Utrecht University

School of Economics

Husband's labour supply after a breast cancer diagnosis

Zornitza Kambourova
Wolter Hassink

U.S.E. Working Paper Series nr: 19-10

Utrecht University School of Economics

Utrecht University School of Economics (U.S.E.) is part of the faculty of Law, Economics and Governance at Utrecht University. The U.S.E. Research Institute focuses on high quality research in economics and business, with special attention to a multidisciplinary approach. In the working papers series the U.S.E. Research Institute publishes preliminary results of ongoing research for early dissemination, to enhance discussion with the academic community and with society at large.

The research findings reported in this paper are the result of the independent research of the author(s) and do not necessarily reflect the position of U.S.E. or Utrecht University in general.

U.S.E. Research Institute
Kriekenpitplein 21-22, 3584 EC Utrecht, The Netherlands Tel: +31 30 253 9800, e-mail: use.ri@uu.nl www.uu.nl/use/research

U.S.E. Research Institute
Working Paper Series 19-10

Husband's labour supply after a breast cancer diagnosis

Zornitza Kambourova*
Wolter Hassink*~
*Utrecht School of Economics
Utrecht University
~IZA Institute of Labor Economics
Germany

July 2019

Abstract

This paper evaluates the spillover effects on the males' labour supply after their partner was diagnosed with breast cancer. We use Dutch administrative monthly data for the period 2006-2012. The estimates indicate that husbands are 0.71 percentage points less likely to be employed due to the diagnosis of their wife. It implies that the negative caregiving effect is stronger than the positive income effect on the males' labour supply. Furthermore, the estimates suggest that effect is related to the employment status of the women prior to the medical diagnosis. If the women were employed at the moment of the diagnosis of breast cancer, their husbands would reduce their employment on average by 0.86 percentage points after the diagnosis. In contrast, there was no change of the husbands' employment in case their partner was not employed at the moment of the diagnosis of breast cancer. Those differences can be explained by the sickness leave arrangements in the Netherlands, which mitigate the negative consequences on the incomes of the women who become sick.

Keywords: breast cancer; caregiving; added-worker effect; spouse; labour supply

JEL classification: I12, I14, J22, J28

Comments welcomed to: W.H.J.Hassink@uu.nl

Husband's labour supply after a breast cancer diagnosis

1. Introduction

Breast cancer is the most common type of cancer among women and the second deadliest in the developed countries (GLOBOCAN, 2012). The Netherlands ranks fourth in the incidence of breast cancer in 2012, after Belgium, Denmark and France (GLOBOCAN, 2012), with one out of eight women being diagnosed with breast cancer at some point in her life (RIVM, 2014). The costs associated with breast cancer could be related not only to the direct costs of healthcare goods and services, but also to the indirect costs of unpaid caregiving by family members, as well as lost work time for the sick women. This could have financial consequences for the family. To reduce these financial consequences, the Netherlands has an institutional setting, which provides income replacement during the period of caregiving leave, as well as during the period of sick leave, and thus it could be seen as a social insurance mechanism.

A broad literature has examined the negative effect of caregiving on the labor supply of the individual (Carmichael and Charles, 1998, 2003; Charmichael, Charles and Hulme, 2010; Ettner, 1996; Heitmueller, 2007; Hassink and van den Berg, 2011; Van Houtven, Coe and Skira, 2013; Schmitz and Westphal, 2017). Husbands of diagnosed wives may decide to take up informal care, so that they can spend more leisure time with their sick wife, have more home production and/or provide specific medical care activities. Thus, informal care is likely to result in a (temporary) decline of the partner's labor supply – he may decide to work fewer hours or he may even resign from work. This is referred to as the caregiving effect or home production effect.[1] An important issue in this literature is that the estimates of the effect of care on labor supply are plagued by endogeneity (reverse causality). Consequently, it may be useful to focus on exogenous health shocks.

Other indirect costs of the sickness are related to the lost income of the unhealthy individual due to inability to work (Halla and Zweimüller, 2013; García-Gómez, Van Kippersluis, O'Donnell and Van Doorslaer, 2013). As such, it is possible that rather than staying at home to provide informal care, the husband may increase his labor supply to compensate for the lost income of his partner (Berger, 1983). This is referred to as the added-worker effect or the income effect. While this effect is mostly present when the husband suffers from an adverse health event (Parsons, 1977; Charles, 1999), there is also evidence for added-worker effect after a health deterioration of the wife (Coile, 2004).

[1] We will use the combined term 'care giving' to represent unpaid caregiving, home production and leisure complementarities.

While examining these two effects – the caregiving and income effect, and the resulting indirect cost for the healthy spouse's labor supply – has been done extensively by the existing literature, the intermediation role of the institutional setting has not been considered yet. In the Netherlands, the country investigated in this study, sick leave schemes provide short-term income replacement after an adverse health event. As such, they reduce the financial burden to the diagnosed woman from the reduction in labor supply due to the sickness. Furthermore, caregiving leave provides income replacement for the healthy spouse, so that the healthy spouse could provide care for his/her sick partner without incurring additional financial loss. In a way, the institutional setting in the Netherlands provides a social insurance in the occasion of a health problem. The aim of this paper is to examine whether this social insurance could be related to more caregiving from the husband for his sick wife.

To address this question, we will perform an empirical analysis on Dutch administrative monthly data for the period 2006 to 2012. We focus on couples in which the wife receives a medical diagnosis of breast cancer between the ages of 47 and 53, and we will estimate the consequences for their husband's labor supply. As cancer diagnoses are exogenous shocks – because of their severity and unanticipated nature (Jeon and Pohl, 2017) – an empirical analysis of their impact would lead to causal interpretation of the estimated parameters. We will compare couples in which the wife receives a medical diagnosis of breast cancer with couples in which the wife does not receive such a diagnosis. To account for observed and unobserved heterogeneity in both groups, we will perform a combination of Coarsened Exact Matching and a difference-in-difference estimation strategy. In addition, to capture the differences in the coverage of the social insurance – namely the sick leave coverage – we will compare couples in which the wife was employed before the diagnosis with couples in which the wife was not employed. Furthermore, because all women in the Netherlands from the age of 50 onwards are invited to participate for free in a nationwide breast cancer screening program, we will use the access to the program as an indicator of the severity of the medical diagnosis.

The estimates indicate that husbands are 0.71 percentage points less likely to be employed after their wife receives a breast cancer diagnosis (for an average employment rate of 81.5 percent). This result suggests that the caregiving effect is stronger than the added-worker effect. This result is in line with the previous literature (García-Gómez et al., 2013; Jeon and Pohl, 2017). Our main contribution is related to disentangling the income and caregiving effect by considering the employment state of the wife prior to the medical diagnosis. While husbands whose wives were employed before the diagnosis were likely to reduce their employment rate by 0.86 percentage points after she was diagnosed, husbands whose wives were not employed, did not change employment. Such a result could be related to the replacement income during sick leave, which is likely to reduce the financial loss for the couple and could aid the husband to spend more time with his wife. On the other hand, in the families where the wife was not earning any salary, it is likely that the family fully depends on the husband's salary and therefore, he is less likely to reduce his employment to provide unpaid home care for his wife. The estimates indicate that the financial constraint could be important for this decision. Interestingly, we do not observe any change in the husband's number of working hours. This is likely the case as we observe contractual working time. If the husband takes the number of hours that are allowed by law to provide unpaid homecare for his wife, we would not observe any decrease of working hours. Nevertheless, observing a contractual decrease in employment probability (even a small one) suggests that the hours of caregiving leave provided by the law are likely to not be sufficient for unpaid caregiving. This result could be important for policy matters, as it suggests need for more caregiving opportunities for the spouse.

Interestingly, when we considered the differences in the employment probability of the husbands in relation to the severity of the diagnosis of their wife, we did not observe any statistically significant difference. This suggests that the caregiving and income effect from a breast cancer diagnosis are not likely to be related to the stage of the disease. Furthermore, our results suggest important differences for the presence of children in the household. There seems to be a stronger income effect if there are children in the household – this effect is stronger in the households where the wife was not employed before the diagnosis.

The structure of the paper is as follows. Section 2 presents the theoretical framework and the institutional setting. Section 3 describes the data and Section 4 the statistical model. Results are presented in Section 5, robustness checks in Section 6 and conclusions in Section 7.

2. Economic framework

2.1. Caregiving effect and added-worker effect

The spillovers of one's health deterioration on the other spouse's employment patterns can be explained by two opposing effects – the caregiving effect and the added-worker effect.

The caregiving effect is a reduction of one's labor supply so that they have time to take unpaid home care of their sick family member. A broad literature has examined the negative implications of providing informal care for the caregiver's labor supply (Carmichael and Charles, 1998, 2003; Ettner, 1996; Heitmueller, 2007), as well as the time-bound opportunity cost of the caregiving tasks (Hassink and Van den Berg, 2011). Specifically, for cancer patients, De Moor et al. (2017) find that their caregivers are likely to make employment changes during the treatment and recovery period. For married women diagnosed with breast cancer, the main caregiver is their husband (Petrie, Logan and DeGrasse, 2001; Grunfeld et al., 2004). Thus, we would expect to find changes in the labor supply of husbands whose wives have been diagnosed with breast cancer.

Besides the caregiver effect, there could also be an income effect. Due to the health problem, the diagnosed wife may not be able to work, which could have a negative impact on the family financial situation. Previous studies show that after an adverse health event, women are less likely to be employed than healthy women (García-Gómez, Van Kippersluis, O'Donnell and Van Doorslaer, 2013; Halla and Zweimüller, 2013; Kambourova, Hassink and Kalwij, 2019). Studies considering women diagnosed with breast cancer also find negative impact from the disease on the employment probability of women both in the short term (Bradley et al., 2005, 2006) as well as in the long term (Bradley et al., 2002; Heinesen and Kolodziejszyk, 2013). Thus, we would expect that husbands of employed wives will increase their employment to compensate for the lost income.

The literature has found mixed results about the strongest spillover effect. Berger (1983) argues that the difference comes from the tasks that the sick person cannot perform. According to him, since wives are specialized in home production, their sickness reduces the amount of their home production and as a result their husband has to spend more time on house chores, which ultimately decreases his time available for work. However, the task division in the households has changed over time with more wives entering the labor market. Therefore, it is likely that the spillover from the wives' health deterioration may differ between women who are employed at the time of the health deterioration and those that are not. The husbands of employed wives may have to work more to compensate for the lost income; while those of the non-employed wives may have to compensate in the household production.

Recent studies such as Jeon and Pohl (2017) and García-Gómez et al. (2013), consider the impact of a spouses' health condition on the individual by considering both genders separately. Jeon and Pohl (2017) look at individuals in Canada whose spouse was diagnosed with cancer. They find a reduction in employment probability (2.4 percentage points, on average), annual personal income and family income for both genders during the first five years after the diagnosis of their spouse. Based on their findings, the authors claim that the caregiver and leisure complementarities mechanisms are stronger than the added-worker mechanism for both genders. Differently than them, García-Gómez et al. (2013) found gender asymmetry in the employment adjustments after an acute hospitalization of the spouse in the Netherlands. They found a 1.6 percentage point reduction in the employment probability of husbands whose wives fell sick, while they did not find any statistically significant effect for women. However, when the authors divided the healthy spouses into selections of initially employed and initially non-employed individuals, they found similar effects for each gender, namely a reduction in the employment probability of the initially employed individuals; and no statistically significant effect for the initially non-employed individuals after a sickness of their spouse. As such, their results suggest that rather than gender differences, the adjustments in employment could be related to the initial employment state of the healthy individual. It is likely that due to the unequal distribution of employed individuals among the two genders, on average, when considering a gender on its own, one of the mechanisms prevails.

Different from the existing literature, we will differentiate between husbands based on the employment of their spouse who received a diagnosis. Following Grossman (1972), the individual who suffers from an adverse health event is the one whose time allocation is directly affected: the individual loses part of her health capital and therefore she needs to spend more time on recovering it. As a result, she has less time available for work and leisure, and ultimately, she works less. The spouse, therefore, is indirectly affected based on the tasks that he needs to compensate for.

Based on the existing literature, we would expect that if the diagnosed wife was not employed before the medical diagnosis, this would suggest that she was specialized in home production and therefore, her husband would have to compensate for the losses in home production. Such a mechanism would suggest a reduction in the employment probability of the husband. However, as he is the only breadwinner in the family, it is likely that he would not be able to reduce his employment, as that would lead to reduction in the family income. Thus, it is not clear from a theoretical stand point which of the two effects will be stronger. On the other hand, if the wife was employed before the diagnosis, then it is likely that she was not the main contributor to the home production, as well as that she has been contributing to the family budget. Thus, the husband may have to work harder to compensate for the lost income. Last, no matter the employment situation of the wife, in the occasion of a severe health condition such as breast cancer, it is likely that the husband would want to provide care for his wife.

2.2. Dutch institutional setting

There are two regulations in the institutional setting in the Netherlands that could mitigate the indirect negative financial effects of an adverse health event. First, an employee can take time off work to care for their sick spouse ('zorgverlof'). Besides taking one day as an emergency leave, the employee is allowed to take short-term care leave of a maximum of two weeks per year. To be able to take those weeks off work, the employee has to show that he/she is the only one who can take care for the individual. During this time, the employee receives at least 70% of their salary. In the occasion that the employee needs to take long-term care leave, he can take six times his weekly work hours and spread this time over a period of 12 to 18 weeks. However, during this long-term care leave the employee does not receive a salary. Therefore, it could introduce a financial burden to the family. Furthermore, there is no job protection during the period of care leave, which implies that the employee could be laid off while taking care of a sick family member.

Second, employees who suffer from an adverse health event can take sick leave, which provides income replacement until they can return to work. Since 2004, employees in the Netherlands can take up to two years of sick leave after a severe health problem. During the first year of sick leave they receive 100% of their salary and in the second year they receive 70%. In the occasion that they are unfit to work after that period, they can enroll on disability insurance (see Koning and Lindeboom, 2015).

Given the institutional setting in the Netherlands, we expect to find differences in the employment adjustments of husbands whose wives were employed before the adverse health event and thus receive replacement income, and husbands whose wives were not employed before the adverse health event. We expect that in the former case, the financial burden will be less for the family, thus the husband will be able to take more time off work so that he can provide care for his wife.

2.3. Breast cancer and breast cancer screening program

Breast cancer is a life-threatening disease, which is more common for older women. The average age at diagnosis is 61 years and in most cases at the time of diagnosis the tumor is already invasive (Health Council of the Netherlands, 2014); the five-year survival rate in the Netherlands is 86 percent (Dutch Cancer Registration, 2017). The occurrence of breast cancer, however, cannot be attributed purely to genetics, which have been shown to explain about 8-10 percent of the cases (Breastcancer.org, 2017). The risk of breast cancer is positively related to age, education (Palme and Simeonova, 2015), having a first pregnancy after the age of 30, drinking and smoking, and birth-control pills (Breastcancer.org, 2017).

The high incidence rate of breast cancer and the high mortality have resulted in the introduction of a medical screening program in the Netherlands in 1998, which aims at an early detection and improved chance of survival of breast cancer. The participation in the screening program is free of charge to all women in the Netherlands. They receive a first invitation to participate at the age of 50 and, if they are not diagnosed with breast cancer at that time, they are invited again for screening every other year until they reach the age of 75.

In 2014, there were 68 screening units in the Netherlands, which screen a total of more than one million women every year (Health Council of the Netherlands, 2014). Based on the screening results, women are referred to special clinics for further evaluation if needed.[2] The Health Council of the Netherlands (2014) evaluated the screening program and found that it has a high participation rate (82 percent in 2007 (highest); 80 percent in 2012); low referral rate (the number of women referred for further diagnostic because of abnormal screening results); and a reliable test performance. The high participation rate in the program implies that even if we do not observe whether an individual woman has been screened, we can assume that this is indeed the case if she is at least 50 years old. As a result, we can distinguish between women diagnosed at an age younger than 50, who are diagnosed before the screening program is available for them and therefore, on average, are diagnosed at a later stage of the disease; and women who are diagnosed at an age between 50 and 75 – when the nationwide screening is available and, on average, are diagnosed at an earlier stage of the disease.

Women below the age of 50 can ask to be screened for breast cancer if they have higher risk of suffering from the disease by for example having a family member diagnosed with breast cancer. The group of women diagnosed at the age of 50 is likely to be heterogeneous with respect to the stage of breast cancer. Because they are invited for screening for a first time, some of the diagnosed women are likely to have more advanced stages of breast cancer, while others will have early diagnoses. However, on average, the severity of their disease is expected to be less than the ones of the women diagnosed before the nationwide screening is available (at the age of 48 and 49).[3]

3. Data

We use individual monthly level administrative data for the years 2006 to 2012 that contain information on employment, demographics and health status. The data have been retrieved from four different sources, which are provided by Statistics Netherlands. First, the employment spells, working hours and income information were obtained from the Social

[2] For more details see: Health Council of the Netherlands, 2014.

[3] For further insights into the impact of the breast cancer screening program on the survival and employment of women in the Netherlands, please see Kambourova & Kalwij (2019).

Statistical Dataset on Jobs (Sociaal Statistisch Bestand, SSB-banen, 2006-2012; Bakker et al., 2014). Second, information about the age, gender and family situation were retrieved from the Municipality Registry (Gemeentelijke Basisadministratie, GBA, 2006-2012; CBS, 2015). Third, the medical information, in the form of hospital entries, was obtained from the National Medical Registration (Landelijke Medische Registratie, LMR, 2000-2012; CBS, 2016), which was provided to Statistics Netherlands by the foundation for Dutch Hospital Data. Because of LMR's limited coverage in some of the years, we used the final data set – the Housing Registry (Woonruimteregister, WRG, 2000-2012; CBS 2013), to correct for the coverage (see Appendix A for further details).

3.1. Treatment, controls and endogeneity of treatment

In the hospital data, we observe if a woman is diagnosed with a breast cancer, but we do not have an indication whether it is a first-time diagnosis or a repeated visit. To identify the first-time visit, we consider the woman's history of hospital visits. In the occasion that she has not received a diagnosis of breast cancer during the last four years, a breast cancer diagnosis is considered as a first-time occasion.

While women can receive a breast cancer diagnosis at any age, we focus on the sample of women who are diagnosed for a first time between the age of 47 and 53. For this group of women, we can observe a heterogeneity in the stage of the disease, namely from the age of 50 women can participate for free in a country wide breast cancer screening program, which aims at early detection of the disease. As a result, women diagnosed when the screening is available are likely to be diagnosed at an earlier stage than women diagnosed before the screening is available.

For our sample of interest, we have monthly information from the husbands from 12 months before the female's diagnosis to 24 months afterwards. We select the husbands of women from the age group 47 to 53 in the period 2007 to 2010, who have not received a breast cancer diagnosis during the last four years. This means that if their wife is diagnosed in the current calendar year, it would be a first-time diagnosis of breast cancer, and then they will belong to the treatment group; otherwise they will belong to the control group.

For the treatment group, we denote the month of diagnosis and for the control group we identify all the months in the corresponding calendar year in which the couple has been together. One of those months will become the placebo month of treatment in the matching process.

3.2. CEM: Coarsened exact matching

Following the arguments of Jeon and Pohl (2017), we assume that the breast cancer diagnosis of the wife is exogenous and unanticipated for the husband. To improve the balance in the data between the treated and controls, we use a coarsened exact matching technique (see Blackwell et al., 2009). It coarsens temporarily the matching variables and performs an exact match on that coarsened data.

We match on demographic data – birth year of the husband, birth year of the wife[4]; household data – province of residence (12 provinces), number of children in the household (3 categories: no child, 1 or 2 children, more than 2 children), age of the youngest child in the household (4 categories: age 0 to 10; age 11 to 18; older than 18; and no children).

We match in the specific calendar month of treatment the treated individual to one control individual. Once we find a match for the treated observation we exclude the corresponding control observation from the pool of controls. To make sure that there is no bias in the probability of each observation to be chosen as a control in each month, we randomize the order of the months in which we perform the matching. We match a second time to ensure that there is at least one and at most two control observations for each treated observation. The result is 6,071 treated observations and 11,979 control observations.

In Table 1 are presented the averages of the matching variables for the treated and non-treated individuals before and after the matching. The t-test of the means of the observed characteristics shows that the two groups are significantly different from each other before the matching. After the matching, we observe that the two groups are comparable based on their observable characteristics.

3.3. Further cleaning of the data

We perform further cleaning of the treated observations based on their characteristics. This results in cleaning as well the corresponding control observations. Thus, it should not affect the quality of our matched sample. In the month of treatment one individual from the treated sample dies and two from the control sample, so we leave them out the sample. Furthermore, we limit the age of the husband at the time of diagnosis between 40 and 66. This leads to dropping 77 treated and 110 control observations. We exclude the individuals for whom there is missing household data: for example, for a specific month we may not observe where the individual lives and who else is in their household. This could be the result from living abroad

[4] The birth year of the wife is used as a matching covariate as women have different probability to be diagnosed at different ages because of the nationwide breast cancer screening program.

or moving to an institutional household, for example. The outcome is an exclusion of 226 treated and 330 control observations. Lastly, we exclude individuals for whom there is missing income information or working hours information, namely 5 treated and 6 control observations. The final sample consists of 5,762 treated observations, out of which the wives of 3,238 husband are diagnosed when the screening program is available, and 11,531 control observations.[5]

We follow those individuals from 12 months before the treatment to at most 24 months after the treatment. During the period after the treatment, the individuals could die. This happens 36 times in the treated sample and 75 times in the control sample.

Table 1. Matching covariates

Panel A: Pre-matching variables

	Non-Treated		Treated					
Variable	Mean	Std. Dev	Mean	Std. Dev	t-statistic	p-value	Controls	Treated
Birth year husband	1956.12	5.31	1955.93	4.85	2.86	0.00	7,645,236	6,227
Birth year wife	1958.65	2.62	1958.34	2.16	9.31	0.00	7,645,236	6,227
Age	52.43	5.09	52.57	4.75	-2.21	0.03	7,645,236	6,227
Province	7.80	2.90	7.71	2.96	2.46	0.01	7,645,236	6,227
Number of children	1.20	1.08	1.22	1.05	-1.18	0.24	7,645,236	6,227
Age of youngest child	16.83	4.89	17.31	4.66	-6.45	0.00	5,095,655	4,295

Panel B: Post-matching variables, before cleaning the data

	Non-Treated		Treated					
Variable	Mean	Std. Dev	Mean	Std. Dev	t-statistic	p-value	Controls	Treated
Birth year husband	1955.90	4.40	1955.89	4.52	0.21	0.83	11,979	6,071
Birth year wife	1958.34	2.17	1958.33	2.17	0.07	0.94	11,979	6,071
Age of husband	52.60	4.29	52.61	4.41	-0.21	0.83	11,979	6,071
Province	7.75	2.93	7.74	2.94	0.28	0.78	11,979	6,071
Number of children	1.21	1.05	1.21	1.03	0.01	0.99	11,979	6,071
Age of youngest child	17.38	4.71	17.39	4.59	-0.09	0.93	8,204	4,166

Note: Birth year represents the birth year of the husband. Age represents the age of the husband. Province denotes in which of the 12 provinces the husband lives. Number of children denotes the number of children who live in the household. Age of the youngest child denotes the age of the youngest child that lives in the household.

[5] A comparison table per matching covariate is available in Appendix B. It shows that the two groups are comparable based on their observed characteristics.

4. Descriptive statistics

Table 2 shows the descriptive statistics for the husbands at the time of the diagnosis. We observe that the largest group is 50 to 55 years old, half of the women are older than 50 and on average the spouses have 2.42 years of age difference. Furthermore, 9.24% of the husbands had a health condition during the last 12 months.

We are interested in their employment patterns. We measure employment with a binary variable, which is equal to 1 if the husband is employed and 0 otherwise. On average, 81.47% of the husbands are employed. The employed husbands work on average 37.81 hours per week and earn 23.03 euro per hour, which results in a monthly salary of 3,689 euro.

Table 2. Summary of all husbands at the month of diagnosis (t=0)

Variable	Number of observations	Mean	Std. Dev.
Age 40-44 (0/1)	17,293	0.0433	0.2036
Age 45-49 (0/1)	17,293	0.2898	0.4537
Age 50-54 (0/1)	17,293	0.4888	0.4500
Age 55-59 (0/1)	17,293	0.1481	0.3552
Age 60-65 (0/1)	17,293	0.0299	0.1705
Wife above 50 (0/1)	17,293	0.5632	0.4960
Age difference	17,276	2.4206	3.5056
Health problem the last 12 months (0/1)	17,293	0.0924	0.2896
Employment (0/1)	17,293	0.8147	0.3885
Hourly wage (in euro)	14,090	23.030	20.893
Working hours per week	14,090	37.815	6.082
Monthly income (in euro)	14,090	3689.65	3287.91

Note: Age is a binary variable equal to 1 if the husband is in the corresponding age group. Wife above 50 is equal to 1 if the wife was 50 years or older. Age difference denotes the age difference between the two partners. Health problems in the last 12 months is equal to 1 if the husband received a diagnosis from a hospital in the previous 12 months; and it is equal to 0 otherwise. Employment is equal to 1 if the husband is employed. Hourly wage reports the hourly wage of the husband in euro. Working hours per week report the value for the husband. Monthly income is the husband's monthly income measured in euro. All variables are measured in the month of diagnosis of breast cancer. Period: 2007-2010.

4.1. Common trend in the main variables of interest

To check for a common trend in each of the variables of interest prior to the diagnosis of breast cancer, we estimate the following equation for the matched sample of males:

$$Y_{i,t} = \varphi_0 + \sum_{\tau=-12}^{0}[\,\omega_\tau\, Treated_i \text{ x } D_{i,t}^{\tau} + \theta_\tau D_{i,t}^{\tau}] + year_t + month_t + v_{i,t} \qquad (1)$$

where Y refers to one of the outcomes 0-1 employment, the number of working hours, the natural logarithm of the hourly wage and the natural logarithm of the monthly income of the male. D is a binary variable denoting the specific month with respect to the month of treatment of his spouse (i.e. diagnosis of the wife) from -12 months to 0 months. The reference period is the month of diagnosis (namely D^0). Therefore, ω_{-12} to ω_{-1} capture the difference in labor participation between the treated and controls from month -12 to month -1 before the diagnosis. $year_t$ denotes the calendar year and $month_t$ refers to the calendar month. $v_{i,t}$ is an idiosyncratic error term.

We perform F-tests on ω_{-12} to ω_{-1} to infer if there is a common trend in each of the dependent variables before the diagnosis. The F-statistics are statistically insignificant, which confirms that there is no difference between the trends of the treated and non-treated individuals before t=0.[6]

4.2. Family composition

By construction, all individuals are married in the month of treatment, since we selected the husbands based on being a partner with a woman who could be or is diagnosed with breast cancer.[7] During the time span that we consider, there may be changes in the household composition, such as marriages, divorces and re-marriages. The beginning of a marriage is defined as the first month in which a man lives in the same household as his partner. We observe 127 beginnings of marriage for the control sample and 83 for the treated observations. We also observe divorces, when the partners do not live together anymore, but both are alive. There are 214 divorces in the control sample and 109 in the treated sample. It is also possible rather than divorcing, the man to be registered as a partner in a different household in the next month. We call such a pattern "re-marry". We observe it 38 times in the treatment group and 35 times in the control group.

Lastly, the woman could also die. We observe 17 widowers in the control group and 81 widowers in the treatment group. Widowhood happens in our sample from the month of treatment for both the controls and treated. Therefore, the longest period that someone could

[6] The estimates of equation (1) and the corresponding F-statistics are presented in Appendix C.

[7] We consider as married two individuals who live together and are registered in the municipality as partners.

be a widower is 25 months and the shortest one month. The average length of widowhood is 12 months. A widowhood stops with the end of period under observation or when the man marries another woman.

4.3. Employment of the women before the diagnosis

The employment of the wife before the diagnosis may be important for the employment adjustments of the husband, as outlined in the theoretical framework. In the month before the diagnosis 69.32% of the wives of the man in the control sample are employed, while 70.04% of the wives of the man in the treated sample are employed. A t-test on the means, does not reject their equality at the 5% significance level (p=0.33). Therefore, we can conclude that the employment of the wives of the treated and controls are equally likely to be employed before the treatment.

In table 3 we observe that the husband characteristics are slightly different when we divide the data into subsamples based on the employment of the wife. The husband is slightly younger in the families where the wife is employed. Those husbands are also more likely to be employed, though they work similar hours per week in comparison to the husbands whose wives are not employed.

Table 3. Summary and t-test based on wife's employment

	Wife is not employed		Wife is employed					
Variable	Mean	Std Dev	Mean	Std Dev	t-statistic	p-value	obs1	obs2
Age 40-44	0.04	0.20	0.04	0.21	-0.90	0.37	5265	12028
Age 45-49	0.27	0.44	0.30	0.46	-3.64	0.00	5265	12028
Age 50-54	0.48	0.50	0.49	0.50	-0.71	0.48	5265	12028
Age 55-59	0.16	0.37	0.14	0.35	3.97	0.00	5265	12028
Age 60-65	0.04	0.19	0.03	0.16	4.59	0.00	5265	12028
Wife above 50	0.60	0.49	0.55	0.50	6.52	0.00	5265	12028
Age difference	2.52	3.60	2.38	3.46	2.51	0.01	5259	12017
Health problem (last 12 months)	0.10	0.30	0.09	0.28	2.37	0.02	5265	12028
Employment	0.74	0.44	0.85	0.36	-16.89	0.00	5265	12028
Hourly wage	23.28	31.95	22.93	14.61	0.89	0.37	3896	10194
Working hours per week	37.97	5.94	37.76	6.14	1.82	0.07	3896	10194
Monthly income	3788.91	5333.15	3651.72	2017.06	2.22	0.03	3896	10194
Treated	0.33	0.47	0.34	0.47	-0.99	0.32	5265	12028

Note: See Table 4.2 for the definitions of the variables. Treated is equal to 1 if the wife is diagnosed with breast cancer; and equal to 0 otherwise. All variables are measured in the month of diagnosis. t-statistic reports the absolute value of the t-statistic.

5. Empirical framework

We follow the matched sample of males over a 37-month period: 12 months before the treatment, the month of treatment and 24 months after. Where for the controls month 0 is considered the month in which they are matched to the treated observation. The empirical framework is presented for the estimation of the spillover effects of breast cancer diagnosis of the wife on the husband's employment probability. In a similar way we estimate the effect of the diagnosis on the hourly wage, working hours and monthly income of the husband.

To estimate the spillover effects of breast cancer diagnosis on the husband's employment, we estimate the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 Treatment_i \text{x}\, Post_{i,t} + \beta_2 Post_{i,t} + \boldsymbol{X}_{i,t}\boldsymbol{\eta}' + \delta_t + \alpha_i + \epsilon_{i,t} \qquad (2)$$

where $Y_{i,t}$ represents the employment status of individual *i* in month *t*, which is equal to 1 if he is employed, and 0 otherwise. $Treatment_i$ is equal to 1 if individual *i* belongs to the treatment group, and 0 otherwise. $Post_{i,t}$ is equal to 1 in the months after the treatment, and 0 in the months before the treatment. The row vector $\boldsymbol{X}_{i,t}$ includes additional controls for the health status of the individual, namely whether he experienced health problems during the last 12 months, and the structure of the household, namely the number of children living in the household, other adults living in the household and whether the husband is a widower. δ_t are monthly and year fixed effects, α_i are individual-specific fixed effects, and $\epsilon_{i,t}$ is an idiosyncratic error term. The standard errors of the estimated parameters are clustered by individual.

The parameter β_1 registers the difference in the employment probability in the period after the diagnosis of the husbands of the diagnosed with breast cancer wives and the control group, whose wives were not diagnosed. A negative (positive) value of β_1 suggests that the caregiver effect is stronger (weaker) than the income effect.

We also allow for any heterogeneity of the impact on employment based on individual-specific characteristics, such as widowhood of the husband, the severity of diagnosis, presence of children in the household, and the age of the husband at the time of the wife's diagnosis. It will be specified as a triple difference-in-differences specification:

$$Y_{i,t} = \rho_0 + Post_{i,t} \text{ x } Treatment_i\, \boldsymbol{G}_{i,t}\boldsymbol{\gamma}' + \varphi_1 Post_{i,t} \text{ x } Treatment_i + Post_{i,t}\boldsymbol{G}_{i,t}\boldsymbol{\kappa}' +$$
$$Treatment_i \boldsymbol{G}_{i,t}\boldsymbol{\pi}' + \rho_2 Post_{i,t} + \boldsymbol{G}_{i,t}\boldsymbol{\psi}' + \boldsymbol{X}_{i,t}\boldsymbol{\mu}' + \delta_t + \alpha_i + \epsilon_{i,t} \qquad (3)$$

where ***G*** is a row vector which includes the following individual-specific characteristics: a 0-1 variable if the husband is a widower; a 0-1 variable which is one if the woman is younger than 50 (no automatic participation in the nation-wide program of breast-screening); a 0-1 variable for the presence of children (below the age of 18) in the household; and 0-1 variable for the husband being older than 55 years. The parameters in the four-dimensional vector $\boldsymbol{\gamma}$

register the difference in the employment probability in the period after the diagnosis for one of the groups of $\boldsymbol{G}$.

6. Empirical results

First, we considered the estimates of equation (2) (see left panel of Table 4). It indicates that husbands whose wives were diagnosed with breast cancer are 0.71 percentage points less likely to be employed in the two years after the diagnosis in comparison to husbands whose wives were not diagnosed. We do not find any statistically significant difference in the husbands' working hours, wage, nor monthly income. As a result, in what follows we will focus only on employment probability. The parameter estimate of the effect on employment is in line with the previous literature, which finds that husbands reduce their employment after an adverse health event of the wife (García-Gómez et al., 2013; Jeon and Pohl, 2017). The reduction in employment suggests a presence of a caregiver effect after the breast cancer diagnosis.

Next, we considered separately the husbands based on whether their wives were employed before the diagnosis. The middle panel of Table 4 shows the estimation results of equation (2) for the husbands whose wives were not employed before the diagnosis, and the right panel of Table 4 shows the results for the husbands whose wives were employed before the diagnosis. Our results show that the husbands of employed wives are 0.86 percentage points less likely to be employed after the diagnosis in comparison to husbands whose wives were not diagnosed. In contrast, this effect is statistically insignificant for the subsample of husbands of the non-employed wives. In other words, husbands of non-employed diagnosed and non-diagnosed wives have a similar employment probability. This difference in the empirical results for the husbands of employed and non-employed women could be related to the different financial constraints of the two types of families. If the wife is employed before the diagnosis, she would enter sick leave after the diagnosis and receive a replacement income during this time. As a result, it is likely that the husband would not have the need to compensate for the potential reduction of income due to her sickness, and he would be able to take time off to care for her. The situation is likely to be different in the families where the wife was not employed. Since she does not bring any financial contribution to the family budget, it is likely that the husband is the major contributor to the family budget and as such he may not be able to reduce his employment to take care of his sick wife. Overall, our results indicate a caregiver effect when the wife was employed before the diagnosis, which suggests that her replacement income mitigates the income effect, whereas no effect is observed when she was not employed before the diagnosis, which suggests a balancing of the income and caregiver effects.

In Table 5, we report the estimates, the so-called triple interaction terms, of the vector $\boldsymbol{\gamma}$ of equation (3), which allows us to consider how the impact of the wife's breast cancer diagnosis on the employment probability of the husband differs based on four characteristics of the individual and/or the family situation.[8] We consider the estimates for the full sample (first column) as well as for the two selected samples based on the wife's employment before the diagnosis (second and third column).

The first row of Table 5 suggests that husbands reduce their employment after their wife receives a breast cancer diagnosis (column 1); husbands whose wives were not employed before the medical diagnosis do not change their employment (column 2); husbands whose wives were employed before the diagnosis reduce their employment (column 3). These results are consistent with the results of equation (2), where we did not allow for heterogeneity from the four characteristics.

The parameter estimates of the second row of Table 5 suggest that there is no statistically significant difference in the employment probability of the widowers and non-widowers. This is the case for all of the three selections. The parameters of the third row of Table 5 suggest that there is no statistically significant difference of the effect of the medical diagnosis on the husbands' labor supply when the diagnosis is more severe, namely screening was not available (woman is younger than 50).

The fourth row of Table 5 gives the parameters of the triple interaction term for whether there are any children in the household. The results suggest that in the households with children, the husbands increase their employment probability by 1.21 percentage points after their wife received a breast cancer diagnosis in comparison to the households without children. Nevertheless, the net effect (the effect of diagnosis and effect of children in the household) is (slightly) negative,[9] which suggests that on average, even in the households with children, husbands reduce their employment in comparison to households where the wife was not diagnosed with breast cancer.

[8] While in the analysis presented, equation (3) is estimated with all characteristics included at the same time, we also estimated separately equation (3) for each of the four characteristics. The results are similar and thus not included in the paper.

[9] F-test on the two coefficients is 2.62 with p-value=0.0725, which implies that the net effect is statistically significant at the 10% level.

Table 4. Estimates of equation (2)

Specification	Full sample				Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00705**	0.00172	-0.0377	-0.00369	-0.00332	0.00401	-0.100	-0.00412	-0.00864***	0.000844	-0.0126	-0.00350
	(0.00286)	(0.00228)	(0.0503)	(0.00308)	(0.00567)	(0.00469)	(0.0964)	(0.00553)	(0.00328)	(0.00258)	(0.0589)	(0.00370)
Observations	638,523	515,907	515,907	515,907	194,269	142,586	142,586	142,586	444,254	373,321	373,321	373,321
R-squared	0.0067	0.0223	0.0017	0.0071	0.0071	0.0201	0.0030	0.0058	0.0067	0.0234	0.0015	0.0079
Individuals	17,293	14,881	14,881	14,881	5,265	4,182	4,182	4,182	12,028	10,699	10,699	10,699

*Note: The parameter estimates of the interaction term β_1 is reported. Standard errors clustered by individual in parentheses. All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1*

Table 5. Estimates of equation (3) for husband's employment

	Full sample	Wife is not employed	Wife is employed
	Employment	Employment	Employment
Base line	-0.0138**	-0.0176	-0.0118*
	(0.00609)	(0.0121)	(0.00693)
Husband is widower	-0.0497	-0.0454	-0.0441
	(0.0758)	(0.113)	(0.0382)
Woman younger than 50	-0.0001	-0.0150	0.00625
	(0.00595)	(0.0118)	(0.00683)
Presence of children in the household	0.0121*	0.0341***	0.00222
	(0.00639)	(0.0124)	(0.00740)
Husband older than 55	-0.00755	-0.0138	-0.00514
	(0.00801)	(0.0143)	(0.00968)
Observations	638,523	194,269	444,254
R-squared	0.0083	0.0086	0.0088
Individuals	17,293	5,265	12,028

*Note: The parameter estimates of the triple interaction term is reported. Standard errors clustered by individual in parentheses. All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1*

This effect seems to be present in the households where the wife was not employed before the diagnosis (column 2), but not in the households were the wife was employed before the diagnosis (column 3). For the first selection of column 2, the husband raises his employment by 3.41 percentage points when there are children in the household. This result suggests an income effect. Because the husbands in those households are the only breadwinner, the financial burden is likely to be higher when there are any children in the household, and as a result, they are more likely to be employed. It is important to note that in the households with children, it could also be the case that the children could provide care for the diagnosed wife, and as a result there is a reduced need for caregiving from the husband. However, since we observe children only if they are under 18 years old, it is not likely that they can provide care. The previous literature found that for married women diagnosed with breast cancer, the main caregiver is their husband (Petrie et al., 2001; Grunfeld et al., 2004).[10]

The fifth row of Table 5 reports the parameter estimate of the interaction term for husbands older than 55 years at the time of diagnosis. The results suggest that there is no statistically significant difference in the employment probabilities of husbands younger and older than 55 years.

7. Robustness checks[11]

First, we perform various robustness checks in relation to the possibility of serial correlation in the estimates (see Bertrand et al. (2004) for a detailed discussion of this issue). We estimate equations (2) and (3) as AR(1) models. The results are similar to the main results, which suggests that our correction for serial correlation by clustering the standard errors by individual is a valid solution. Next, we estimate equations (2) and (3) by using observation from four specific months, rather than all 37 monthly observations. We use the observations from the 12th month before the treatment, the month of treatment, the 12th month after the treatment and the 24th month after the treatment. The month of treatment is used as a reference period. We find similar results as the main results. Therefore, we can conclude that serial correlation is not an important issue in our preferred specification.

Second, we perform robustness checks related to the sample selection. We divide the sample of families based on the employment of the wife six months before the diagnosis, rather than the month before the diagnosis. The correlation between the employment of the wives in the two periods is 0.92.[12] The estimates of equations (2) and (3) are similar to our main results. This suggests that a change in the wife's employment in anticipation of the diagnosis is unlikely. As a next robustness check we exclude the husbands of the women diagnosed at the age of 47, as well as the husbands of the women who are 47 in the placebo month of diagnosis. The results are similar to the main results. Last, we consider only the husbands who are younger than 60 years old.[13] Their employment patterns are similar to the full sample. This result suggests that the possibility of transitioning into retirement of the older husbands so that they can take care of their diagnosed wife is not likely to be driving our main results.

---

[10] We control in all models for other people living in the household, who could potentially provide care giving.

[11] The estimates are presented in Appendix F.

[12] The crosstabulation is presented in Appendix C.

[13] See Appendix E for a summary table and t-test comparison based on the wife's employment.

8. Conclusion

This paper has investigated the indirect effect of a breast cancer diagnosis of the wife on the husbands' labor supply. Our main outcomes are fourfold.

First, our results suggest that the caregiving effect is stronger than the income effect. This conclusion is based on the estimates that indicate that husbands are 0.71 percentage points less likely to be employed after their wife is diagnosed with breast cancer. To benchmark this result, the average employment probability of the sample is 81.50 percent. The finding that the caregiving effect is stronger is in line with the previous literature (García-Gómez et al., 2013; Jeon and Pohl, 2017).

Second, while we found a statistically significant reduction in the husband's employment probability, we did not find any statistically significant difference in the husband's working hours, wage, nor monthly income. The finding that there is no reduction in the working hours is likely to be related to the caregiving leave hours allowed by law. Since we observe contractual working hours, rather than actual working hours, we would not observe a reduction in working hours if the husband takes the allowed by law caregiving leave hours. Interestingly, even though husbands can take care leave, we still find a small reduction in employment probability, which would suggest that the caregiving hours provided by the law are likely to be insufficient for unpaid caregiving.

Third, we observe different impact on different types of couples. We consider couples for which the woman was employed before the diagnosis, thus she is entitled to sick leave and her salary during the sick leave period, and couples for which the woman was not employed before the diagnosis. Our results suggest that husbands whose wives were employed before the breast cancer diagnosis decreased their employment by 0.86 percentage points after her diagnosis. In contrast, husbands whose wives were not employed before the diagnosis did not change their labor supply. Thus, it implies that the income replacement to the employed woman during sick leave is likely to reduce the financial burden of the disease so that the husband could provide caregiving. Moreover, in the families where the husband is the only breadwinner, the family is likely to be financially dependent on him, thus it is likely that it is financially more difficult for him to leave work in order to provide caregiving.

Fourth, we considered whether husbands have different labor supply which is related to their wife being diagnosed if she does (or does not) have access to the nationwide breast cancer screening program, thus her diagnosis is likely to be less (or more) severe. We did not find any statistically significant difference. Further heterogeneity could be introduced by differences in the family composition. We found differences related to whether there are children in the household. In the families with children, husbands raised their employment by

1.21 percentage points. The labor supply difference is even larger when the women were not employed before the diagnosis. In those families, we observe that the husbands are 3.41 percentage points more likely to be employed when there are children in the household. These results could be related to stronger financial constraints in the presence of children in the household.

A limitation of our analysis is the unavailability of actual work hours. Further research with more detailed leave data could be beneficial for estimating the effect more precisely. Furthermore, while we considered situation where the wife receives a diagnosis, research into the opposite situation, where the husband receives a diagnosis, could provide more insight into whether the social insurance has a similar relation to employment adjustments for both genders.

In conclusion, we found that social insurance – such as sick leave arrangements – could have an impact on the employment behavior of the husband after his wife has been diagnosed with breast cancer. The finding that caregiving behavior is dominant in the couples in which the woman has access to sick leave policy, suggests that the income replacement of the woman could contribute to more caregiving from the husband. This is an innovative way of considering the opposing forces of added-worker and caregiving effects, and it suggests that the amount of provided caregiving could be affected by replacing the lost income from the adverse health event. As a result, policies providing financial insurance in the occasion of an adverse health event could be beneficial for enabling individuals to provide more care to their sick family members.

References

Bakker, B. F., Van Rooijen, J., & Van Toor, L. (2014). The system of social statistical datasets of Statistics Netherlands: An integral approach to the production of register-based social statistics. *Statistical Journal of the IAOS*, *30*(4), 411-424.

Berger, M.C. (1983). Labor Supply and Spouse's Health: The Effects of Illness, Disability, and Mortality. *Social Science Quarterly*, *64*(3), 494-509.

Blackwell, M., Iacus, S.M., King, G., & Porro, G. (2009). cem: Coarsened exact matching in Stata. *The Stata Journal*, *9*(4), 524-546.

Bradley, C. J., Oberst, K., & Schenk, M. (2006). Absenteeism from work: the experience of employed breast and prostate cancer patients in the months following diagnosis. *Psychooncology*, *15*(8), 739-747.

Bradley, C.J., Neumark, D., Bednarek, H.L., & Schenk, M. (2005). Short-term effects of breast cancer on labor market attachment: results from a longitudinal study. *Journal of Health Economics*, 24(1), 137-160.

Bradley, C.J., Bednarek, H. L., & Neumark, D. (2002). Breast cancer survival, work, and earnings. *Journal of Health Economics*, *21*(5), 757-779.

Breastcancer.org (2017). Think Pink, Live Green Booklet and Checklist. Retrieved May 29, 2017, from http://www.breastcancer.org/risk/factors/tplg-booklet-checklist

Breastcancer.org (2017). Breast Cancer Risk Factors. Retrieved May 29, 2017, from http://www.breastcancer.org/risk/factors

Carmichael, F., Charles, S., & Hulme, C. (2010). Who will care? Employment participation and willingness to supply informal care. *Journal of Health Economics*, *29*(1), 182-190.

Carmichael, F., & Charles, S. (2003). The opportunity costs of informal care: does gender matter?. *Journal of Health Economics*, *22*(5), 781-803.

Carmichael, F., & Charles, S. (1998). The labour market costs of community care. *Journal of Health Economics*, *17*(6), 747-765.

CBS (2016). Documentatierapport Landelijke Medische Registratie (LMR) 2012. Retrived from https://www.volksgezondheidenzorg.info/sites/default/files/lmr-microdata.pdf

CBS (2015). *Documentatierapport Huishoudenskenmerken van in de Gemeentelijke Basisadministratie Persoonsgegevens (GBA) ingeschreven personen (GBAHUISHOUDENSBUS). Retreived from* https://www.cbs.nl/NR/rdonlyres/24249E88-5895-4BB9-811F-9A9013AE6B59/0/ssbgbahuishoudensbusmicrodata.pdf

CBS (2013). *Documentatierapport Woonruimteregister verrijkt (WRGplus) 2012V1*. Retrieved from https://www.cbs.nl/NR/rdonlyres/EE915925-FD52-490C-A846-D0888A230187/0/woonruimteregisterverrijktmicrodata.pdf

Coile, C. C. (2004). *Health shocks and couples' labor supply decisions* (No. w10810). National Bureau of Economic Research.

Charles, K. K. (1999). Sickness in the family: Health shocks and spousal labor supply. *Ann Arbor, MI: Gerald R. Ford School of Public Policy, University of Michigan*.

de Moor, J. S., Dowling, E. C., Ekwueme, D. U., Guy, G. P., Rodriguez, J., Virgo, K. S., ... & McNeel, T. S. (2017). Employment implications of informal cancer caregiving. *Journal of Cancer Survivorship*, *11*(1), 48-57.

Dutch Cancer Registration, managed by IKNL. Retrieved March 21, 2017, from http://www.cijfersoverkanker.nl

Ettner, S. L. (1996). The opportunity costs of elder care. *Journal of Human Resources*, 189-205.

García-Gómez, P., & Gielen, A. C. (2014). Health effects of containing moral hazard: Evidence from Disability Insurance Reform. Discussion paper 14-102/V. Tinbergen Institute.

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. *Journal of Human Resources*, *48*(4), 873-909.

García-Gómez, P. (2011). Institutions, health shocks and labour market outcomes across Europe. *Journal of Health Economics*, *30*(1), 200-213.

GLOBOCAN (2012) v1.0. Ferlay J, Soerjomataram I, Ervik M, Dikshit R, Eser S, Mathers C, Rebelo M, Parkin DM, Forman D, Bray, F.. Cancer Incidence and Mortality Worldwide: IARC CancerBase No. 11 [Internet]. Lyon, France: International Agency for Research on Cancer; 2013. Retrieved March 20, 2017, from http://globocan.iarc.fr

Grossman, M. (1972). On the concept of health capital and the demand for health. *The Journal of Political Economy*, *80*(2), 223.

Grunfeld, E., Coyle, D., Whelan, T., Clinch, J., Reyno, L., Earle, C.C., Willan, A., Viola, R., Coristine, M., Janz, T., & Glossop, R. (2004). Family caregiver burden: results of a longitudinal study of breast cancer patients and their principal caregivers. *Canadian Medical Association Journal*, *170*(12), 1795-1801.

Halla, M., & Zweimüller, M. (2013). The effect of health on earnings: Quasi-experimental evidence from commuting accidents. *Labour Economics*, *24*, 23-38.

Hassink, W.H.J., & Van den Berg, B. (2011). Time-bound opportunity costs of informal care: consequences for access to professional care, caregiver support, and labour supply estimates. *Social Science & Medicine*, *73*(10), 1508-1516.

Health Council of the Netherlands. Population screening for breast cancer: expectations and developments. The Hague: Health Council of the Netherlands, 2014; publication no. 2014/01E.

Heinesen, E., & Kolodziejczyk, C. (2013). Effects of breast and colorectal cancer on labour market outcomes—Average effects and educational gradients. *Journal of Health Economics*, *32*(6), 1028-1042.

Heitmueller, A. (2007). The chicken or the egg?: Endogeneity in labour market participation of informal carers in England. *Journal of Health Economics*, *26*(3), 536-559.

Jeon, S. H., & Pohl, R. V. (2017). Health and work in the family: Evidence from spouses' cancer diagnoses. *Journal of Health Economics, 52*, 1-18.

Kambourova, Z., Hassink, W.H.J., & Kalwij, A.S. (2019). Women's labor market participation after an adverse health event. in Solomon W. Polachek , Konstantinos Tatsiramos (ed.) *Health and Labor Markets (Research in Labor Economics, Volume 47)* Emerald Publishing Limited, 25-70.

Kambourova, Z., & Kalwij, A.S. (2019). The Effects of Breast Cancer Screening on Survival and Employment after being diagnosed. Mimeo.

Koning, P., & M. Lindeboom (2015). The rise and fall of disability insurance enrollment in the Netherlands. Journal of Economic Perspectives, *29*(2), 151-172.

Palme, M., & Simeonova, E. (2015). Does women's education affect breast cancer risk and survival? Evidence from a population based social experiment in education. *Journal of Health Economics, 42*, 115-124.

Parsons, D. O. (1977). Health, Family Structure, and Labor Supply. *American Economic Review*, *67*(4), 703-712.

Petrie, W., Logan, J., & DeGrasse, C. (2001, November). Research review of the supportive care needs of spouses of women with breast cancer. In *Oncology Nursing Forum* (Vol. 28, No. 10).

RIVM (2014). Breast cancer in the Netherlands. Retrieved May 29, 2017, from http://www.rivm.nl/en/Topics/B/Breast_cancer_screening_programme/Breast_cancer_in_the_Netherlands

Schmitz, H., & Westphal, M. (2017). Informal care and long-term labor market outcomes. *Journal of Health Economics*, *56*, 1-18.

Van der Laan, J. (2013). Quality of the Dutch Medical Registration (LMR) for the calculation of the Hospital Standardised Mortality Ratio. Discussion paper 201308, Statistics Netherlands, Statistics Netherlands.

Van Houtven, C. H., Coe, N. B., & Skira, M. M. (2013). The effect of informal care on work and wages. *Journal of Health Economics*, *32*(1), 240-252.

Appendix A. Hospital data

The Hospital registry does not contain exhaustive information pertaining to all hospitals in the Netherlands. Up to and including 2005, the data contains information about inpatient and daycare patients from all general and university hospitals in the Netherlands (García-Gómez et al., 2013). However, from 2006 the participation in the registry has become voluntary and, therefore, the coverage has decreased (García-Gómez and Gielen, 2014). Overall, according to Van der Laan (2013), the data provides record about approximately 88% of the inpatient hospital stays in the country, which is retrieved from general and university hospitals and one specialty hospital. This implies that if we do not correct for the limited coverage of the data, we would underestimate the cases of health conditions in the Dutch population and our results will suffer from attenuation bias. To limit this problem, we use the Housing registry to compute the percentage of people in each municipality who have visited a hospital. We use the postal code distribution across municipality borders from the year 2012, namely 415 municipalities, to avoid bias from changes in the borders. The percentage of individuals who have visited a hospital measured on a municipality level before the years of voluntary reporting is consistently above 5%, and after that it falls to 1% for some municipalities. This statistic guides us to choose 5% as a lower boundary for censoring the data. The result of the censoring is excluding a minimum of seven municipalities in 2005, and a maximum of 44 in 2008.

Appendix B Matching covariates of the cleaned sample

Table B.1. Post-matching variables, after cleaning the data

Variable	Non-Treated Mean	Non-Treated Std Dev	Treated Mean	Treated Std Dev	t-statistic	p-value	Controls	Treated
Birth year husband	1955.91	4.12	1955.95	4.16	-0.59	0.56	11,531	5,762
Birth year wife	1958.33	2.17	1958.34	2.17	-0.22	0.82	11,522	5,754
Age	52.59	4	52.55	4.04	0.63	0.53	11,531	5,762
Province	7.75	2.93	7.73	2.94	0.47	0.64	11,531	5,762
Number of children	1.2	1.05	1.2	1.04	0.11	0.91	11,531	5,762
Age of youngest child	17.37	4.7	17.35	4.57	0.25	0.8	7,873	3,923

Note: Birth year represents the birth year of the husband. Age represents the age of the husband. Province denotes in which of the 12 provinces the husband lives. Number of children denotes the number of children who live in the household. Age of the youngest child denotes the age of the youngest child that lives in the household.

Appendix C. Common trends

Specification	Employment	Working Hours	LnHourly Wage	LnMontly Income
Month-11xTreatment	0.00156	-0.0134	0.00492*	0.00197
	(0.00139)	(0.0509)	(0.00296)	(0.00379)
Month-10xTreatment	0.00173	0.0455	-0.00233	-0.00371
	(0.00181)	(0.0554)	(0.00316)	(0.00399)
Month-9xTreatment	0.000954	0.0349	0.00203	0.00220
	(0.00221)	(0.0590)	(0.00345)	(0.00426)
Month-8xTreatment	-0.000782	-0.0111	0.00533	0.00216
	(0.00248)	(0.0627)	(0.00357)	(0.00449)
Month-7xTreatment	0.000600	-0.0299	0.00338	-0.000521
	(0.00263)	(0.0631)	(0.00344)	(0.00446)
Month-6xTreatment	0.000949	0.00394	-0.000128	-0.00111
	(0.00284)	(0.0664)	(0.00364)	(0.00460)
Month-5xTreatment	0.000771	-0.00733	0.000633	-0.00214
	(0.00295)	(0.0644)	(0.00372)	(0.00470)
Month-4xTreatment	-0.000617	-0.00309	-0.000797	-0.00304
	(0.00304)	(0.0686)	(0.00375)	(0.00476)
Month-3xTreatment	-0.000104	-0.0156	0.00398	0.0000708
	(0.00316)	(0.0686)	(0.00367)	(0.00484)
Month-2xTreatment	-0.000268	-0.0782	0.00443	0.00302
	(0.00328)	(0.0729)	(0.00388)	(0.00501)
Month-1xTreatment	0.00112	-0.0365	0.00403	-0.00315
	(0.00333)	(0.0714)	(0.00379)	(0.00485)
Constant	0.823***	37.99***	2.996***	8.054***
	(0.00185)	(0.0400)	(0.00230)	(0.00277)
F-test[a]	0.51	0.50	1.23	0.68
P-value	0.9006	0.9016	0.2573	0.7592
Observations	207,516	170,316	170,316	170,316
R-squared	0.0013	0.0008	0.0070	0.0021
Individuals	17,293	14,629	14,629	14,629

Note: Standard errors clustered by individual in parentheses. Estimates of equation (1). All models include controls for: the specific month with respect to the month of treatment, calendar year and calendar month. *** p<0.01, ** p<0.05, * p<0.1

[a] The null hypothesis of the F-test is that the employment probability, working hours, ln wage rate and ln monthly income, respectively, are the same for the treated and control observations during the 12 months before the diagnosis.

Appendix D. Crosstabulation of women's employment T-6 and T-1

Table D.1. Crosstabulation of women's employment T-6 and T-1

Wife employment	Month T-6		
Month T-1	Not employed	Employed	Total
Not employed	4,982	283	5,265
Employed	304	11,724	12,028
Total	5,286	12,007	17,293

Note: Month T-1 refers to the month before the treatment. Month T-6 refers to six months before the treatment. The table reports a total number of women: both women who will receive a diagnosis and women who would not receive a diagnosis.

Appendix E. Summary and t-test based on wife's employment

Table E.1. Subsample of husbands under 60 years old

	Wife is not employed		Wife is employed					
Variable	Mean	Std Dev	Mean	Std Dev	t-statistic	p-value	obs1	obs2
Age 40-44	0.04	0.20	0.05	0.21	-0.70	0.48	4980	11554
Age 45-49	0.29	0.45	0.31	0.46	-3.08	0.00	4980	11554
Age 50-54	0.51	0.50	0.51	0.50	0.20	0.84	4980	11554
Age 55-59	0.16	0.36	0.13	0.34	4.21	0.00	4980	11554
Wife above 50	0.59	0.49	0.54	0.50	5.87	0.00	4980	11554
Age difference	2.05	3.06	2.02	3.01	0.54	0.59	4975	11543
Health problem (last 12 months)	0.10	0.30	0.09	0.28	2.53	0.01	4980	11554
Employment	0.76	0.42	0.86	0.35	-15.38	0.00	4980	11554
Hourly wage	23.36	32.24	22.97	14.67	0.99	0.32	3804	9945
Working hours per week	38.05	5.79	37.87	5.91	1.63	0.10	3804	9945
Monthly income	3806.40	5380.13	3665.30	2011.95	2.24	0.03	3804	9945
Treated	0.33	0.47	0.34	0.47	-1.20	0.23	4980	11554

Note: Age is a binary variable equal to 1 if the husband is in the corresponding age group. Wife above 50 is equal to 1 if the wife was 50 years or older. Age difference denotes the age difference between the two partners. Health problem (last 12 months) is equal to 1 if the husband received a diagnosis from a hospital in the previous 12 months; and it is equal to 0 otherwise. Employment is equal to 1 if the husband is employed. Hourly wage reports the hourly wage of the husband in euro. Working hours per week report the value for the husband. Monthly income is the husband's monthly income measured in euro. Treated is equal to 1 if the wife is diagnosed with breast cancer; and equal to 0 otherwise. All variables are measured in the month of diagnosis. t-statistic reports the absolute value of the t-statistic.

Table E.2. Subsample of husbands whose wife is between 48 and 53 years old

	Wife is not employed		Wife is employed					
Variable	Mean	Std Dev	Mean	Std Dev	t-statistic	p-value	obs1	obs2
Age 40-44	0.03	0.17	0.03	0.18	-0.59	0.56	4753	10507
Age 45-49	0.23	0.42	0.26	0.44	-2.73	0.01	4753	10507
Age 50-54	0.51	0.50	0.53	0.50	-1.81	0.07	4753	10507
Age 55-59	0.18	0.38	0.15	0.36	3.84	0.00	4753	10507
Age 60-65	0.04	0.20	0.03	0.17	4.34	0.00	4753	10507
Wife above 50	0.67	0.47	0.63	0.48	4.63	0.00	4753	10507
Age difference	2.55	3.63	2.36	3.45	3.04	0.00	4747	10496
Health problem (last 12 months)	0.10	0.30	0.09	0.29	2.24	0.03	4753	10507
Employment	0.74	0.44	0.84	0.36	-15.79	0.00	4753	10507
Hourly wage	23.15	33.21	22.96	15.02	0.44	0.66	3504	8872
Working hours per week	37.96	5.92	37.69	6.25	2.16	0.03	3504	8872
Monthly income	3767.63	5539.06	3646.94	2039.63	1.77	0.08	3504	8872
Treated	0.33	0.47	0.34	0.47	-0.89	0.38	4753	10507

Note: Age is a binary variable equal to 1 if the husband is in the corresponding age group. Wife above 50 is equal to 1 if the wife was 50 years or older. Age difference denotes the age difference between the two partners. Health problem (last 12 months) is equal to 1 if the husband received a diagnosis from a hospital in the previous 12 months; and it is equal to 0 otherwise. Employment is equal to 1 if the husband is employed. Hourly wage reports the hourly wage of the husband in euro. Working hours per week report the value for the husband. Monthly income is the husband's monthly income measured in euro. Treated is equal to 1 if the wife is diagnosed with breast cancer; and equal to 0 otherwise. All variables are measured in the month of diagnosis. t-statistic reports the absolute value of the t-statistic.

Appendix F. Robustness checks

Table F.1. AR(1): estimates of equation (2)

Specification	Full sample				Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00370**	0.000554	-0.0788**	-0.00538**	-0.00415	0.00224	-0.0595	-0.00140	-0.00352**	0.000116	-0.0830**	-0.00614**
	(0.00146)	(0.00158)	(0.0328)	(0.00256)	(0.00274)	(0.00311)	(0.0647)	(0.00501)	(0.00173)	(0.00183)	(0.0380)	(0.00296)
Observations	621,230	501,026	501,026	501,026	189,004	138,404	138,404	138,404	432,226	362,622	362,622	362,622
R-squared	0.00104	0.0142	0.00399	0.0191	0.00125	0.0197	0.00324	0.0269	0.00105	0.0220	0.00220	0.0290
Individuals	17,293	14,838	14,838	14,838	5,265	4,164	4,164	4,164	12,028	10,674	10,674	10,674

Note: Estimates of equation (2). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.2. AR(1): estimates of equation (3) for husband's employment

	Full sample	Wife is not employed	Wife is employed
	Employment	Employment	Employment
Base	-0.00330	-0.00196	-0.00383
	(0.00303)	(0.00557)	(0.00360)
Widowhood	-0.0124	-0.0195	0.000339
	(0.0234)	(0.0316)	(0.0359)
No screening	0.00265	-0.00220	0.00484
	(0.00307)	(0.00587)	(0.00361)
Children	0.000749	0.000255	0.000568
	(0.00299)	(0.00556)	(0.00355)
Old age	-0.00837**	-0.00520	-0.00985**
	(0.00328)	(0.00597)	(0.00393)
Observations	621,230	189,004	432,226
Individuals	17,293	5,265	12,028
R-squared	0.00110	0.00133	0.00112

Note: Estimates of equation (3). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.3. Four periods: estimates of equation (2)

Specification	Full sample				Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00505	0.00410	-0.112	-0.00475	0.00465	0.0102	-0.102	0.00311	-0.00923**	0.00175	-0.113	-0.00763
	(0.00354)	(0.00339)	(0.0716)	(0.00483)	(0.00702)	(0.00748)	(0.140)	(0.00953)	(0.00407)	(0.00370)	(0.0832)	(0.00558)
Observations	69,014	55,696	55,696	55,696	20,998	15,381	15,381	15,381	48,016	40,315	40,315	40,315
R-squared	0.0098	0.0390	0.0021	0.0136	0.0102	0.0331	0.0020	0.0126	0.0100	0.0421	0.0023	0.0142
Individuals	17,293	14,797	14,797	14,797	5,265	4,151	4,151	4,151	12,028	10,646	10,646	10,646

Note: Standard errors clustered by individual in parentheses. Estimates of equation (2). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.4. Four periods: estimates of equation (3) for husband's employment

	Full sample	Wife is not employed	Wife is employed
	Employment	Employment	Employment
Base	-0.00748	0.000768	-0.0109
	(0.00842)	(0.0157)	(0.00993)
Widowhood	-0.0180	-0.0226	-0.00708
	(0.0713)	(0.103)	(0.0871)
No screening	-0.00120	-0.0208	0.00732
	(0.00727)	(0.0144)	(0.00838)
Children	0.00522	0.0208	-0.00179
	(0.00876)	(0.0163)	(0.0104)
Old age	-0.00223	-0.0181	0.00444
	(0.0117)	(0.0207)	(0.0141)
Observations	69,014	20,998	48,016
R-squared	0.0118	0.0117	0.0127
Individuals	17,293	5,265	12,028

Note: Standard errors clustered by individual in parentheses. Estimates of equation (3). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.5. Employment t-6: estimates of equation (2)

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00491	0.00457	-0.108	-0.00407	-0.00791**	0.000635	-0.00933	-0.00350
	(0.00572)	(0.00467)	(0.0984)	(0.00549)	(0.00326)	(0.00258)	(0.0584)	(0.00370)
Observations	195,095	143,046	143,046	143,046	443,428	372,861	372,861	372,861
R-squared	0.0067	0.0197	0.0028	0.0050	0.0069	0.0236	0.0016	0.0083
Individuals	5,286	4,198	4,198	4,198	12,007	10,683	10,683	10,683

Note: Standard errors clustered by individual in parentheses. Estimates of equation (2). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.6. Employment t-6: estimates of equation (3) for husband's employment

	Wife is not employed	Wife is employed
	Employment	Employment
Base	-0.0150	-0.0129*
	(0.0120)	(0.00697)
Widowhood	-0.0484	-0.0456
	(0.119)	(0.0386)
No screening	-0.0136	0.00559
	(0.0121)	(0.00673)
Children	0.0302**	0.00413
	(0.0124)	(0.00741)
Old age	-0.0234	-0.000114
	(0.0147)	(0.00952)
Observations	195,095	443,428
R-squared	0.0089	0.0086
Individuals	5,286	12,007

Note: Standard errors clustered by individual in parentheses. Estimates of equation (3). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table F.7. Wife Age 48 to 53: estimates of equation (2)

Specification	Full sample				Wife is not employed				Wife is employed			
	Employment	Wage	Working hours	Monthly income	Employment	Wage	Working hours	Monthly income	Employment	Wage	Working hours	Monthly income
Basic model	-0.00598**	0.00241	-0.0272	-0.00214	-0.00353	0.00393	-0.127	-0.00641	-0.00708**	0.00178	0.0126	-0.000472
	(0.00301)	(0.00245)	(0.0540)	(0.00327)	(0.00590)	(0.00508)	(0.103)	(0.00598)	(0.00347)	(0.00277)	(0.0633)	(0.00390)
Observations	563,415	453,015	453,015	453,015	175,366	128,136	128,136	128,136	388,049	324,879	324,879	324,879
R-squared	0.0069	0.0224	0.0021	0.0067	0.0074	0.0197	0.0034	0.0055	0.0069	0.0239	0.0018	0.0075
Individuals	15,260	13,075	13,075	13,075	4,753	3,755	3,755	3,755	10,507	9,320	9,320	9,320

Note: Standard errors clustered by individual in parentheses. Estimates of equation (2). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.8. Wife Age 48 to 53: estimates of equation (3) for husband's employment

	Full sample	Wife is not employed	Wife is employed
	Employment	Employment	Employment
Base	-0.0135**	-0.0168	-0.0116
	(0.00625)	(0.0122)	(0.00717)
Widowhood	-0.0398	-0.0471	-0.0179
	(0.0814)	(0.113)	(0.0360)
No screening	0.00423	-0.0137	0.0119
	(0.00627)	(0.0121)	(0.00728)
Children	0.0112*	0.0296**	0.00253
	(0.00661)	(0.0126)	(0.00772)
Old age	-0.00656	-0.00902	-0.00573
	(0.00808)	(0.0142)	(0.00983)
Observations	563,415	175,366	388,049
R-squared	0.0087	0.0087	0.0094
Individuals	15,260	4,753	10,507

Note: Standard errors clustered by individual in parentheses. Estimates of equation (3). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.9. Husband Age below 60: estimates of equation (2)

Specification	Full sample				Wife is not employed				Wife is employed			
	Employment	Wage	Working hours	Monthly income	Employment	Wage	Working hours	Monthly income	Employment	Wage	Working hours	Monthly income
Basic model	-0.00701**	0.00191	-0.00285	-0.00203	-0.00488	0.00434	-0.0652	-0.00315	-0.00794**	0.000990	0.0230	-0.00157
	(0.00281)	(0.00230)	(0.0478)	(0.00296)	(0.00571)	(0.00475)	(0.0912)	(0.00532)	(0.00319)	(0.00260)	(0.0562)	(0.00354)
Observations	610,585	504,062	504,062	504,062	183,810	139,231	139,231	139,231	426,775	364,831	364,831	364,831
R-squared	0.0051	0.0232	0.0012	0.0087	0.0062	0.0208	0.0023	0.0072	0.0048	0.0244	0.0010	0.0096
Individuals	16,534	14,448	14,448	14,448	4,980	4,055	4,055	4,055	11,554	10,393	10,393	10,393

Note: Standard errors clustered by individual in parentheses. Estimates of equation (2). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** p<0.01, ** p<0.05, * p<0.1

Table F.10. Husband Age below 60: estimates of equation (3) for husband's employment

	Full sample	Wife is not employed	Wife is employed
	Employment	Employment	Employment
Widowhood	-0.0909	-0.116	-0.0429
	(0.0795)	(0.126)	(0.0396)
No screening	0.00102	-0.0125	0.00679
	(0.00570)	(0.0114)	(0.00650)
Children	0.0139**	0.0344***	0.00506
	(0.00634)	(0.0127)	(0.00723)
Base	-0.0170***	-0.0234**	-0.0144**
	(0.00580)	(0.0117)	(0.00652)
Observations	610,585	183,810	426,775
R-squared	0.0052	0.0069	0.0048
Individuals	16,534	4,980	11,554

Note: Standard errors clustered by individual in parentheses. Estimates of equation (3). All models include controls for: number of children in the household, other people living in the household, whether the individual is a widower, the health status of the individual during the last 12 months, year dummies, month dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.1$