.032	0.000	0.948	0.043	0.056	0.005	0.005
Antidepressant medication	0.044	0.048	0.001	0.512	0.082	0.092	0.005	0.062
Opioid medication	0.020	0.021	−0.001	0.240	0.019	0.021	0.000	0.930
Charlson comorbidity index	0.110	0.114	−0.008	0.027	0.105	0.125	0.008	0.038
Spouse dies within 10 years	0.000	0.255	0.254	< 0.001	0.000	0.437	0.438	< 0.001
N	34484	23298			35849	20264		

Notes: This table presents sample means for the treatment and the control groups, broken down separately for men and women, for the year preceding the index diagnosis. Columns 3 and 7 report the age-adjusted mean difference in the background characteristics between the treatment and control groups, and columns 4 and 8 present the corresponding p-values. The sample comprises adults aged 28–64 whose spouses were diagnosed with cancer in Finland during the periods 2000 to 2008 (treatment group) and 2011 to 2019 (control group)

individual, i.e., the breadwinner status. Following Bünnings et al. (2021); Foster and Stratton (2021), we define a breadwinner as a spouse who out-earns the other. We constructed a binary variable that assumes a value of 0 if the individual's income contribution share was below 50% (indicating the secondary earner) 1-year prior to the index diagnosis and 1 if the share was above 50% (indicating the main breadwinner).

Table 1 describes the study sample, comparing the treatment and control groups before the index diagnosis. The index diagnosis denotes the year of cancer diagnosis for treated individuals and a placebo diagnosis year for the control group, occurring 11 years prior to the actual diagnosis year of the control group. Men (husbands of the cancer patient) were predominantly in the breadwinner category (72%), while women (wives of the cancer patient) were less represented (31%). Notable differences between the groups include employment status, retirement probability, and health, as measured by the Charlson comorbidity index (Charlson et al. 1987) using hospital data from 1996 until the year preceding the index diagnosis. These disparities are largely due to the different age distributions between the groups. Adjusting for a birth year reduces the average differences in the background characteristics, though some small differences remain, such as in earnings, disposable income, the likelihood of tertiary education, and health. These variations justify the use of difference-in-differences estimation with individual fixed effects.

Cancer-related mortality reduced the household size by one in 34% of families during the follow-up period within the treatment group. Notably, men who were diagnosed with cancer had a considerably higher likelihood of death (44%) compared to women (26%) during the 10-year post-cancer follow-up period.

4 Results

4.1 Main effects of spousal cancer

We start our empirical analysis by presenting the overall results based on Eq. 1. The estimates from this specification, accompanied by the corresponding 95% confidence intervals are depicted graphically in Fig. 2, while the parameter coefficients are reported in Appendix Tables A1–A4.

The figures plot the change in the outcomes of interest relative to the year before spousal cancer diagnosis in the treatment group. Importantly, the figures do not exhibit clear pre-trends, thereby supporting the key identification assumption underlying our empirical specification.

For women, we find evidence that they reduce their employment in the short-term but increase employment in the long-term after their spouse's cancer diagnosis (Panel A of Fig. 2). The average difference-in-differences estimate for women is zero (Appendix Table A2). Among male spouses, the effect was indistinguishable from zero throughout the follow-up. Overall, the labor market impacts are close to zero, which in contrast to the results in Jeon and Pohl (2017) for Canada according to which spouses of the cancer patients decrease substantially their labor supply (about 2 to 3 pp.) at the extensive margin leading to a lower level of earnings. Moreover, the changes

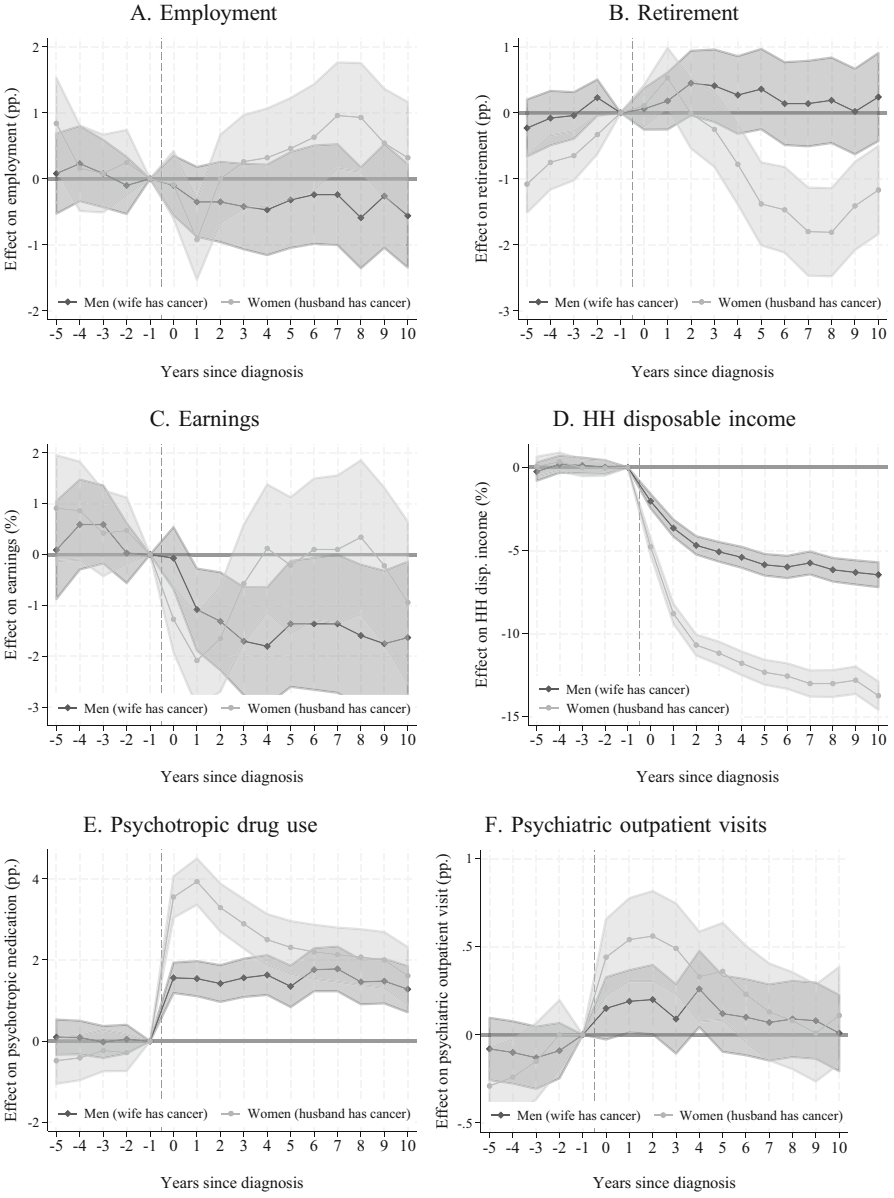

Fig. 2 The effect of spousal cancer on labor supply, income, psychotropic drug use, and psychiatric outpatient visits. The point estimates, with the shaded areas indicating the 95% confidence intervals, represent the differences in outcomes compared to the control group relative to the year preceding the index cancer diagnosis. The control group is composed of individuals diagnosed with cancer 11 years later relative to the treatment group. The vertical line at time $r = -0.5$ depicts the moment of the cancer diagnosis. Standard errors are clustered at the individual level. The corresponding event study estimates are detailed in Tables A1–A4

in employment for women were reflected in the probability of retiring from the labor market (Panel B). Consistent with the employment effects, the effect on the probability of retiring was larger for women compared to men in the long-term. While this result contrasts with that of regarding Nordic countries in Jolly and Theodoropoulos (2023), it is in accordance with a negative effect on (early) pension benefits among widows found by Fadlon and Nielsen (2021). As the social insurance structure is very similar between Denmark and Finland, and data and empirical strategy are almost identical, the concordant results with Fadlon and Nielsen (2021) are unsurprising.

However, when it comes to annual earnings (Panel C), the magnitude of the effect was negligible for women. Additionally, for male spouses, their earnings decreased after their spouse fell ill. This finding is consistent with the family effect, although the effect was modest with less than a 2% reduction in earnings.

The estimates for the household's disposable income (Panel D) (as well as for household's total income and household disposable income adjusted by using OECD modified equivalence scale shown in Appendix Tables A1 and A2) reveal a meaningful decrease, from 10 to 15% in the medium to long run among female spouses and approximately 5% among the male spouses. This result reveals that a female spouse's increase in earnings does not compensate for the loss of the sick spouse's income within the household. Our results highlight that financial consequences following a spouse's death tend to be harsher for women, which might explain the finding that cancer leads to a larger decrease in owner-occupancy in housing among women but not among men (Appendix Tables A1 and A2). Women may need to liquidate their assets to support household income and maintain material well-being.

Importantly, in addition to consequences in the labor market, cancer also affects the spouse's mental well-being. According to Panel E of Fig. 2, the probability of using psychotropic medication initially increased by approximately 4 percentage points (pp.) for women and about 2 pp. for men, and the impacts stabilized at around 1.5–2 pp. for both sexes. Relative to the baseline probability of psychotropic medication use, the relative increase in psychotropic medication was 13.0% for men and 14.1% for women on average during the full follow-up period. This result is in line with the evidence from Sweden and Denmark, suggesting a 13% risk increase in psychiatric disorders following a spouse's cancer (Hu et al. 2023). Appendix Tables A3 and A4 also report the corresponding estimates regarding sub-categories of psychotropic medication such as antipsychotic, anxiolytic, antidepressant, and sleep (hypnotics/sedatives) medicine. Overall, the dynamics of the effects are largely similar to psychotropics in general. These tables also report increases in the probability of visiting psychiatrists in specialized public health care. This outcome indicates more severe psychiatric symptoms. The increase is larger for women (DD estimate 0.3 pp. vs. baseline 1.1 pp.) than for men (DD-est 0.2 pp. vs. baseline 0.8 pp.). Hereafter we report psychiatric impacts only in (any) psychotropic medication.

A potential concern regarding the validity of the estimates is the endogenous nature of cancer. The event study specification ensures that the comparisons are conducted for individuals of the same sex, age, and cancer type of the spouse, and education level but with the timing difference of the spouse's cancer diagnosis of 11 years. The main concern therefore is related to the timing of the diagnosis. The timing difference can

potentially reveal differences between household living conditions and their health behaviors. Hence, as a robustness check, we re-estimated the effects of spousal cancer using only a subset of cancer diagnoses that are less related to health behaviors. This subset of cancers includes (ICD-10 category in parentheses): Gallbladder cancer (C23), Breast cancer (C50), and Ovarian cancer (C56), Prostate cancer (C61), Testicular cancer (C62), Thyroid cancer (C73), Myeloma (C90), Non-Hodgkin lymphoma (C82-85,C96), Leukaemia (C91-C95), and Brain and other central nervous system cancers (C70-72). The selection of cancers was based on the British (Brown et al. 2018) and Australian (Wilson et al. 2018) estimates of the fraction of cancers that are preventable within each cancer diagnosis category. In our analysis, we adopted a conservative approach and included only those types of cancer estimated to be preventable by up to 30%. Encouragingly, the results based on this subsample (Appendix Tables A5 and A6) are by and large very similar to the baseline results presented in Fig. 2. As an additional robustness check, we also restricted the sample to couples who had lived together for the entire 5-year period and found that results were quantitatively very similar (Appendix Tables A7 and A8).

Moreover, we examined whether the use of an event study approach affects the interpretation of the main results. Appendix Fig. A4 shows the results of this exercise for our preferred choice, FN DiD with a control group affected by cancer 6 years later, using a stacked event study design and matching with unaffected households. We find that the estimates are qualitatively the same across all four approaches and, for the most part, also quantitatively very similar.

As previously stated, the cancer survival rates differed notably by gender. 44% of men and 26% of women died during the 10-year follow-up (Table 1). This could lead to potential differences in the spousal labor supply responses between genders. For this reason, we next proceed to estimate the effects separately by the survival of the cancer patient.

4.2 Heterogeneity by breadwinner status in non-fatal cancers

We examine whether the pre-cancer relative income status within the household influences the impacts of spousal cancer in non-fatal cancers. We separately estimated the breadwinner heterogeneity effects for female and male spouses using Eq. 2 on earnings, employment, and psychotropic drug use in the short-, medium- and long-term. These results are presented in Table 2. The impact estimates for employment, psychotropic drug use, and marital status are presented in percentage points and as a percentage relative to the baseline values. The pre-cancer mean of the outcome within the breadwinner status is reported in the rightmost column.

We find that there is a reduction in earnings for secondary earners both for men and women in non-fatal cancers. In secondary-earner women, earnings decrease by 3 % throughout the follow-up period. In contrast, secondary-earner men experience an initial decrease of 2%, followed by income deficits of 4% and 3% in the medium- and long-term, respectively. The point estimates are negative also for breadwinners but they are not statistically significant. The difference in earnings responses by breadwinner status is statistically significant for women in the short-term and suggestively different

Table 2 Effects of spousal cancer by breadwinner status in non-fatal cancers

	Breadwinner status	Short-term		Medium-term		Long-term		Control group mean
		Est.	%	Est.	%	Est.	%	
A. Women (husband has cancer)								
Earnings (%)	Breadwinner	−0.6 [0.8]		−0.7 [1.1]		−2.7 [1.4]		27549.1
	Secondary earner	−2.8 [0.7]*		−3 [0.9]		−3.3 [1.1]		16880.1
Employment (pp.)	Breadwinner	0 [0.5]	0	−0.2 [0.6]	−0.3	−0.4 [0.7]	−0.6	72.3
	Secondary earner	−1.1 [0.4]†	−1.8	−0.3 [0.4]	−0.6	−0.2 [0.5]	−0.4	59.2
Psychotropic	Breadwinner	0.7 [0.5]	4.7	−0.1 [0.5]	−0.4	0.4 [0.6]	2.7	15.4
drug use (pp.)	Secondary earner	1.5 [0.3]	8.7	1.3 [0.3]*	7.2	1.1 [0.4]	6.4	17.4
Married with	Breadwinner	0.2 [0.3]	0.3	0 [0.4]	0	−0.2 [0.5]	−0.3	84.7
cancer patient (pp.)	Secondary earner	0.6 [0.2]	0.6	0.9 [0.3]†	1	0.9 [0.3]†	1.1	89
B. Men (wife has cancer)								
Earnings (%)	Breadwinner	0.1 [0.4]		−0.7 [0.6]		−1.5 [0.8]		36195.2
	Secondary earner	−1.8 [1.3]		−3.6 [1.5]†		−3.3 [1.7]		15184
Employment (pp.)	Breadwinner	−0.2 [0.3]	−0.3	−0.3 [0.3]	−0.5	−0.1 [0.4]	−0.1	71
	Secondary earner	−0.1 [0.5]	−0.1	0 [0.6]	0	−0.2 [0.7]	−0.4	52.2
Psychotropic	Breadwinner	0.6 [0.2]	5.6	0.4 [0.2]	3.5	0.6 [0.3]	6.2	10.2
drug use (pp.)	Secondary earner	0.6 [0.4]	4.4	0.7 [0.4]	5.3	0.8 [0.5]	5.9	13.2
Married with	Breadwinner	0 [0.2]	0	−0.2 [0.3]	−0.2	0 [0.3]	0	87.1
cancer patient (pp.)	Secondary earner	0.3 [0.3]	0.4	0.6 [0.4]	0.7	0.1 [0.5]	0.1	83.2

Notes: Short-, medium-, and long-term impacts of spousal cancer by different breadwinner status in non-fatal cancers. Standard errors (clustered at individual level) are reported beside the point estimates in parentheses. Short-term refers to DD estimates using post-event periods 0–2, medium-term to periods 3–5, and long-term to periods 6–10. Symbols †, * and ** refer to statistical significance 10%, 5% and 1% of the point estimates relative to the reference group (Breadwinner). All estimates are based on the triple-difference models presented in Eq. 2

for men in the medium-term. Interestingly, the responses are considerably more subtle in terms of employment, being negative only for secondary-earner women in the short-term. This suggests that in non-fatal cancers, the spouses of the patients adjust their labor supply more on the intensive margin than on the extensive margin, in line with the evidence presented by Fadlon and Nielsen (2021).

The purchases of prescribed psychotropic medications increase for both men and women. The effects are most pronounced in secondary earners, with a 1.5 percentage point (pp) increase in the short-term, and 1.3 pp. and 1.1 pp. increases in the medium and long-term, respectively. Heterogeneity in relative income is statistically significant only for women in the medium-term.

A potential factor affecting economic and mental health responses is union stability. In the final panels of Table 2, we report the impact of cancer on being married with the cancer patient. Approximately 87% of the couples were married at the baseline. We find that cancer has a positive effect on marriage for the secondary earner (cancer patient is the breadwinner) and no effect on the breadwinner (cancer patient is the secondary earner). This result is in line with prior research by Ehlert (2021) that found that health shock increases the probability of marriage among cohabiting couples more the higher are expected survivor pension for the widow. However, no such effects are found for men.

4.3 Heterogeneity by breadwinner status in fatal cancers

Finally, we investigate whether the impact of a cancer diagnosis resulting in death within the 10-year follow-up period differs by breadwinner status. In this analysis, we exclude marital outcomes, as death terminates marriage in the treatment group unless it had already dissolved beforehand. The analysis is based on a sample from which we exclude households where the cancer patient did not die during the follow-up period. These results are reported in Table 3.

We find that fatal spousal cancer initially decreases earnings by 3% and 2% for secondary and breadwinner women, respectively. In the long-term, there is a considerable contrast in the response in terms of relative income. Earnings of breadwinner women remained unchanged, whereas those of the secondary earners exhibited a 6% increase. A similar pattern is observed at the extensive margin; breadwinners showed no change in employment, while secondary earners experienced a significant 4 pp. increase in the long-term. The labor market responses were statistically significantly different for the secondary earner and breadwinner women only in the long-term. However, the increase in the probability of psychotropic medication purchases was consistently higher (1.4 pp. to 1.9 pp. higher) for the secondary earners compared to breadwinner women.

The breadwinner heterogeneity was markedly different for men. For men, we found no statistically significant differences by the breadwinner status for the most part, but the coefficients point towards statistically significant responses in the long-term with breadwinner men decreasing and secondary earners increasing their labor supply at the intensive margin. Additionally, breadwinner men showed higher increases in

Table 3 Effects of spousal cancer by breadwinner status in fatal cancers

	Breadwinner status	Short-term		Medium-term		Long-term		Control group mean
		Est.	%	Est.	%	Est.	%	
A. Women (husband has cancer)								
Earnings (%)	Breadwinner	−2 [0.8]		−0.1 [1.1]		−0.2 [1.3]		27398.9
	Secondary earner	−2.7 [0.8]		1.8 [1]		6.2 [1.2]**		16709.7
Employment (pp.)	Breadwinner	−0.3 [0.6]	−0.5	0.5 [0.7]	0.7	0 [0.7]	0	72
	Secondary earner	−0.3 [0.4]	−0.6	1.7 [0.5]	2.9	4.3 [0.6]**	7.3	58.8
Psychotropic	Breadwinner	6.4 [0.6]	41.7	4.2 [0.6]	27.5	2.7 [0.6]	17.4	15.3
drug use (pp.)	Secondary earner	7.8 [0.4]*	44.8	6.1 [0.4]**	35.4	4.3 [0.5]*	24.5	17.3
B. Men (wife has cancer)								
Earnings (%)	Breadwinner	−1.9 [0.7]		−3.1 [0.9]		−2.3 [1.1]		36131.4
	Secondary earner	−2.5 [2]		−2.1 [2.2]		2.2 [2.5]†		15116.9
Employment (pp.)	Breadwinner	−0.7 [0.5]	−1	−0.6 [0.5]	−0.8	0 [0.6]	0	70.9
	Secondary earner	0.7 [0.8]	1.3	0.4 [0.9]	0.7	1.1 [1.1]	2.1	52.1
Psychotropic	Breadwinner	4.3 [0.4]	42.2	4 [0.4]	39.3	3.8 [0.5]	37.2	10.2
drug use (pp.)	Secondary earner	2.9 [0.6]*	21.7	4.6 [0.7]	34.7	3.3 [0.8]	24.9	13.2

Notes: This table presents the short-, medium-, and long-term impacts of spousal cancer by different breadwinner statuses in fatal cancers. Standard errors, clustered at individual level, are presented alongside the point estimates in parentheses. Short-term refers to DD estimates for post-event periods 0–2, the medium-term to periods 3–5, and the long-term to periods 6–10. Symbols †, * and ** denote statistical significance 10%, 5%, and 1% levels, respectively, for the point estimates relative to the reference group (Breadwinner). All estimates are derived from the triple-difference models presented in Eq. 2

psychotropic medication purchases in the short-term compared to secondary earners, but not in the medium- and long-term.

Overall, we find that death is the primary driver behind the increased psychotropic drug use among spouses of cancer patients. When the cancer patient survives, spouses are relatively unaffected, but fatal cancer leads to notable increases in psychotropic drug purchases. While the estimates are not directly comparable, our results align with those of Angelini and Costa-Font (2023), which suggest that fatal cancer leads to a substantial increase in self-reported depression symptoms, while non-fatal cancers exhibit more subtle changes in psychological symptoms among spouses.

4.4 Reconciling the evidence across the relative income distribution

Overall, the results from the previous section suggest that the role of relative earnings is stronger for women than for men in responses to spousal cancer. However, a binary indicator for breadwinner status, determined strictly by a 0.5 cut-off does not capture the subtle responses along the relative income spectrum. To better understand the role of relative earnings in the responses to spousal cancer, we divided the sample into five equal-sized groups by the pre-shock earnings income share of the individual. For illustrative purposes, we focus solely on long-term responses, i.e., the impacts of spousal cancer on outcomes measured 6 to 10 years after the cancer diagnosis. Essentially, we conducted difference-in-differences analyses to estimate the long-term impacts separately for each relative income quintile and by sex.

Figure 3 shows the point estimates along with their 95% confidence intervals. On the x-axis, the income quintile shares represent the spouse's share of the total household income 1 year prior to the diagnosis. The mean values of income shares within each quintile are reported in the parentheses.

We find that the lower a spouse's relative income share within the household, the larger the increase in their earnings. The relationship is nearly linear in terms of earnings for both men and women (as shown in Panels A and B). This suggests that greater income losses due to losing a spouse correlate with a larger increase in labor supply at the intensive margin, relative to the counterfactual trajectory. This result aligns with the evidence from Fadlon and Nielsen (2021), which shows that the amount of a spouse's income lost due to fatal cardiovascular events is positively linked to labor supply responses among surviving spouses. Notably, our analysis also suggests that this pattern exists in both fatal and non-fatal cancers.

The heterogeneity in the responses at the extensive margin of labor supply is less evident (Panels C and D). We find that a spouse's baseline income share is negatively correlated with the added worker effect but only for women in fatal cancers. For both men and for women with non-fatal cancers, relative income does not appear to influence employment responses. Collectively, these results suggest that men are more likely to adjust their labor supply at the intensive margin, whereas for women, the extensive margin accounts for a larger share of the changes in earnings following a spouse's cancer diagnosis.

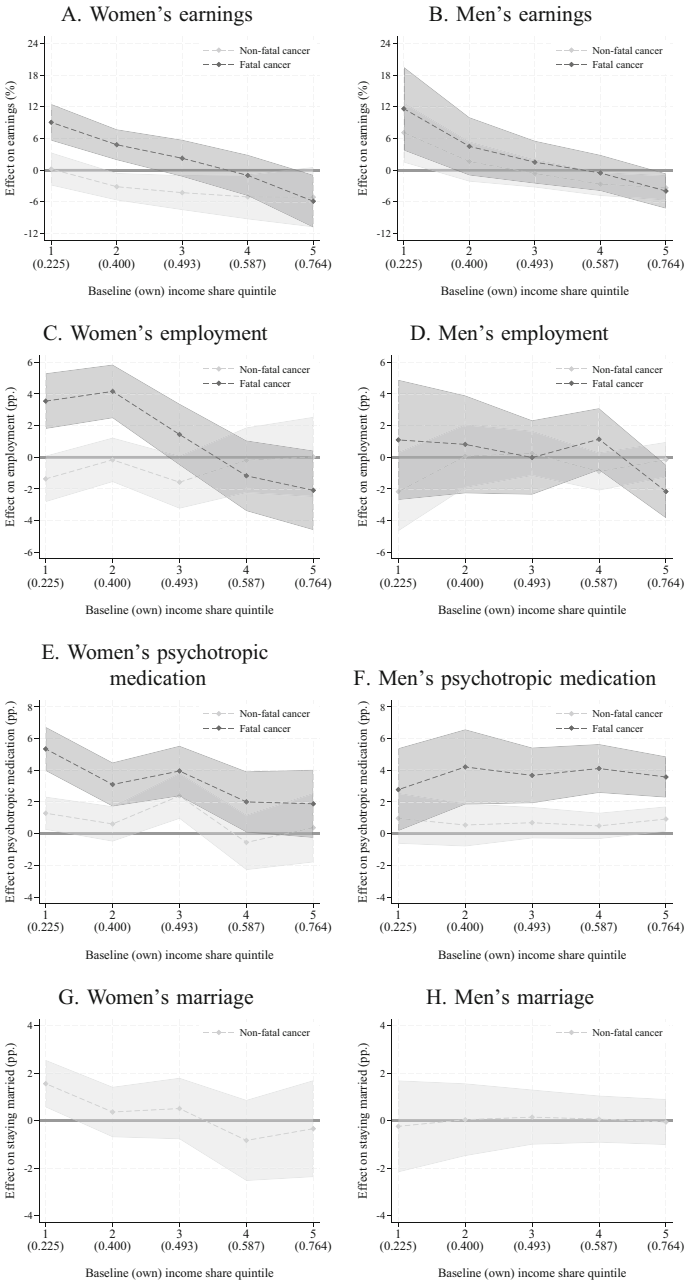

Fig. 3 Spouses' long-term response estimates along with 95% confidence intervals (years 6–10 after vs. 5 years preceding the cancer diagnosis) to fatal cancer, categorized by their pre-shock income share quintile within the household's total earnings. We divided the sample into five equal-sized groups based on the spouses' pre-cancer share of the total household income. Subsequently, we plotted the average outcome response against the pre-cancer mean income share for each quintile

Generally, we find that compositional differences between sexes in terms of relative income contribution within the household mask this heterogeneity. For men, the negative effect on income in the main results stems from the fact that they are predominantly breadwinners, with positive responses at the other end of the relative income spectrum receiving less weight. For women, it is both the relative income contribution and the survival status which drive the main results to zero effect in earnings and positive effect in employment.

Regarding psychotropic medication, there is a largely linear relationship between relative income contribution and increased usage of psychotropic medication, following a spouse's cancer diagnosis among women (Panel E). However, this is more evident for fatal cancers. For men, no noticeable heterogeneity is evident with respect to the relative income contribution within the household (Panel F). Given that the relative income effect in psychotropics occurs only for women in fatal cancers, it is possible that this is linked to the increased need for women to increase labor supply as a response to lost income following spouse's death.

Panels A to F highlight a distinct impacts of spousal cancer based on survival outcomes. To compare the effects of fatal versus non-fatal cancer (where the spouse survives beyond 10 years post-diagnosis), in Appendix Fig. A5 we conducted an illustrative analysis on post-diagnosis outcomes and after a spouse's death. This analysis involved comparing three groups: (i) individuals with a spouse diagnosed with cancer, (ii) individuals whose spouse received a cancer diagnosis 11 years later, and (iii) individuals whose spouse died 2 years post-diagnosis. Overall, these results indicate earnings losses in the short-term occur in tandem with the emotional shock but the impact on psychotropic medication is more long-term relative to labor market losses.

Finally, we also examine the effect of relative income on the marital status with the cancer patient in non-fatal cancers (Panels G and H). For men, no statistically significant effect is detected in any of the relative income contribution quintiles. For women, the effects are not statistically significant either, apart from the lowest relative income quintile for which we find a positive effect.

These findings indicate that while the relative income status is somewhat correlated with labor supply responses at the intensive margin and marital stability for women in non-fatal spousal health shocks, it does not significantly affect psychological well-being. In fatal cancers, however, relative income seems to have a more significant impact on both the decision to participate in the labor market and on psychological well-being, particularly among women. Women earning less than their deceased spouses often increase their long-term labor supply and are more prone to suffer from psychological symptoms. In contrast, for men, the consequences appear to be limited to labor supply decisions.

Differences in social safety nets, along with gender disparities in income and survival rates, may explain why our findings on labor supply responses to a spouse's health shock differ from previous studies in Canada (Jeon and Pohl 2017) and the USA (Berger and Fleisher 1984; Coile 2004), but are more consistent with recent European research (Fadlon and Nielsen 2021; Giaquinto et al. 2022).

5 Discussion and conclusion

Cancer not only affects individuals but also has significant repercussions for their families, including economic and non-economic challenges. While most research has focused on the labor market effects on the diagnosed individual, emerging studies have begun exploring broader family impacts (Jeon and Pohl 2017; Fadlon and Nielsen 2021; Breivik and Costa-Ramón 2024; Vaalavuo et al. 2023). Our research, utilizing comprehensive Finnish data from 1995 to 2019, examines the effects of a spouse's cancer diagnosis on the healthy spouse's labor, mental health, and marital stability, contributing to the understanding of household labor division dynamics.

Our empirical analysis reveals two main findings. First, labor market responses among spouses are modest, but we find a clear increase in the use of psychotropic medication and psychiatric outpatient visits, especially among women. Second, the effects vary based on income contribution within the household and the survival status of the cancer patient. In non-fatal cancer cases, labor supply decreases, particularly for secondary earners, and psychotropic medication use increases, especially among women. Marital stability also appears to increase for potential female caregivers who earn much less than the cancer patient, suggesting that higher economic dependency may act as a protective factor for marital stability. In contrast, fatal cancer cases show more pronounced labor supply responses and increased psychotropic medication use, particularly among secondary-earner women.

These results suggest the importance of considering gender, breadwinner status, and spouse survival in understanding family responses to health shocks. In the short-term, following a cancer diagnosis, spouses may reduce their work hours to care for their ill partner or to spend more time together, showing a caregiver or family effect. However, following a spouse's death, secondary earners often delay retirement and work longer, aligning with the findings by (Fadlon and Nielsen 2021) on increased labor as self-insurance against severe health shocks. This is particularly evident in fatal cancer cases, where secondary earners increase their labor supply more than primary breadwinners, often accompanied by greater psychological distress, possibly due to financial strains or the need for social interaction at work during stressful times.

Our empirical approach has three limitations. First, there are significant socioeconomic inequalities in cancer survival probabilities (Vaccarella et al. 2023) and they potentially complicate the interpretation of the indirect economic effects at the family level. Cancer diagnoses are diverse, with each cancer type having unique selection processes and survival probabilities. Our study, which focuses on cancers in general, may overlook differences in spousal responses based on cancer type and education level. Second, while we use nationwide register data, we deduce the importance of the caregiver role indirectly based on the spouse's labor market participation. Evidence suggests that women experience more caregiving burden than men (Glauber 2017). It is possible that some spouses increase their work hours due to financial needs while also providing more care, reducing their personal leisure time. This dual burden might explain observed gender-specific effects on psychotropic medication and marital stability. Understanding the link between these gender disparities and economic dependence is a valuable direction for future research.

Labor supply responses of the spouse are correlated with the share of household income that the deceased had earned prior to the cancer diagnosis. As Fadlon and Nielsen (2021) emphasize, this suggests that policies accounting for the pre-health shock characteristics are likely to improve welfare for those facing the largest losses. Our study suggests that healthcare professionals should also pay attention to those characteristics. Losing the breadwinner appears to be particularly distressing for the women, as indicated by long-term increases in psychotropic drug use. Sudden health shocks disrupt established household labor divisions, leading to significant labor market adjustments and mental distress. This is particularly relevant in contexts like Finland with a strong welfare state, and the effects might be more pronounced in countries with weaker social safety nets.

To conclude, our findings highlight that future research on health shocks in the family context should pay more attention to the heterogeneity of the effects by the breadwinner status and consider the role of household division of labor. This information would be helpful for targeting policy measures, such as social income transfers and related public interventions, to those most in need.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00148-025-01070-x.

Acknowledgements We would like to thank the Editor, Xi Chen, and three anonymous referees for their comments that greatly improved the paper. We also acknowledge participants of the American Society of Health Economics Conference, Nordic Health Economics Study Group, Labore seminar, TSER seminar, and JSBE seminar for their comments and suggestions. This research was supported by the INVEST Research Flagship Centre.

Funding Open Access funding provided by Finnish Institute for Health and Welfare. This project has been financed by the Social Insurance Institution of Finland (Kela) and Research Council of Finland (decision number: 345546).

Data availability The analysis is based on data that require a license from Statistics Finland, Finnish Institute for Health and Welfare and FinData. Access to these data is not restricted to any particular institution or research group. The data can be analyzed at Statistics Finland's remote server from universities and research institutes in the EU, subject to Statistics Finland's data security approval. Details of the application process are available at Statistics Finland and Findata websites.

Declarations

Conflict of interest The authors declare no competing interests.

References

Anand P, Dague L, Wagner KL (2022) The role of paid family leave in labor supply responses to a spouse's disability or health shock. J Health Econ 83:102621. https://doi.org/10.1016/j.jhealeco.2022.102621

Angelini V, Costa-Font J (2023) Health and wellbeing spillovers of a partner's cancer diagnosis. J Econ Behav Organ 212:422–437. https://doi.org/10.1016/j.jebo.2023.06.001

Arrieta GR, Li G (2023) Caring to work or working to care: the intra-family dynamics of health shocks. Am J Health Econ 9(2):175–204. https://doi.org/10.1086/722588

Becker GS (1991) A Treatise on the Family: Enlarged edition. Harvard University Press

Becker GS, Landes EM, Michael RT (1977) An economic analysis of marital instability. J Polit Econ 85(6):1141–1187. https://doi.org/10.1086/260631

Berger MC (1983) Labor supply and spouse's health: the effects of illness, disability, and mortality. Soc Sci Q 64(3):494

Berger MC, Fleisher BM (1984) Husband's health and wife's labor supply. J Health Econ 3(1):63–75. https://doi.org/10.1016/0167-6296(84)90026-2

Bertrand M, Kamenica E, Pan J (2015) Gender identity and relative income within households. Q J Econ 130(2):571–614. https://doi.org/10.1093/qje/qjv001

Blundell R, Walker I (1982) Modelling the joint determination of household labour supplies and commodity demands. Econ J 92(366):351–364. https://doi.org/10.2307/2232445

Bünnings C, Hafner L, Reif S, Tauchmann H (2021) In sickness and in health? Health shocks and relationship breakdown: empirical evidence from Germany. J Econ Behav Organ 190:164–190. https://doi.org/10.1016/j.jebo.2021.07.029

Bobinac A, Van Exel NJA, Rutten FF, Brouwer WB (2010) Caring for and caring about: disentangling the caregiver effect and the family effect. J Health Econ 29(4):549–556. https://doi.org/10.1016/j.jhealeco.2010.05.003

Böckerman P, Ilmakunnas P (2009) Unemployment and self-assessed health: evidence from panel data. Health Econ 18(2):161–179. https://doi.org/10.1002/hec.1361

Bom J, Bakx P, Schut F, van Doorslaer E (2019) Health effects of caring for and about parents and spouse. J Econ Ageing 14:100196. https://doi.org/10.1016/j.jeoa.2019.100196

Bonekamp J, Wouterse B (2023) Do different shocks in health matter for wealth? J Health Econ 87:102719. https://doi.org/10.1016/j.jhealeco.2022.102719

Borusyak K, Jaravel X, Spiess J (2024) Revisiting event-study designs: robust and efficient estimation. Rev Econ Stud. https://doi.org/10.1093/restud/rdae007

Bradley CJ, Neumark D, Bednarek HL, Schenk M (2005) Short-term effects of breast cancer on labor market attachment: results from a longitudinal study. J Health Econ 24(1):137–160. https://doi.org/10.1016/j.jhealeco.2004.07.003

Breivik A-L, Costa-Ramón A (2024) The Impact of Children's Health Shocks on Parents' Labor Earnings and Mental Health. Rev Econ Stat 1–45. https://doi.org/10.1162/rest_a_01499

Brown KF, Rumgay H, Dunlop C, Ryan M, et al (2018) The fraction of cancer attributable to modifiable risk factors in England, Wales, Scotland, Northern Ireland, and the United Kingdom in 2015. Br J Cancer 118(8):1130–1141. https://doi.org/10.1038/s41416-018-0029-6

Callaway B, Sant'Anna PH (2021) Difference-in-differences with multiple time periods. J Econom 225(2):200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Cengiz D, Dube A, Lindner A, Zipperer B (2019) The effect of minimum wages on low-wage jobs. Q J Econ 134(3):1405–1454. https://doi.org/10.1093/qje/qjz014

Charlson ME, Pompei P, Ales KL, MacKenzie CR (1987) A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chron Dis 40(5):373–383. https://doi.org/10.1016/0021-9681(87)90171-8

Chen J, Roth J (2024) Logs with zeros? Some problems and solutions. Q J Econ 139(2): 891–936. https://doi.org/10.1093/qje/qjad054

Coile CC (2004) Health shocks and couples' labor supply decisions. NBER Work Pap No. 10810

Ehlert A (2021) The effects of health shocks on family status: do financial incentives encourage marriage? Eur J Health Econ 22(9):1393–1409. https://doi.org/10.1007/s10198-021-01319-8

Fadlon I, Nielsen TH (2019) Family health Behavs. Am Econ Rev 109(9):3162–3191. https://doi.org/10.1257/aer.20171993

Fadlon I, Nielsen TH (2021) Family labor supply responses to severe health shocks: evidence from Danish administrative records. Am Econ J Appl Econ 13(3):1–30. https://doi.org/10.1257/app.20170604

Foster G, Stratton LS (2021) Does female breadwinning make partnerships less healthy or less stable? J Popul Econ 34(1):63–96. https://doi.org/10.1007/s00148-020-00783-5
García-Gómez P, Van Kippersluis H, O'Donnell O, Van Doorslaer E (2013) Long-term and spillover effects of health shocks on employment and income. J Hum Resour 48(4):873–909. https://doi.org/10.1353/jhr.2013.0031
Giaquinto AM, Jones AM, Rice N, Zantomio F (2022) Labor supply and informal care responses to health shocks within couples: evidence from the UK. Health Econ 31(12):2700–2720. https://doi.org/10.1002/hec.4604
Glauber R (2017) Gender differences in spousal care across the later life course. Res Aging 39(8):934–959. https://doi.org/10.1177/01640275166445
Global Burden of Disease 2019 Cancer Collaboration (2022) Cancer incidence, mortality, years of life lost, years lived with disability, and disability-adjusted life years for 29 cancer groups from 2010 to 2019: a systematic analysis for the global burden of disease study 2019. JAMA Oncol 8(3):420–444. https://doi.org/10.1001/jamaoncol.2021.6987
Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. J Econom 225(2):254–277. https://doi.org/10.1016/j.jeconom.2021.03.014
Guan T, Qan'ir Y, Song L (2021) Systematic review of illness uncertainty management interventions for cancer patients and their family caregivers. Support Care Cancer 29:4623–4640. https://doi.org/10.1007/s00520-020-05931-x
Haukka J, Suvisaari J, Tuulio-Henriksson A, Lönnqvist J (2007) High concordance between self-reported medication and official prescription database information. Eur J Clin Pharmacol 63(11):1069–1074
Hu K et al (2023) Risk of psychiatric disorders among spouses of patients with cancer in Denmark and Sweden. JAMA Netw Open 6:e2249560. https://doi.org/10.1001/jamanetworkopen.2022.49560
Jeon S (2017) The long-term effects of cancer on employment and earnings. Health Econ 26:671–684. https://doi.org/10.1002/hec.3342
Jeon S-H, Pohl RV (2017) Health and work in the family: evidence from spouses' cancer diagnoses. J Health Econ 52:1–18. https://doi.org/10.1016/j.jhealeco.2016.12.008
Jeon S-H, Pohl RV (2019) Medical innovation, education, and labor market outcomes of cancer patients. J Health Econ 68:102228. https://doi.org/10.1016/J.JHEALECO.2019.102228
Jolly NA, Theodoropoulos N (2023) Health shocks and spousal labor supply: an international perspective. J Popul Econ 36:973–1004. https://doi.org/10.1007/s00148-022-00929-7
Kvaerner JS (2022) How large are bequest motives? Estimates based on health shocks. Rev Financ Stud 36:3382–3422. https://doi.org/10.1093/rfs/hhac093
Leira A (1992) Welfare states and working mothers: the Scandinavian experience. Cambridge University Press, Cambridge
Lundberg S (1985) The added worker effect. J Labor Econ 3:11–37. https://doi.org/10.1086/298069
Mellon S, Kershaw TS, Northouse LL, Freeman-Gibb L (2007) A family-based model to predict fear of recurrence for cancer survivors and their caregivers. Psycho-Oncol 16:214–223. https://doi.org/10.1002/pon.1074
Mincer J (1962) Labor force participation of married women: a study of labor supply. In: Aspects of labor economics, pp 63–105. Princeton University Press, Princeton
Northouse LL, McCorkle R (2015) Spouse caregivers of cancer patients. In: Psycho-Oncology. Oxford University Press. https://doi.org/10.1093/med/9780199363315.003.0075
Parsons DO (1977) Health, family structure, and labor supply. Am Econ Rev 67:703–712
Picchio M, Ubaldi M (2024) Unemployment and health: a meta-analysis. J Econ Surv 38:1437–1472. https://doi.org/10.1111/joes.12588
Riekhoff A-J, Vaalavuo M (2021) Health shocks and couples' labor market participation: a turning point or stuck in the trajectory? Soc Sci Med 276:113843. https://doi.org/10.1016/j.socscimed.2021.113843
Schwartz CR, Gonalons-Pons P (2016) Trends in relative earnings and marital dissolution: are wives who outearn their husbands still more likely to divorce? RSF J Soc Sci 2(4):218–236. https://doi.org/10.7758/rsf.2016.2.4.08
Stöckel J, Bom J (2022) Revisiting long-term effects of informal caregiving: evidence from the UK. J Econ Ageing 21:100343. https://doi.org/10.1016/j.jeoa.2021.100343
Syse A (2008) Does cancer affect marriage rates? J Cancer Surviv 2(3):205–214. https://doi.org/10.1007/s11764-008-0062-1

Tai P, Yu E, Cserni G, Vlastos G, Royce M, Kunkler I, Vinh-Hung V (2005) Minimum follow-up time required for the estimation of statistical cure of cancer patients: verification using data from 42 cancer sites in the SEER database. BMC Cancer 5:48. https://doi.org/10.1186/1471-2407-5-48

Vaalavuo M (2021) The unequal impact of ill health: earnings, employment, and mental health among breast cancer survivors in Finland. Labour Econ 69:101967. https://doi.org/10.1016/j.labeco.2021.101967

Vaalavuo M, Salokangas H, Tahvonen O (2023) Gender inequality reinforced: the impact of a child's health shock on parents' labor market trajectories. Demography 60:1005–1029. https://doi.org/10.1215/00703370-10828906

Vaccarella S, Georges D, Bray F, Ginsburg O et al (2023) Socioeconomic inequalities in cancer mortality between and within countries in Europe: a population-based study. Lancet Reg Health-Europe 25, 100555. https://doi.org/10.1016/j.lanepe.2022.100551

Wilson LF, Antonsson A, Green AC, Jordan SJ et al (2018) How many cancer cases and deaths are potentially preventable? Estimates for Australia in 2013. Int J Cancer 142(4):691–701. https://doi.org/10.1002/ijc.31088

Authors and Affiliations

Petri Böckerman[1,2,3] · Mika Kortelainen[4,5] · Henri Salokangas[5] · Maria Vaalavuo[5]

✉ Henri Salokangas
henri.salokangas@thl.fi

Petri Böckerman
petri.bockerman@labore.fi; petri.bockerman@labour.fi

Mika Kortelainen
mika.kortelainen@thl.fi; mika.kortelainen@utu.fi

Maria Vaalavuo
maria.vaalavuo@thl.fi

1 Labour Institute for Economic Research LABORE, Arkadiankatu 7 (Economicum), FI-00100 Helsinki, Finland

2 School of Business and Economics, University of Jyväskylä, FI-40014 Jyväskylä, Finland

3 IZA Institute of Labor Economics, Bonn, Germany

4 Department of Economics, Turku School of Economics, InFLAMES Research Flagship Center, Turku, Finland

5 INVEST Research Flagship Centre, Finnish Institute for Health and Welfare, Mannerheimintie 166, FI-00300 Helsinki, Finland