Women’s Adverse Health Events and Labor Market Participation

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To my family

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Chapter 1: Introduction

1.1. Background and motivation

The improvements in medical treatment have resulted in more people of working age being cured from life-threatening diseases and being able to return to work. However, after having had a health-induced work disruption, some of the survivors do not return to their old work pattern: they become less active on the labor market, enter retirement or enter a disability program (García-Gómez, 2011). With the aging of the population and the risk of severe health problems increasing with age, the number of people suffering from severe health problems is likely to increase (Loisel and Anema, 2013). Besides this being a burden for the economy, it may also have a negative income effect on the survivors (Halla and Zweimüller, 2013; García-Gómez, Van Kippersluis, O'Donnell and Van Doorslaer, 2013), as well as affect the employment of other family members (García-Gómez et al., 2013; Jeon and Pohl, 2017).

1.1.1. Direct effects of adverse health on work

During the last half a century, economists have been researching the impact of adverse health events on productivity. The leading theoretical model explaining the productivity changes after an adverse health event has been developed by Grossman in 1972 (Grossman, 1972). According to his model, individuals have a choice for allocating their time between work and leisure. However, in the occasion that their health deteriorates, they need to invest time in restoring their health. As a result, the time available for work and leisure is reduced by the amount of recovery time. The necessary recovery time is in turn related to the severity of the health condition – more severe health conditions require a longer recovery time. Indeed, the empirical evidence shows that working time is affected negatively by an adverse health event. Kessler et al. (2001) considered a US sample (from January 1995 to January 1996) and found that health problems, such as chronic diseases, impact negatively the intensive margin of labor market participation. Out of the health problems discussed, cancer stands out as the one causing the highest number of work impairment days – 16.4 out of the 30-day observation period. In that line of research, Bradley, Oberst and Schenk (2006) estimated that the women in the US who are employed six months after being diagnosed (between June 2001 and May 2002) with breast cancer have 44.5 average days (median 22 days) of absenteeism. Furthermore, Bradley, Neumark, Bednarek and Schenk (2005) found that a health shock such as breast cancer reduces the probability of employment of women in the US with 25 percentage points in the sixth month after receiving a diagnosis (time period: June 2001 to April 2002). They also note that from the ex-ante employed women, 14 percent have a job but are on sick leave.

However, this short-term behavior may not necessarily have a negative impact on individual's long-term labor market participation. In the cases where the individual recovers and does not need to spend extra time on health maintenance, nor the illness has resulted in a work limitation, she can return to her old work pattern. Pelkowski and Berger (2004) found on a US data (1992 – 1993) that, while temporary health conditions do not impact working hours and hourly wages, this is not the case for permanent health conditions. They offer two possible explanations. First, temporary health problems are likely to be a burden for the employer, however only permanent problems may induce the employee to change her employment state. And, second, temporary problems may not be severe enough to have a long-term impact. The study of Lundborg, Nilsson and Vikström (2015) goes further in the comparison between health conditions and considers the ten most common medical diagnoses in Sweden (data coverage: 1987 – 2004). The study assesses whether there are differential income adjustments between employees who suffer from the same disease but have different levels of education. The authors find similar magnitudes across diseases. However, they do not compare the income differential between employees who suffered from a health condition and those who did not. Based on those previous studies, two key questions remain in the literature discussing the relation between severity of the health condition and its impact on employment, namely, first, whether different long-term health conditions have a similar impact on employment, and, second, whether an earlier detection of a severe health condition could mitigate the effect on employment.

Besides the severity of the health problem, the literature considers different personal attributes which could be related to the long-term impact. For example, Heinesen and Kolodziejczyk (2013) consider Danish administrative covering the period 2000 – 2004 and found that the impact of cancer in the labor market supply depends on the education of the individual. Individuals with the lowest level of education have the highest risk of being out of the labor force three years after diagnosis. They also have the highest propensity to receive disability pension. However, the authors did not find an education gradient in the income effects. Another example is the study by Torp et al. (2013), who estimated on an administrative Norwegian data from the period 1998 to 2004 that socio-economic and work-related factors explain more of the variation in employment status of five-year cancer survivors than receiving a diagnosis. They find that high education, high income, having a job and being young at the time of diagnosis are important factors for being employed five years after the diagnosis. Furthermore, in their sample the female cancer survivors were significantly less likely to be employed in comparison to the control group, and especially breast cancer survivors. From the demographic characteristics, the impact of the disease may depend on the age of the individual. Zhang, Zhao and Harris (2009) considered permanent health problems in Australia (time period: 2001 – 2005), such as chronic illnesses and find that the negative impact is stronger for 50+ individuals. As such while researching the impact of adverse health events on employment, it is important to take into account the background characteristics of the individual.

1.1.2. Indirect effects of an adverse health event on work

In addition to affecting one's own employment, an adverse health event could also affect the employment of other family members. A large literature considers the effect of caregiving to elderly parents and sick spouses on the employment of the caregiver[1]. Caregiving could lead not only to lower employment probability (Ettner, 1996; Charmichael and Charles, 1998, 2003; Heitmueller, 2007), but could also be related to lower wages (Heitmueller and Inglis, 2007), as well as worse mental health of the caregiver (Bauer and Souza-Poza, 2015).

Considering cancer patients in the US in 2011, De Moor et al. (2017) found that their caregivers are likely to make employment changes during the treatment and recovery period. Additionally, Hollenbeak et al. (2011) found gender differences in the effect of caregiving on employment in a sample of spouses of cancer survivors in the US (time period: 1997 to 2004): while wives were likely to reduce their employment by 7.5% in the two to six years after the diagnosis of their spouse, this effect was not present for the husbands. The authors suggest that the behavior of the husbands can be attributed to financial constraints. Bradley and Dahman (2013) contribute to this discussion by showing that in the US (time period: 2007 to 2011) husbands of breast cancer survivors are likely to reduce their employment probability in the short term, but not in the long-term.

Instead of reducing employment to provide caregiving, an individual may work more after an adverse health event experienced by his (or her) spouse (known also as an added-worker effect or an income effect). In his seminal study, Berger (1983) argues that the spillover effects on employment could be positive or negative in relation to the tasks that the sick spouse cannot perform. When the sick spouse is working before the adverse health event, the healthy spouse has to compensate for the loss of income and thus work more; and vice versa, when the sick

[1] See for example, Carmichael and Charles, 1998, 2003; Charmichael, Charles and Hulme, 2010; Ettner, 1996; García-Gómez et al, 2013; Heitmueller, 2007; Hassink and van den Berg, 2011; Jeon and Pohl, 2017; Van Houtven, Coe and Skira, 2013; Schmitz and Westphal, 2017.

spouse is not working before the diagnosis, thus is specialized in home production, the healthy spouse has to compensate by spending more time on home production. In both situations, the healthy spouse may also want to spend time on caregiving. As such, due to the historical roles of the two genders in the family task allocation, a gender effect is expected: a reduction of employment for the husbands, and an increase in the employment of the wives after an adverse health event of their spouse. The empirical results, however, are mixed. While an added-worker 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). However, it is also possible that the added-worker effect is not observed for either of the spouses (Jeon and Pohl, 2017). To explain the gender differences of the spillover effects, García-Gómez et al. (2013) considered the employment adjustments after an acute hospitalization of the spouse in the Netherlands (time period: 1998 to 2005) by dividing the healthy spouses into selections of initially employed and initially non-employed individuals. The authors found similar effects for each gender: 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. Thus, a key question remains whether the spillover effects could be related to the employment of the sick individual.

1.1.3. Institutions, health conditions and work

Overall, studies have shown that adverse health events reduce the employment probability (e.g., Jones et al., 2016; Halla and Zweimüller, 2013; García-Gómez et al., 2013; Moran, Short and Hollenbeak, 2011; Heinesen and Kolodziejczyk, 2013). However, this reduction increases over time, which is the opposite of what the Grossman model (1972) predicts. The delayed impact on employment could be explained by the institutionalized job protection period in the developed countries, during which the employee can take sick leave without losing her job while she recuperates. Furthermore, some countries also have integration policies, which encourage the employee to come back to work and, if needed, provide her with extra training. As such the institutional setting plays an important role in augmenting the relationship between adverse health events and employment. The institutional setting, according to García-Gómez (2011), could partially explain why employees in nine European countries reduced differently their employment after a health shock. The author shows that in countries where the disability policies have a lower integration dimension[2] (such as Ireland), individuals reduce more their labor market activity in comparison to individuals in countries where the integration dimension is higher (such as Denmark and the Netherlands). Bradley et al. (2013) also find that the institutional setting is important for the employment decision of women after a severe health condition. After surviving breast cancer, women in the US who were not eligible for a health insurance through their spouses were less likely to leave their job in order to keep their eligibility for health insurance.

An important issue that emerges from this literature is the interplay of the severity of the health condition and the institutional setting. While they both influence the labor market behavior of the individual after an adverse health event, the literature has not considered yet which one is more important and whether tailoring the institutional setting to the type of health problem could result in societal benefits. Additionally, the sick leave provision of replacement income could also affect the behavior of the spouse: it may reduce the need for working more to compensate for the lost household income.

1.2. Objectives

The objective of this dissertation is to contribute to the understanding of individuals' labor market outcomes in response to female adverse health events and to consider how elements of the Dutch institutional setting can be related to this outcome. The analysis focuses on the institutional setting of the Netherlands and it considers as an adverse health event a medical diagnosis received during a hospital admission (clinical or day care). As it is likely that there are gender differences, this dissertation focuses on situations where women suffer from adverse health events.

To answer the overarching question, each chapter considers a different dimension and answers one of the following sub-questions:

- ❖ Does the job protection policy in the Netherlands mitigate the negative effect of an adverse health on employment? (Chapter 2)
- ❖ To what extent can the change in employment after an adverse health event be explained by the job protection policy and/or the severity of the health condition? (Chapter 2)

[2] The integration dimension consists of employment and rehabilitation measures: "coverage consistency, assessment structure, employer responsibility for job retention and accommodation, supported employment program, subsidized employment program, sheltered employment sector, vocational rehabilitationprogram, timing of rehabilitation, benefit suspension regulations and additional work incentives" (García-Gómez, 2011; p.201).

- Does the nationwide breast cancer screening program, which aims at reducing the severity of the health condition by providing early checks, result in productivity gains? (Chapter 3)
- Can the income replacement during sick leave after a breast cancer diagnosis be related to the provision of caregiving by the spouse? (Chapter 4)

1.3. Institutional setting in the Netherlands

This dissertation has a strong focus on the job protection and sick leave regulation in the Netherlands. This section presents this regulation, as well as the partner leave regulation, which should be considered as well when looking into spillover effects after one's health deterioration.

1.3.1. Sick leave

Since 2004, employees in the Netherlands are allowed to take up to two years sick leave if they suffer from an adverse health event. During this time, they continue to receive their salary[3] and they cannot be dismissed. To encourage their re-integration into the work place, the Gatekeeper Improvement Act obliges the employee to exert effort corresponding to her available work capacity (Wet verbetering poortwachter, 2001). Additionally, after six weeks from the beginning of the adverse health event, the employer and the employee have to agree on a participation plan which specifies how the employee will be re-integrated back to work, which could involve reducing the number of working hours, finding suitable tasks to the new physical situation of the employee, and/or re-adjusting the workplace to accommodate better the employee's needs. If one of the parties does not comply with the re-integration measures, then the law specifies sanctions, such as extension of the sick leave period during which the employee is entitled of salary (a maximum of one year); or no salary during the sick leave period. When the employee recovers, she is expected to return to work and her remuneration is then related to her performance. However, not all employees recover. If in the end of the two-year period, the employee has not recovered, she could apply for disability benefits. The decision, whether they are granted and for how long, is based on the level of disability, the expected recovery, and the integration efforts during the period of sickness absence.

Interestingly, the employer has different obligations based on the type of contract of the employee. If the employee has a temporary contract which expires during the two-year period,

[3] A total of 170% for the two years, which is usually split into 100% during the first year and 70% during the second year.

the employer has a responsibility for payments until the end of the contractual time, after that the individual is entitled to sickness benefits from the government for the remainder of the time period (Sickness Benefit Act, Ziekte Wet, 1999). In this occasion, the law does not oblige the employer to extend the temporary contract until the end of the protection period. Thus, an employee may lose her job during the sickness leave period.

In conclusion, the current institutional framework in the Netherlands provides the employees with job security in the event of a health condition. It enables them to continue working during the first two years of the illness as it requires from the employer to find suitable tasks to accommodate their physical limitations. The income effects of the health condition are also limited in the short-term due to the continuation of the salary payment.

1.3.2. Partner leave

Besides the sick leave for the employee that suffers from an adverse health event, the institutional setting in the Netherlands allows an employee to take time to care for a sick spouse (Work and Care Act, WAZ; Chapter 5: Short- and long-term care leave). Initially, the employee can take one day as an emergency leave. Then, the employee can take short-term care leave of a maximum of two weeks per year. During this period, the employee is entitled to a minimum of 70% of their salary. To be eligible for short-term leave, the employee has to show that he/she is the only one who can take care for the individual. After that, the employee can take unpaid long-term care leave, which is at maximum six times his weekly work hours and could be spread over a period of 12 to 18 weeks. As the long-term care leave is unpaid, it could introduce a financial burden to the family. Additionally, there is no job protection during the short- nor the long-term care leave, which implies that the employee could be laid off while taking care of a sick family member.

1.4. Why is breast cancer important?

Two of the three analyses within this dissertation focus on breast cancer. The reason for this research is the societal impact of this disease. Breast cancer is the most common type of cancer for women and the second deadliest in developed countries (GLOBOCAN, 2012). After Belgium, Denmark and France, the Netherlands ranks fourth in the incidence of breast cancer in 2012 (World Cancer Research Fund International), with one out of eight women being diagnosed with breast cancer at some point in her life (RIVM, 2014).

1.4.1. Facts

Breast cancer 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). In 2017, the five-year survival rate in the Netherlands was 86 percent (Dutch Cancer Registration, 2017). While 8 – 10 percent of the breast cancer diagnosis can be attributed to genetics, the rest of the cases can be related to life-style (Breastcancer.org, 2017). Previous research shows that (some of) the risk factors for women, besides age, are higher education (Palme and Simeonova, 2015), first pregnancy after the age of 30, drinking and smoking, and birth control pills (Breastcancer.org, 2017).

1.4.2. Screening for breast cancer

Since 1998, there is a nationwide breast screening program in the Netherlands, which aims at early detection of breast cancer and improved chances of survival for the diagnosed women. Women at the age of 50 receive a first invitation to participate and, if they are not diagnosed with breast cancer at that time, they are invited again for screening every second year until the age of 75. Participation in the program is free of charge. When a cohort begins to be screened, there are more diagnosis than before, since both the women who would have been diagnosed without screening are diagnosed, as well as the women who otherwise would be diagnosed in the future.

Currently there are 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[4]. The Health Council of the Netherlands (2014) evaluated the screening program and found that it has high participation rate (82 percent in 2007 (highest); 80 percent in 2012); low referral rate (approx. 2.35 percent of screened women are referred for further diagnostic because of abnormal screening results); and reliable test performance (approximately 17.2 percent false positive results). By observing the age of the diagnosed women, we can distinguish between women diagnosed at an age younger than 50, who are diagnosed before the screening program is available to them and therefore, on average, are diagnosed at a later stage of the disease than diagnosed women aged 50-75 who are covered by the nationwide screening.

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

1.5. Outline and contributions

This dissertation considers first how the employment of women changes after adverse health events and whether there are differences which can be related to the type of adverse health event. Then it focuses on a specific health problem, breast cancer, and considers whether the employment adjustments are different among women with different severity of the disease. Last, it considers whether employment of the spouses is affected by the breast cancer diagnosis.

1.5.1. Women's labor market participation after an adverse health event

Chapter 2 performs a broad analysis of the employment adjustments of women after an adverse health event. It relates their employment adjustments to the institutional job protection system in the Netherlands and the severity of the health condition.

From an economic point of view, Grossman (1972) argues that health shocks negatively impact the distribution of the individual's time between work and leisure, as they demand time for health recovery. Thus, an individual suffering from a health condition would reduce her labor supply immediately after the health shock, but upon recovery the impact should be smaller or may even disappear. To offset the negative effect of adverse health on employment, the institutional framework in the Netherlands provides employment protection during the first two years after the diagnosis.

The analysis is performed on Dutch administrative data from 2004 to 2012, which follow women aged 25 to 55 for four years after an adverse health event and report on their employment, working hours and wage developments. The results show that women who experienced an adverse health event are likely to leave their employment from the time of diagnosis up to four years later, which is in line with previous studies. The observed reduction in employment of about one percentage point in the fourth year after the diagnosis is comparable to the additional observed mortality among this group of women over the same time period. For the women who stay in employment, we found that they are likely to work less hours after an adverse health event, namely 4.5 hours a year in the year of diagnosis and 12 hours a year four years later. For women who are in permanent employment and therefore cannot be laid off during the first two years after the onset of the health condition, the job separation is likely to happen only after the initial protection period and to a lesser extent (0.44 percentage points). Lastly, considering the wage adjustments, the findings do not show differences between the women who were and were not diagnosed, which is in accordance with the findings of the rest of the literature. This was also the case for the women in permanent employment. However, there were some important differences in the wage adjustments when we considered the different types of adverse health events. First, temporary health conditions seem to be related to a temporary decrease in the wage profile: 1.7 percent reduction one year after the diagnosis for breast cancer patients, and 0.5 percent for other cancer patients, followed by partial wage recovery for the former and full wage recovery for the later by the fourth year after the diagnosis. Second, the chronic and incapacitating conditions such as circulatory conditions seem to be related to a long term decrease in the wage profile (approximately 0.5 percent). Third, the results suggest two different patterns after chronic and non-incapacitating health conditions, namely no wage difference after respiratory conditions and continuously lower wage profile after nutritional conditions. Interestingly, the wage patterns were similar for the permanently employed women, except for the women diagnosed with chronic and non-incapacitating health conditions. There the results suggest an initially lower wage at the time of diagnosis, followed by a full wage recovery in the consequent year.

The contribution of this chapter is four-fold. First, it contributes to the literature on how labour market institutions affect the behaviour of employees after an adverse health event by comparing the employment changes of women during the period of institutionalized job protection and the years after that. The second contribution is with respect to the degree of institutional job protection. The chapter compares the employment adjustments of women fully covered by this policy to all women. Third, it contributes to the literature related to impact of health conditions on employment based on their severity by distinguishing among different types of adverse health events and comparing the labor market adjustments after each of them. Last, by considering simultaneously the severity of the health condition and the degree of institutional protection, the chapter contributes to the literature that disentangles how these two characteristics affect employment probability, working hours and wage adjustments.

1.5.2. The effects of nationwide breast cancer screening on survival and employment after being diagnosed

Chapter 3 of this dissertation considers the difference in the employment of women diagnosed with breast cancer based on the severity of the diagnosis. It compares the employment of women who have been diagnosed when they had access to the Nationwide breast cancer screening program in the Netherlands and women who did not have access to the program.

This chapter builds upon Grossman's model (1972), according to which the recovery time from an adverse health event is related to the severity of the health event. Thus, the more severe the problem, the longer the individual needs to take time off work (and leisure) to recover their health. Indeed, Thielen et. al. (2015) find that, compared to an early diagnosis of breast cancer, a later diagnosis has a stronger negative effect on the employment probability of Danish women three years after the diagnosis.

While there are extensive studies about the mortality benefits of breast cancer screening, chapter 3 is the first one to consider whether there are also employment gains from the program. The empirical analysis is performed on a Dutch administrative data from 2000 to 2012 that contain information on the age at diagnosis, mortality and employment. It focuses on a sample of 9040 women diagnosed with breast cancer between the ages of 48 and 53 and exploits the fact that the access to the breast cancer screening program starts at the age of 50.

The results show that access to breast cancer screening reduces the mortality rate by 30.8 percent in the first year after diagnosis, which is in line with previous research (Njor et al., 2012). A new empirical finding is that access to breast cancer screening leads to a 6.3 percent higher probability of employment in the first year after the diagnosis. Thus, suggesting that besides the mortality gains, there are also productivity gains from the nationwide breast cancer screening program. Furthermore, the results show that both the mortality and productivity gains do not diminish in the four years after the diagnosis.

This chapter contributes to the literature on cost-benefit analysis of nationwide breast cancer screening by providing evidence of mortality and productivity gains from the program.

1.5.3. Husband's employment adjustments after their wife receives a breast cancer diagnosis

Chapter 4 of this dissertation considers the indirect costs of a breast cancer diagnosis of the wife on the labor market participation of the husband. It uses the employment legislation, namely the sick leave policy, to disentangle the two opposing effects that lead to changes in the employment participation of the spouse, namely caregiving effect and income effect.

To reduce the negative spillover effect on the spouse's labor supply, the institutional setting in the Netherlands allows an employee to take time to care for their sick spouse (zorgverlof). Furthermore, if the individual is working at the time of diagnosis, he/she can take sick leave, which provides income replacement until the person can return to work.

The novelty of this chapter is that it considers separately families where the wife was employed before of diagnosis, and thus there is income protection from her sick leave, and families where the wife was not employed before the diagnosis and the husband is the only breadwinner in the family.

Based on individual level Dutch administrative data for the period 2006 to 2011, the chapter uses a combination of Coarsened Exact Matching and a difference-in-difference strategy to compare families where the wife has received a breast cancer diagnosis and families where this is not the case. The results suggest that, in general, husbands were likely to reduce their employment probability with 0.71 percentage points after their wife's health deteriorates. Meanwhile, husbands whose wives were employed before the diagnosis were likely to reduce their employment probability by 0.86 percentage points after she is diagnosed; while husbands whose wives were not employed, were not likely to reduce their employment probability. The chapter argues that this result is related to the replacement income during the sick leave, which reduces the financial loss for the family and could aid the husband to spend more time with his wife. On the other hand, in the families where the wife is not earning a salary, it is likely that the family depends on the husband's salary and therefore, he is less likely to reduce his employment to take care of his wife. In a way, this result suggests that the financial constraint is likely to be crucial for this decision. Interestingly, the results show no changes in the working hours of the husbands. This is likely the case as the data reports only contractual obligations, thus if the husband takes the allowed from the law hours to take care for his wife, this decrease will not be observed in the data. Nevertheless, observing a contractual decrease in employment probability suggests that the hours provided by the law are likely to not be sufficient for caregiving.

The chapter considers as well whether differences in the severity of the diagnosis of the wife and the family composition could be related to the employment adjustments of the husband. While the results suggest that later diagnosis, widowhood, and older age of the husband are not related to a different employment probability of the husband, there seems to be differences related to having children in the household. In general, husbands were likely to have a higher employment probability when there were children in the household, as well as in the households where the wife was not employed before the diagnosis. These results can be related to a stronger financial constraint in the presence of children in the household.

The contribution of this chapter is three-fold. First, it contributes to disentangling the income and caregiving effect by considering the employment state of the wife prior to the diagnosis. Second, it contributes to understanding better how the severity of the diagnosis of the wife and the family composition relate to the employment adjustments of the husband. Third, it contributes to the discussion about caregiving leave by finding caregiving behavior after a sickness of the spouse.

All the chapters have been written as standalone papers, thus it is likely that there is repetition in the information presented in them.

Chapter 2: Women's labor market participation after an adverse health event[5]

2.1. Introduction

Adverse health events may cause individuals to stop working, reduce their hours of work or decrease their wages. Previous studies such as Halla and Zweimüller (2013) and García-Gómez, Van Kippersluis, O'Donnell and Van Doorslaer (2013) show that unhealthy women are less likely to be employed than healthy women and this difference in employment increases during the three years after an adverse health event. These empirical findings, however, are not in line with the Grossman model (1972), according to which the largest reduction in employment should be when the adverse health event occurs. At that point, the individuals lose part of their health capital and therefore they need to spend more time on recovering it. As a result, they have less time available for work and leisure, and ultimately work less. This discrepancy between the empirical evidence and the economic theory is likely to arise from the institutionalized employment protection system which is in place in most of the developed countries, and which is likely to mitigate the negative employment consequences of an adverse health event. In the Netherlands, the country investigated in this study, employees could take up to two years of sick leave after an adverse health event (Wet uitbreiding loondoorbetalingsplicht bij ziekte, 1996; Wet verlenging loondoorbetalingsverplichting bij ziekte, 2003). During this time, the employee is entitled to her salary[6] and she could accommodate the (possible) reduction in her employment capacity by changing her working hours and/or job tasks. Furthermore, during this time she could not be laid off; however, if she is on a temporary contract, the employer is not obliged to extend her contract until the end of the second year[7]. As such, the system is designed to mitigate the short-term (financial and employment) impact of a health condition and enable the employee to recover in the meantime. Nevertheless, not all employees recover – some health conditions have a more permanent nature

[5] A paper based on Chapter 2 is published as Kambourova, Z., Hassink, W., & Kalwij, A. (2019). Women's employment adjustments after an adverse health event. In S. Polachek & K. Tatsiramos (Eds.), *Health and Labor Markets* (pp. 25-70*). Research in Labor Economics,* Vol. 47, Emerald Publishing Limited

[6] A minimum of 170% of her last salary, which is spread over the two-year period.

[7] In case the employment contract finishes before that, the employee receives her salary from a government fund (Ziektewetuitkering) and there is a re-integration coach to help her find a new job.

and lead to permanent reduction of employment capacity. Employees with such health conditions can enter disability insurance after the two-year period[8,9]. Indeed, Pelkowski and Berger (2004) show that the long-term impact of health conditions on employment is related to the permanent nature of the health problem. On the other hand, García-Gómez (2011) argues that besides the severity of the health problem, the generosity of the social security system could partially explain the employment outcome.

The aim of this chapter is to investigate women's labor market adjustments after an adverse health event and whether the magnitude of these adjustments could be explained by the institutional job protection and/or the type of health condition. We analyze Dutch administrative data from 2004 to 2012, which follow women for four years after an adverse health event and report on their employment, working hours and wage developments.

Our contributions are four-fold. First, we contribute to the literature on how labor market institutions affect the behavior of employees after an adverse health event by comparing the labor market participation of women during the period of institutionalized employment protection and the years after that. A study most close to ours is García-Gómez et al. (2013), who consider labor market adjustments of women after an acute hospitalization during a different institutional setting in the Netherlands[10]. They consider women diagnosed in 1999, when the institutionalized employment protection period is one year and the disability level required for entry in disability insurance is 15%; our study considers the years after 2004, when the protection is two years and the required disability level is 35%.[11,12] Such a difference in the institutional setting is likely to result in stronger financial incentives for returning to work. Indeed, we find a smaller magnitude of employment adjustments – a reduction in employment of 1.06 percentage points four years after the adverse health event. The smaller magnitude,

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[8] The minimum required reduction of employment capacity to enter DI is 35%.

[9] For details about the disability insurance system in the Netherlands, please see Koning and Lindeboom (2015).

[10] Initially, they consider men and women together, and then separately.

[11] We also have data for 2003, the last year in which the employment protection period was one year. However, as the DI reforms as well entails other aspects like stricter screening, we use data from 2004 onwards only and do not assess the effect of a change in the job protection period.

[12] Hullegie and Koning (2018) consider the combined impact of all DI reforms in the period 2000-2010 on the employment of individuals with health problems or disability. They find that the reforms have been beneficial for the individuals who were already employed: they are more likely to stay in employment in comparison to the unhealthy individuals before the reforms. However, the authors also suggest that the reforms have introduced further hiring barriers for unhealthy individuals.

however, could be attributed to the changes in the social security system, as well as to the less severe health conditions that we consider. Furthermore, our results indicate that even though there is institutional protection, women leave employment in the short term and this continues throughout the four years after the adverse health event. We also observe that during the period of employment protection women adjust their working hours and leave employment, while after the period of protection they predominantly leave employment.

Our second contribution is with respect to the degree of institutional employment protection. Markussen, Mykletun and Røed (2012) outline the benefits of working part-time before the full recovery from the health condition. They find that employees who are required to work up to their available working capacity in order to receive their sickness benefits have better subsequent employment probability in comparison to employees who are not required to work until they fully recover. We build upon their research by considering women who have a permanent employment contract and therefore are employed during the sick leave period. We find no reduction in their employment probability during the two-years of employment protection and only to a lesser extent in the third and fourth year after the diagnosis. Our results suggest that longer employment protection, or the possibility to return to work rather than look for a job, could be beneficial for the re-integration of women in the work environment.

Third, we contribute to the literature related to impact of health conditions on labor market participation based on their severity by distinguishing among different types of adverse health events and comparing the labor market adjustments after each of them. The first study which considers the impact of severity on labor supply is Pelkowski and Berger (2004) and it shows that while temporary health conditions do not impact working hours and hourly wages, this is not the case for permanent health conditions. The study of Lundborg, Nilsson and Vikström (2015) goes further in the comparison between health conditions and considers the ten most common medical diagnoses in Sweden. The study assesses whether there are differential income adjustments between employees who suffer from the same disease but have different levels of education. The authors find similar magnitudes across diseases. However, they do not compare the income differential between employees who suffered from a health condition and those who did not.[13] We find that especially the wage developments are related to the type of health condition: while non-chronic conditions lead to a temporary reduction in the wage,

[13] They find an educational gradient: individuals having a lower education (or low skills) suffer from a stronger negative impact on their earnings. They do not find any significant differences in the income differential across the disease groups.

chronic and incapacitating health conditions lead to a permanent reduction, and while some chronic and not-incapacitating conditions are not related to wage reductions, others are related to lower wages during the observed period. We find similar patterns for women in permanent employment, except for those who were diagnosed with a chronic and non-incapacitating condition.

Fourth, by considering simultaneously the severity of the health condition and the degree of institutional protection we contribute to the literature that disentangles the two effects. To the best of our knowledge, there is no other study that attempts to do that. We find that while the employment adjustments differ between women in temporary and permanent employment, this is not the case for the wage adjustments, except for the women diagnosed with chronic and non-incapacitating conditions. The wage adjustments, however, could be related to the severity of the health condition, while this is not the case for the employment adjustments.

The remainder of the chapter is organized as follows. Section 2.2 outlines the theoretical framework and the Dutch institutional setting. Section 2.3 describes the data and Section 2.4 the empirical methodology. Section 2.5 outlines the results, Section 2.6 presents the robustness checks and Section 2.7 gives the discussion and conclusion.

2.2. Theoretical framework and institutional setting

Grossman (1972) argues that health shocks negatively impact the distribution of the individual's time between work and leisure, as they demand time for health recovery. Poor health also negatively affects productivity and taste for work, and as a result increases the marginal value of leisure (Bradley, Bednarek and Neumark, 2002). This change in preferences moves the utility maximizing choice towards less time spend on work. Therefore, an individual suffering from a health condition would reduce her labor supply immediately after the health shock, but upon recovery the impact should be smaller or may even disappear.

Upon return to work the employee may not possess the same skill set. First, this could be a direct outcome of the health condition, for example partial disability. Second, there could be depreciation or atrophy of skills due to not actively using the human capital (Mincer and Ofek, 1982). Such a setback may lead to lower productivity upon return to work, which ultimately would result in a lower wage. However, some of the 'lost' knowledge could be restored in the short term. Re-learning old skills is faster than acquiring new knowledge (Mincer and Ofek, 1982) and as a result the productivity increase will be steeper during the former and the employee would return to her productivity level from before the work disruption.

Based on these theoretical insights we expect that after an adverse health event, employees will reduce their labor supply and when they return to work, upon recovery, they may have a lower productivity than before the adverse health event.

Previous studies have found that the labor supply immediately decreases after a health condition. For instance, Halla and Zweimüller (2013) consider how accidents to and from work impact the employment of the individual. They find an immediate negative impact on work in the form of absenteeism (on average 46 days), which is followed by increased probability of leaving work through unemployment, and later on entry in disability retirement. The negative employment effects are present even five years after the accident and the individuals who stay in employment suffer from a continuous decrease in earnings.

García-Gómez et al. (2013) also finds that the negative effect on employment after a health condition (acute hospitalization) increases over time: in the beginning it is relatively small, it reaches 8.4 percentage points decrease in the second year, and there is no recovery six years later. The authors explain the small initial effect by the (possible) sick leave, which delays leaving employment. Furthermore, they find that the employees who leave employment are likely to enter disability insurance and the one who stay employed experience long term reduction in annual income from the onset of the disease.

Jones, Rice and Zantomio (2016) find as well an increase of the negative impact on employment over time of a health shock such as the incidence of cancer, stroke or myocardial infarction in the UK. They estimate the decrease at 9.2% three years after the shock. Interestingly, they observe a decrease in working hours in the second year after the shock, but not in the first year or the third year after the shock. The authors suggest that it is a result of an attempt for accommodating the health problem, followed by leaving the labor force since the reduction in employment probability decreases further.

Overall, studies have shown that adverse health events reduce the employment probability (e.g., Moran, Short and Hollenbeak, 2011; García-Gómez et al., 2013; Halla and Zweimüller, 2013; Heinesen and Kolodziejczyk, 2013; Jones et al., 2016). However, this reduction increases over time which is the opposite of what the Grossman model (1972) predicts. The delayed impact on employment could be explained by the institutionalized employment protection period in the developed countries, during which the employee can take sick leave without losing her job while she recuperates. Furthermore, some countries also have integration policies, which encourage the employee to come back to work and, if needed, provide her with extra training. As such the institutional setting plays an important role in augmenting the relationship between adverse health events and employment. The institutional setting, according to García-Gómez (2011), could partially explain why employees in nine European countries reduced differently their employment after a health shock. The author shows that in countries where the disability policies have a lower integration dimension[14] (such as Ireland), individuals reduce more their labor market activity in comparison to individuals in countries where the integration dimension is higher (such as Denmark and the Netherlands). Bradley, Neumark and Barkowski (2013) also find that the institutional setting is important for the employment decision of women after a severe health condition. After surviving breast cancer, the women who were not eligible for a health insurance through their spouses were less likely to leave their job in order to keep their eligibility for health insurance.

In the Netherlands, since 2004, an employee can take up to two years of sick leave after an adverse health event.[15,16] During this time, the employee cannot be dismissed and is entitled to a total of 170% of their last yearly salary over a two-year period. In case the employee has a temporary contract, which expires during this two-year period, the employer has a responsibility for payments until the end of the contractual time, after that the individual is entitled to sickness benefits from the government for the remainder of the time period (Sickness Benefit Act, Ziekte wet, 1999). Furthermore, if the contract expires during the protection period, the law does not oblige the employer to extend the temporary contract until the end of the protection period. On the other hand, for the employee to be entitled to this protection period and benefits, she has to exert effort corresponding to her available work capacity, according to the Gatekeeper Improvement Act (Wet verbetering poortwachter, 2001). The Gatekeeper Act aims at improving the re-integration of the employee in the company and requires the employer to provide the employee with a participation plan for the sickness period. The plan may involve reducing the number of working hours, finding suitable tasks to the new physical situation of the employee, and/or re-adjusting the workplace to accommodate better the employee's needs. The law also specifies sanctions in case of non-compliance: an extension of the sick leave period during which the employee is entitled of salary (a maximum of one year) if the employer is not

[14] The integration dimension consist of employment and rehabilitation measures: "coverage consistency, assessment structure, employer responsibility for job retention and accommodation, supported employment program, subsidized employment program, sheltered employment sector, vocational rehabilitation program, timing of rehabilitation, benefit suspension regulations and additional work incentives" (García-Gómez, 2011; p.201).

[15] See Van den Bemd and Hassink (2012) for a more detailed description of absenteeism regulations in the Netherlands.

[16] See De Vos, Kapteyn and Kalwij (2012) for a more detailed description of the Dutch disability insurance, pension and unemployment schemes.

complying to the legislation; or no salary during the sick leave period if the employee is not complying to the legislation. As soon as the employee recovers, she is expected to return to work and her remuneration from that point onwards is related to her actual work effort. If the employee's health has not recovered after the two-year period, she could apply for disability insurance benefits. The decision, whether they are granted and for how long, is based on the level of disability, the expected recovery, and the integration efforts during the period of sickness absence.

In conclusion, the institutional framework in the Netherlands provides the employees with employment security in the event of an adverse health event. They can continue working during the first two years of the illness as it requires from the employer to find suitable tasks to accommodate their physical limitations. The income effects of the health condition are also limited in the short-term due to the continuation of the salary payment. Therefore, we expect that the (contractual) labor participation would change mostly after the institutional protection is over, namely two years after the adverse health event.

2.3. Data

We use individual level administrative data for the years 2000 to 2012 that contain information on employment, demographics and health and that have been retrieved from five different sources and that are provided by Statistics Netherlands. First, the employment spells data were obtained from the Social Statistical Dataset on Jobs (Sociaal Statistisch Bestand, SSB-banen, 2004-2012; Bakker, Van Rooijen and Van Toor, 2014). Second, personal income and the socio-economic status of the women were obtained from the Integrated Personal Income data set (Integraal Persoonlijk Inkomen, 2004-2012; CBS, 2016a), which has been collected by the tax authorities. Third, information about age, gender and family situation was retrieved from the Municipality Registry (Gemeentelijke Basisadministratie, GBA, 2004-2012; CBS, 2015). Fourth, the medical information, in the form of hospital entries, was obtained from the National Medical Registration (Landelijke Medische Registratie, LMR, 2000-2012; CBS, 2016b), 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 2.A). The combined data follows about 9.35 million women who were registered in a Dutch municipality between 2004 and 2012. Women enter our dataset in 2004 or in a later year if they reach the age of 25 or emigrated to the Netherlands. We cease observing women after 2012 or after an earlier year if they have deceased[17], reached the age 56 or have immigrated from the Netherlands.

2.3.1. Sample selection

For the period 2004 to 2012, we selected women who are between 25 and 55 years for all years of observation. We removed women younger than 25 as they can still be in education and older than 55 to avoid issues related to early retirement. This reduced our sample with about 56 percent. Furthermore, we excluded women who were classified according to their socio-economic status as self-employed (5.91%)[18] and students (0.4%), because their main occupation is not contractual employment, which is what we can observe in the data.

Individuals living in certain areas of the country have been excluded because these areas are not covered by the Hospital registry (the LMR dataset). Based on information from the Housing registry we were able to determine which of the 415 municipalities were fully covered by the LMR. As it turned out, a minimum of seven municipalities in 2005 and a maximum of 44 in 2008 were not fully covered and women residing in these municipalities, and in those years, have been excluded from our sample (see Appendix 2.A for more details). On an individual level, this caused a reduction in sample size of minimum of 1.44% in 2005 and maximum of 8.29% in 2008.

To identify women who suffered from an adverse health event, we considered women's medical history, which consists of diagnoses received during hospital admissions (clinical and day care). If in a given year a woman received a medical diagnosis, but she did not receive one in the four years prior to that year, we define this diagnosis as a new diagnosis and it is referred to as an adverse health event.

A woman enters our sample after four consecutive years without a diagnosis. However, for some women we do not observe four years before the diagnosis, since our data starts in 2000 and even though they received a diagnosis, we cannot identify whether it is an adverse health event or a repeated hospital visit. As a result, we excluded 209,780 women. The first adverse health event could be observed in 2004 and in total, we observe 1,086,073 adverse health events[19].

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[17] See Appendix 2.B and Appendix 2.C for further information about the mortality rates by type of diagnosis and employment state.

[18] Even though they work, we do not observe their contractual working hours and hourly wage rate.

[19] Cumulative number for the period 2004 to 2012.

Lastly, missing values on key variables caused a further reduction in the sample size. As a result, our final sample consists of 3,804,345 women and on average they are observed for six years from 2004 to 2012.

2.3.2. Types of adverse health events

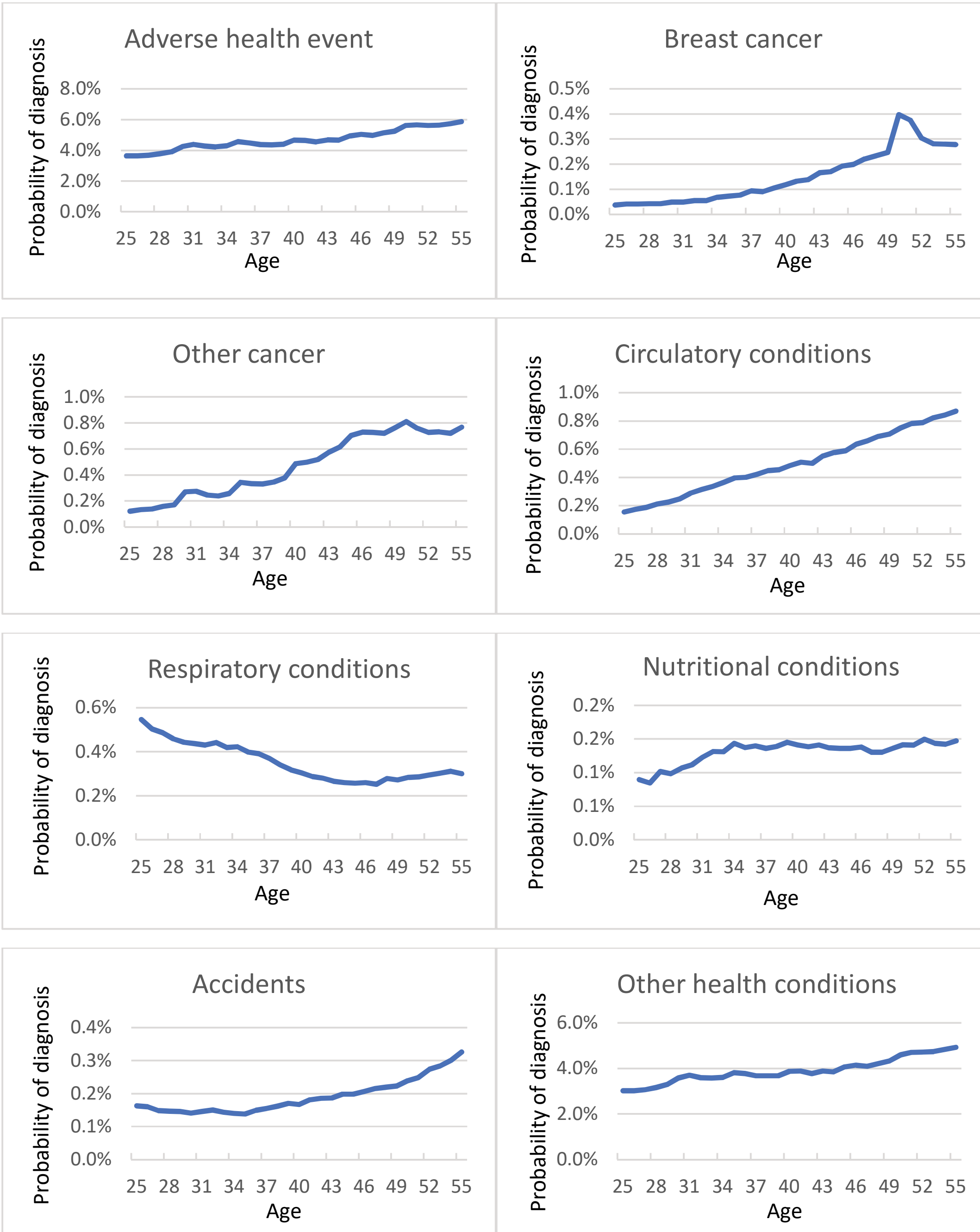
In the analysis, we first consider any diagnosis when defining an adverse health event and next we distinguish seven diagnoses during a hospital visit, namely breast cancer, other cancers, circulatory conditions, respiratory conditions, nutritional conditions, accidents, and other health conditions[20]. In the latter case, a diagnosis is considered new if the patient did not receive the same type of diagnosis during the previous four years.

We consider different groups of health conditions because if they are chronic and/or incapacitating, they may lead to different work adjustments in the short and long term. We expect that conditions that women can recover from, such as cancer, would lead to temporary work adjustments. Furthermore, chronic and incapacitating conditions, such as circulatory conditions, could lead to long-term adjustments in the work participation, in order to accommodate the change in work capabilities. Lastly, we expect that chronic but not-incapacitating conditions, such as respiratory and nutritional conditions, would not impact the work adjustments, since they do not impose long-term restrictions on the work capacity.

The incidence of an adverse health event increases with age (Figure 2.1; top left graph). The incidences of adverse health events differ across disease types and all increase with increasing age except for respiratory health conditions (Figure 2.1). The latter health conditions are often chronic and are often diagnosed already early in life.

[20] See Appendix 2.A for details about the composition of Other health conditions.

Figure 2.1. Adverse health events by age and type of diagnosis



Notes: Own calculations based on population data from Statistics Netherlands for the period 2004-2012.

Some women may receive more than one new diagnosis during the calendar year (see Table 2.D.1, Appendix 2.D). For example, 33.75% of the patients with breast cancer have received another diagnosis in the same year (maximum overlap), while this is the case for only 13.33% of the patients with respiratory conditions (minimum overlap). Considering each health condition, most of the overlap is with other health problems and the least with accidents.

2.3.3. Labor market participation

Labor market participation is described in this chapter by the employment status, the number of contractual hours of work and the hourly gross wage rate. Younger women, on average, are more likely to be employed (90% at age 25 vs 64% at age 55; Figure 2.F.1, top left graph, Appendix 2.F), to work longer hours (1670 hours per year at age 25 vs 1392 hours at age 55; top right graph), and to earn less (€13 at age 25 vs €17 per hour at age 55; bottom graph).

Since job protection differs between employees on temporary and permanent contracts, it is important to take this into account. According to Dutch law, employees cannot stay on a temporary contract in the company for more than three years. After the third year of employment, the contract has to become permanent or the employee is laid off. Therefore, we define that a woman has a permanent contract if she has been with the company for more than three years. Following this definition, we observe 52.05% women (67.44% of the employed sample) in permanent employment; 25.13% women (32.56% of the employed sample) in temporary employment; and 22.82% women not employed throughout the observed period. However, the employee may receive immediately a permanent contract or at any time after that, which implies that in the group of temporary employed women, there may be women who already have a permanent employment contract, even though they have been with the company for less than three years. Since we cannot distinguish between those and the women with temporary employment contracts; and we have no official employment statistic about how big that group may be, we will use for the sub-sample empirical analysis only the sample of women with permanent employment contracts according to our definition.

Table 2.1 shows based on the type of contract, the demographic characteristics of the two groups. Women with a permanent contract are older (41 vs 38 years old), more likely to have a partner (78% vs 72%), and equally likely to have children at home (55% vs 54%) in comparison to women with a temporary contract. Furthermore, Table 2.1 shows that the incidence of each type of health condition, as well as health conditions in general, is similar across the two groups.

Table 2.1. Demographics and health conditions by type of labor contract

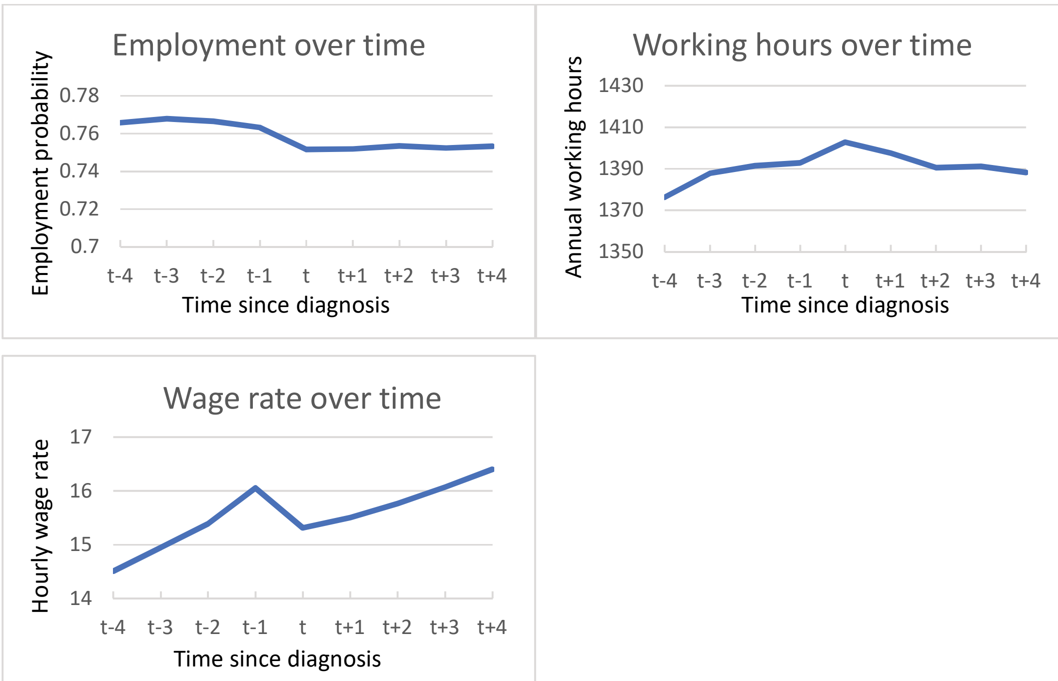
	Permanently employed		Temporary employed	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	41	8.295	38	8.597
Partner	0.784	0.412	0.720	0.449
No children	0.454	0.498	0.462	0.499
Adverse health event	0.047	0.211	0.045	0.207
Breast cancer	0.002	0.041	0.001	0.035
Other cancer	0.005	0.071	0.004	0.065
Circulatory	0.005	0.070	0.004	0.066
Respiratory	0.003	0.056	0.004	0.060
Nutritional	0.001	0.034	0.001	0.034
Accidents	0.002	0.043	0.002	0.044
Other health problems	0.039	0.192	0.037	0.190

Notes: Age is measured in years. Partner is equal to 1 if a woman has a partner, and 0 otherwise. No children is equal to 1 if there are no children in the household, and 0 otherwise. Adverse health event is equal to 1 if the woman received a diagnosis during the calendar year, and 0 otherwise. Breast cancer, Other cancer, Circulatory conditions, Respiratory conditions, Nutritional conditions, Accidents and Other health problems are measured as follows: equal to 1 if the women received the specific diagnosis, and 0 otherwise. The statistics about permanently employed women is based on 11,944,304 observations, and the statistics about temporary employed women is based on 5,768,012 observations.

2.3.4. Before and after the adverse health event

Women may experience changes in their employment patterns after an adverse health event. Figure 2.2 depicts the employment probability, average annual contractual working hours for those who are employed and the average hourly wage rate during the four years before and after the adverse health event. In the top left panel, we observe that women slowly leave employment in the years before the adverse health event and their employment probability does not return to the initial levels in the years after the adverse health event. With respect to the working hours (see top right panel), we observe an increase in the average annual contractual working hours in the years before the diagnosis and reduction in the first two years after the adverse health event. The magnitude of the difference is around 30 hours on a yearly basis, which is insignificant in economic terms. Lastly, we observe a positive trend in the average hourly wage (see bottom panel), which is likely to be related to the yearly increase in wage due to more experience, as well as to calendar effects. Furthermore, there is a drop in the average hourly wage rate in the year of diagnosis, after which the hourly wage rate returns to its previous positive trend.

Figure 2.2. Employment, working hours and wage before and after the adverse health event



Notes: Based on own calculation of the sample of women who experience an adverse health event in the period 2004-2012.

Considering the women with permanent and temporary contract, it is interesting to see if there are differences in their employment probability in the years after the adverse health event (see Table 2.2). We observe that women in temporary employment are more likely to leave employment and four years later the difference between the two groups is almost 6 percentage points.

Table 2.2: Employment trends by type of contract at the time of diagnosis (in %)

Type of contract at time	Time since diagnosis				
of diagnosis	Year 0	Year 1	Year 2	Year 3	Year 4
Temporary	100	91.63	89.38	88.60	88.79
Permanent	100	98.33	96.75	95.26	94.53

Notes: The table reports the percentage of initially employed women per type of contract over the four years after the diagnosis.

2.4. Empirical framework

First, we estimate the effect of an adverse health event on employment using the following linear probability model (LPM):

$$Y_{i,t} = \beta_0 + \beta_1 H_{i,t} + \sum_{k=1}^{4} \beta_{k+1} H_{i,t-k} + \mathbf{X}_{i,t}\boldsymbol{\eta}' + \delta_t + \alpha_i + \epsilon_{i,t} \qquad (1)$$

$$t = 2004, \dots, 2012$$

where $Y_{i,t}$ represents the employment status (employed or non-employed) of individual i and time t. $H_{i,t}$ denotes the health status of individual i in period t: it is equal to 1 if individual i had an adverse health event in period t, and 0 otherwise. Thus, the parameter β_1 is the difference in the employment probability between women who did not experience an adverse health event and women who experienced an adverse health event (c.p.). We include as well, the incidences of adverse health events in the previous four years, $H_{i,t-1}$ to $H_{i,t-4}$ to distinguish short- from long-term effects. For instance, $H_{i,t-1}$ is equal to 1 when a woman had an adverse health event at *t-1*, and if she has another hospital entry at t, $H_{i,t}$ is equal to 0, since it is not a 'new' adverse health event. $H_{i,t-2}$ to $H_{i,t-4}$ are defined in a similar manner. The parameters β_2 - β_5 indicate differences in the employment probability due to previous adverse health events (c.p.). The row vector $\boldsymbol{X}_{i,t}$ includes household characteristics in year t, namely having a partner, the log of his income, log of the number of adults living in the household and, number and ages of the children (categorical variables). Then, δ_t is a time fixed effect, α_i is an individual specific effect and $\epsilon_{i,t}$ is an idiosyncratic error term.

Time-invariant unobserved variables such as education level or type of occupation, could be correlated to the observed characteristics, as well as having its own effects on labor market outcomes. We therefore, next to a random-effects specification which can be miss-specified because of this, also estimate equation (1) using a fixed-effects specification which takes such correlations into account.

Next, we estimate the adjustments in the working hours of women after an adverse health event using the following model.:

$$T_{i,t} = \gamma_0 + \gamma_1 H_{i,t} + \sum_{k=1}^{4} \gamma_{k+1} H_{i,t-k} + \boldsymbol{X}_{i,t}\boldsymbol{\pi}' + \omega_t + \iota_i + \nu_{i,t} \qquad (2)$$

$$t = 2004, \dots, 2012$$

where $T_{i,t}$ denotes the contractual working hours of individual i in year t, measured on an yearly basis; ω_t is a time fixed effect; ι_i is an individual specific random effect and $\nu_{i,t}$ is an idiosyncratic error term. The rest of the notation is identical to the one in equation (1).

We first estimate equation (2) as a random-effects Tobit model. The Tobit model is a non-linear model which takes into account the censoring of the data, namely the fact that individuals cannot work less than 0 hours and more than full time during the whole year resulting in 2080 hours. In this model the error term is assumed to be normally distributed. Then, we estimate a linear model with random effects on the same sample, which includes both employed and non-employed women. Next, we consider the sample of employed women only. We estimate a linear model with random-effects. However, as in the employment equation, it is likely that the time-invariant individual heterogeneity is correlated with the other explanatory variables; therefore, we also estimate the linear model with fixed effects.

Lastly, we observe a wage rate only for the employed individuals. To estimate how an adverse health event affects the earning capability of an individual, we will use Heckman's two-step procedure (Heckman, 1979), which corrects for the initial selection into employment, or the notion that women with better career possibilities and earning potential are more likely to be employed. First, we estimate an employment equation, similar to equation (1) but using a random-effects Probit specification. That is, the error term of the model is assumed to be normally distributed. Based on the Probit estimates, we calculate the inverse Mills ratio. Then, we estimate an outcome equation for the sample of employed women using a random-effects specification:

$$W_{i,t} = \tau_0 + \tau_1 H_{i,t} + \sum_{k=1}^{4} \tau_{k+1} H_{i,t-k} + \boldsymbol{F}_{i,t}\boldsymbol{\kappa}' + \sigma\lambda_{i,t} + \rho_t + \varphi_i + \upsilon_{i,t} \qquad (3.1)$$

$$t = 2004, \dots, 2012$$

where $W_{i,t}$ denotes the log of the wage rate of individual i in year t; $\boldsymbol{F}_{i,t}$ includes controls for previous health and age dummies; ρ_t is a time fixed effect; φ_i is an individual specific random effect and $\upsilon_{i,t}$ is an idiosyncratic error term. $\lambda_{i,t}$ denotes the inverse Mills ratio for individual i in year t, which is calculated from equation (1), and σ is the covariance between the error terms in the employment and wage rate equations. Selection into employment is assumed to be dependent on the household characteristics in time t namely: having a partner, log of his income, log of the number of adults living in the household, number and age of the children. Those variables are assumed not to impact the wage rate directly and therefore are excluded from the wage equation.

We compare the results from the Heckman-selection specification to a random-effects specification of the following linear model for the employed women:

$$W_{i,t} = \theta_0 + \theta_1 H_{i,t} + \sum_{k=1}^{4} \theta_{k+1} H_{i,t-k} + \boldsymbol{F}_{i,t}\boldsymbol{\mu}' + \varsigma_t + \ddot{\imath}_i + u_{i,t} \qquad (3.2)$$

$$t = 2004, \dots, 2012$$

where ς_t is a time fixed effect; $\ddot{\imath}_i$ is an individual specific random effect and $u_{i,t}$ is an idiosyncratic error term. The difference between equation (3.1) and (3.2) is that the latter does not account for the selection into employment. A comparison between the results from the two specifications will indicate whether there is endogenous selection into employment.

Lastly, we estimate equation (3.2) using a fixed-effects specification to allow the unobserved time-invariant individual heterogeneity to be correlated with the explanatory variables.

As a starting point, we estimate equations (1), (2), (3.1) and (3.2) without distinguishing between the types of adverse health events. Subsequently, we consider the different types of adverse health events separately, namely: breast cancer, other cancers, circulatory conditions, respiratory conditions, nutritional conditions, accidents, and other health conditions. The inclusion of the different adverse health events simultaneously limits the misallocation of (estimated) effects across health conditions. The later problem arises from the possibility that an individual suffers from more than one type of an adverse health event at a time.

Finally, we perform the whole analysis on a subsample of permanently employed women to investigate whether they have different adjustments in their labor market participation after an adverse health event in comparison to the full sample of women. Such differences, if present, would be related to the degree of institutional employment protection.

2.5. Results

2.5.1. Employment adjustments

First, we consider the employment adjustments of women after an adverse health event, without distinguishing between the different types of health conditions. We present the corresponding estimation results in Appendix 2.G and below we graphically present the main findings. Figure 2.3 (top left graph) shows the employment adjustments of women who have experienced an adverse health event at time zero (i.e. at the time of diagnosis). The adjustments are measured relatively to the ones of comparable women at that time, who did not experience an adverse health event. The estimates of the linear probability model with random effects show that an employment gap of 0.42 percentage points is already present at the time of diagnosis which may suggest that, on average, women prone to health conditions have a worse position on the labor market. This gap increases in the years thereafter and reaches 1.35 percentage points four years later. However, it is likely that the unobserved time-invariant individual heterogeneity is correlated to the explanatory variables and therefore we estimate a linear probability model with fixed effects. A Hausman test (Hausman, 1978) of the two specifications rejects random-effects suggesting it is important to allow for fixed-effects. The estimates of the fixed-effects model show that there is a small employment gap at the time of diagnosis (0.23 percentage points) and that it reaches 1.09 percentage points in the following three years followed by a slight recovery to 1.06 percentage points after four years. The differences in the magnitude of the results of the random-effects and fixed-effects specifications most likely stem from the fact that non-employed women are more likely to experience an adverse health event, as has been found in the literature on socioeconomic status differences in health (Cutler, Lleras-Muney and Vogl, 2011). Therefore, assuming a random-effects specification may result in larger estimates.[21]

Our findings are in line with García-Gómez et al. (2013), who found a small initial decrease in employment during the first year after acute hospitalization, which reaches 8.4 percentage points in the second year, with no recovery six years later. Since they look only at acute hospitalization, this can explain the stronger effect that they find. Other studies, such as Halla and Zweimüller (2013), also find this long-term negative effect of adverse health on employment. [22]

Even though we did not expect to observe a decrease in the employment probability of women during the first two years after the adverse health event, namely the time of the institutional protection period, we did observe such a decrease. However, when we consider women with permanent contracts separately, we do observe different employment adjustments (see Figure 2.3, top right graph). As above, we first estimate a LPM with random effects. The estimates show that women who receive a diagnosis are more likely to be employed in the year

[21] The employment patterns that we observe could also be influenced by income substitution between the spouses. However, this mechanism is likely to be very small given the institutional setting: women receive a replacement income during the first two years after the adverse health event and after that, they have the possibility to enter a disability insurance scheme. If this is not the case and they could work, but they do not have a job, they could receive unemployment benefits (see Section 2.2 for detailed description of the institutional setting). Nevertheless, since we do not have detailed information about all the sources of income for the family, an analysis of income substitution between the spouses would be highly inaccurate.

[22] A different work disruption event for women is birth giving. Fitzenberger et al. (2013) find that the negative effect of birth giving on employment decreases during the first five-years as the child grows, however it does not completely disappear. They estimate the reduction at 20 percentage points five years after the first child-birth.

of diagnosis (0.10 percentage points) and one year after (0.11 percentage points). After that, their employment slowly decreases over time in comparison to their peers who did not receive a diagnosis and the gap reaches 0.56 percentage points four years later. As before, the assumption of zero correlation between the unobserved time-invariant characteristics and the explanatory variables may be invalid. Therefore, we estimate a fixed-effects LPM and perform a Hausman test on the two specifications. The result of the test rejects random-effects suggesting it is important to allow for fixed-effects. The fixed-effects estimates show that after an adverse health event, women are more likely to be employed in comparison to their peers at the time of diagnosis (0.19 percentage points), year one after the diagnosis (0.21 percentage points), and year two (0.01 percentage point), but they are less likely to be employed in year three (0.37 percentage points) and four (0.44 percentage points). Such a pattern of employment adjustments can be explained with institutionalized employment protection for women on permanent contracts during the first two years after the adverse health event. The finding that women who experienced an adverse health event are more likely to be employed in comparison to women who did not experience such events could be explained by the employment protection: while women who experience an adverse health event cannot be laid off in the next two years, this is not the case for the other women. However, once the protection period of two years is over, the unhealthy women are likely to leave employment and as a result are less likely to be employed than their peers. This pattern differs from our results on the full sample of women, where we observed immediately after the adverse health event that the affected women are less likely to be employed in comparison to their peers, and therefore, we did not observe the institutionalized employment protection. Furthermore, the reduction in employment for women on permanent contracts four years after the adverse health event (0.44 percentage points) is less than half of the reduction of the full sample (1.06 percentage points).

2.5.2. Working hours adjustments

Next, we consider the contractual working hours' adjustments after an adverse health event. Figure 2.3, middle left graph, shows the estimates for of equation (2) outlined in Section 2.4. The gap in contractual working hours represents the difference between the contractual working hours of women who have and those who have not experienced an adverse health event and have otherwise the same observed characteristics. All estimated parameters indicate that there is a gap and that it increases over time. The results of the random-effects Tobit model and the linear random-effects model (full sample, i.e. both employed and non-employed women) are very similar, which suggests that the correction for the data censoring is not important.

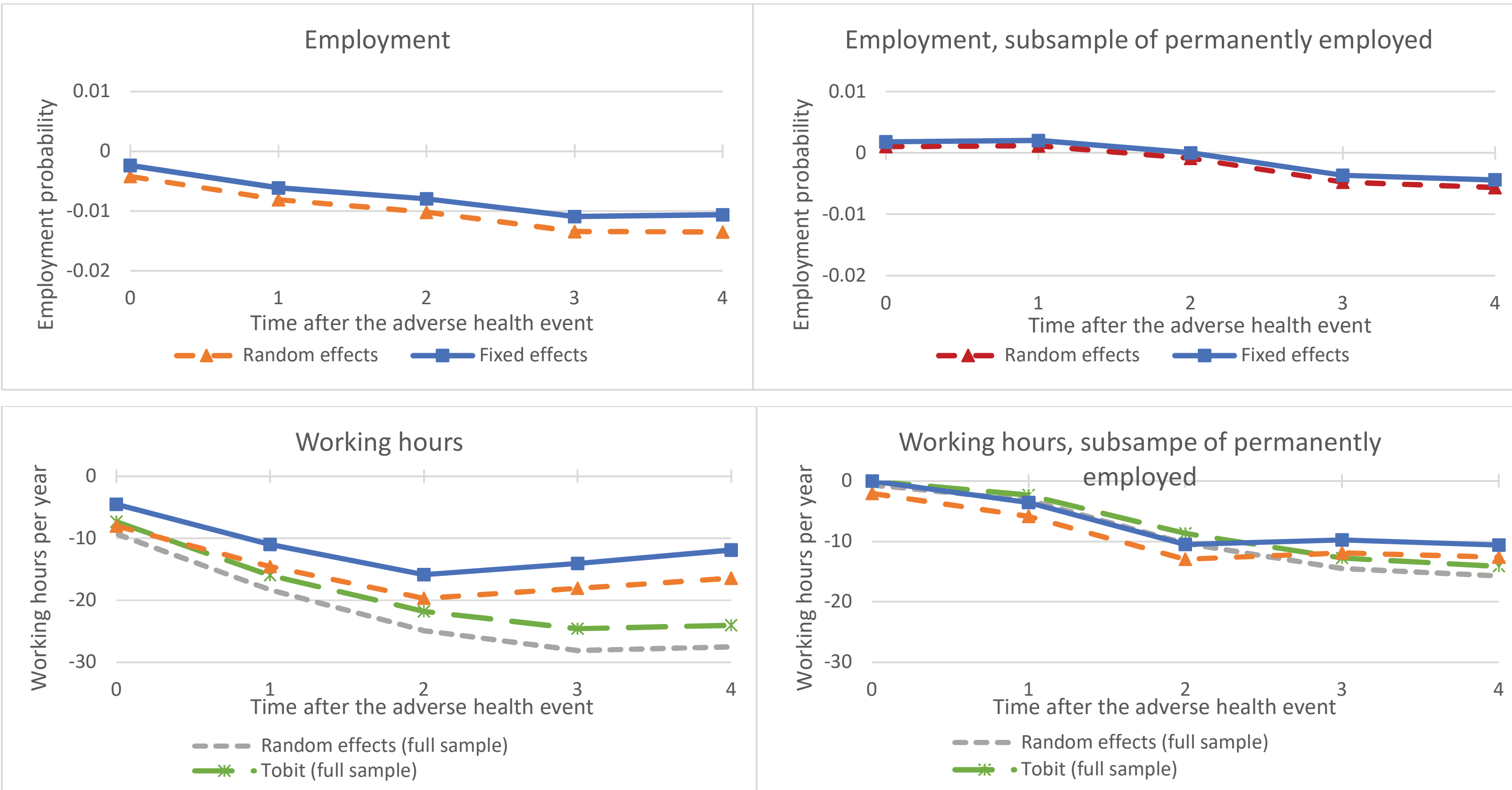
Furthermore, they estimate a larger increase in the gap than the other two models, which reaches 27 hours per year over the four years after the diagnosis. This difference could be explained by the underlying samples: since the Tobit and the linear model (full sample) consider all women, they compare not only the change of contractual working hours of the working women, but also account for the move to zero hours of the women who leave work. As we found that women are more likely to stop working after an adverse health event, this could explain the size of those estimates. On the other hand, the linear random-effects (employed sample) and the linear fixed-effects estimates, in which we only consider the working population, show that women work slightly less hours at the time of diagnosis than their healthy peers: 8 hours per year and 4.5 hours per year, respectively, at the time of diagnosis; reaching four years later 16.5 hours per year and 12 hours per year. The difference between the two estimates can be explained by the underlying assumptions about the correlation between the unobserved time-invariant individual heterogeneity and the explanatory variables. A Hausman test on the two specifications rejects random-effects suggesting it is important to allow for fixed-effects. Though, the effects estimated by both specifications are so small that they are economically insignificant. Furthermore, according to the random-effects (employed sample) and the fixed-effects estimates, the minor adjustments in the working hours stop after the second year; however, according to the random-effects (full sample) and the Tobit estimates, they continue even in the fourth year. This difference could be explained by the different sample composition and it suggests that women are more likely to leave work rather than work contractually fewer hours during year 3 and 4. This trend could be traced back to the legislation. Because the law enables women to take sick leave for the first two years, they are likely to return back to work during this period and take action in adjusting contractually their working time to their new employment capacity and (possibly new) preferences[23].

With respect to the sample of permanently employed women, we performed similar analysis and we found that their working hours' adjustments are similar in direction and slightly smaller in magnitude as the full sample (see Figure 2.3, middle right graph).

Our results are in line with Jones et al. (2016) who find a reduction in working hours in the second years after the health shock and no reduction in the third year after the health shock.

[23] Because the changes in working hours are related to actual adjustments in the contract, we are not able to observe if the employee works partially while she is on sick leave.

Figure 2.3. Employment, working hours and wage adjustments after an adverse health event



(continued)

Notes: The underlying estimates of the graphs can be found in Appendix 2.G. The top-left panel presents Models 1 and 2. The middle-left panel presents Models 3 to 6. The bottom-left panel presents Models 7.2 to 9. The top-right panel presents Models 10 and 12. The middle-right panel presents Models 13 to 16. The bottom-right panel presents Model 17.1 to Model 19. Full sample denotes all employed and non-employed women. Employed sample denotes only the women in employment. The subsample of permanently employed women includes women in permanent employment and non-employed women; i.e. it excludes the women in temporary employment.

2.5.3. Wage adjustments

Last, we consider the wage adjustments after an adverse health event. In Figure 2.3, bottom left graph, we observe differences between a Heckman-selection model, a linear random-effects model, and a linear fixed-effects model. First, the Heckman selection model allows for self-selection into employment – only women with better wage possibilities and/or better career development would (choose to) stay employed. Since those and the linear random-effects estimates of the wage gap between the women who experienced an adverse health event and those who did not are similar, this suggests that selection into employment is not an explanation for the wage gap[24]. Furthermore, while the Heckman-selection and the linear random-effect models consistently estimate a wage gap between the healthy and unhealthy women (0.40% at the time of diagnosis and around 0.73% four years later), the fixed-effects model estimates it at zero percent in the year of diagnosis and expanding to 0.30% in year one, two and three with a slight recovery to 0.24% in year four. We perform a Hausman test on the random-effects and fixed-effects specifications and the test rejects the random-effects suggesting it is important to allow for fixed-effects. As the latter specification estimates the wage differential closer to zero, this suggests that the correlation between the unobserved time-invariant individual characteristics and the other explanatory variables is important for (partially) explaining the wage gap; in other words, the wage development of the women can be mostly related to unobserved characteristics which do not change over time (for example, ability, education, tenure).

Considering the permanently employed women, we observe similar adjustments in their wage (see Figure 2.3, bottom right graph). At the time of diagnosis, women have 0.47% lower wage in comparison to their peers who are not diagnosed, according to the random-effects estimates. The difference increases four years later to 0.61%. In comparison, the main analysis estimated a difference in the wage adjustments in the fourth year of 0.73%. This suggests that women on permanent contracts experience similar 'wage penalty' as women on temporary contracts. Nevertheless, the fixed-effects model estimates the wage differential close to zero in both samples, which suggests that the correlation between the unobserved time-invariant individual characteristics and the other explanatory variables is important for partially explaining the wage gap.

[24] The fraction of employed women in the group of women who receive a diagnosis is 75%, and in the group of women who do not receive a diagnosis is 77%. Since the fraction of women with a job in the two groups is similar, this suggests that the possible selection into employment is minor.

Overall, our results are in line with Jones et al. (2016) who find that the hourly wage is not affected by a severe health shock.[25,26]

2.5.4. Distinction between different types of adverse health events

Women visit the hospital with different health conditions and sometimes they receive more than one diagnosis during the calendar year. We consider the different types of adverse health events simultaneously to compare the labor market adjustments after each of them. We present graphically the estimates of linear models with fixed effects, since the above analysis concluded that this is the preferred specification. Appendix 2.H presents the underlying estimates.

First, we consider the employment adjustments after different types of adverse health events. We find similar trends across the different diagnoses: there is an employment gap between the healthy and unhealthy women, which increases over time (Figure 2.4, left column). However, the size of the gap differs across the different types of health events: in the fourth year after the diagnosis the gap is between 0.37 percentage points after being diagnosed with respiratory conditions and 1.93 percentage points after being diagnosed with breast cancer. Exceptions are nutritional conditions, where the employment gap starts at 1.72 percentage points and decreases in the following four years to 0.52 percentage points. Furthermore, we do not observe the institutionalized job protection after any of the adverse health events. In comparison, women with permanent contracts experience different employment adjustments (Figure 2.4, right column). We do not observe an immediate decrease in their employment probability after the adverse health event. The reduction in their employment probability occurs only after some time. We observe no reduction in employment probability until after the first year for women diagnosed with other cancer and respiratory conditions, for example; while for the rest of the health conditions we observe no reduction in employment probability until after the second year. An exception are nutritional conditions, after which we observe an immediate reduction in employment probability of the diagnosed women. This suggests that there is institutionalized job protection, which enables women with permanent contracts to stay longer in employment.

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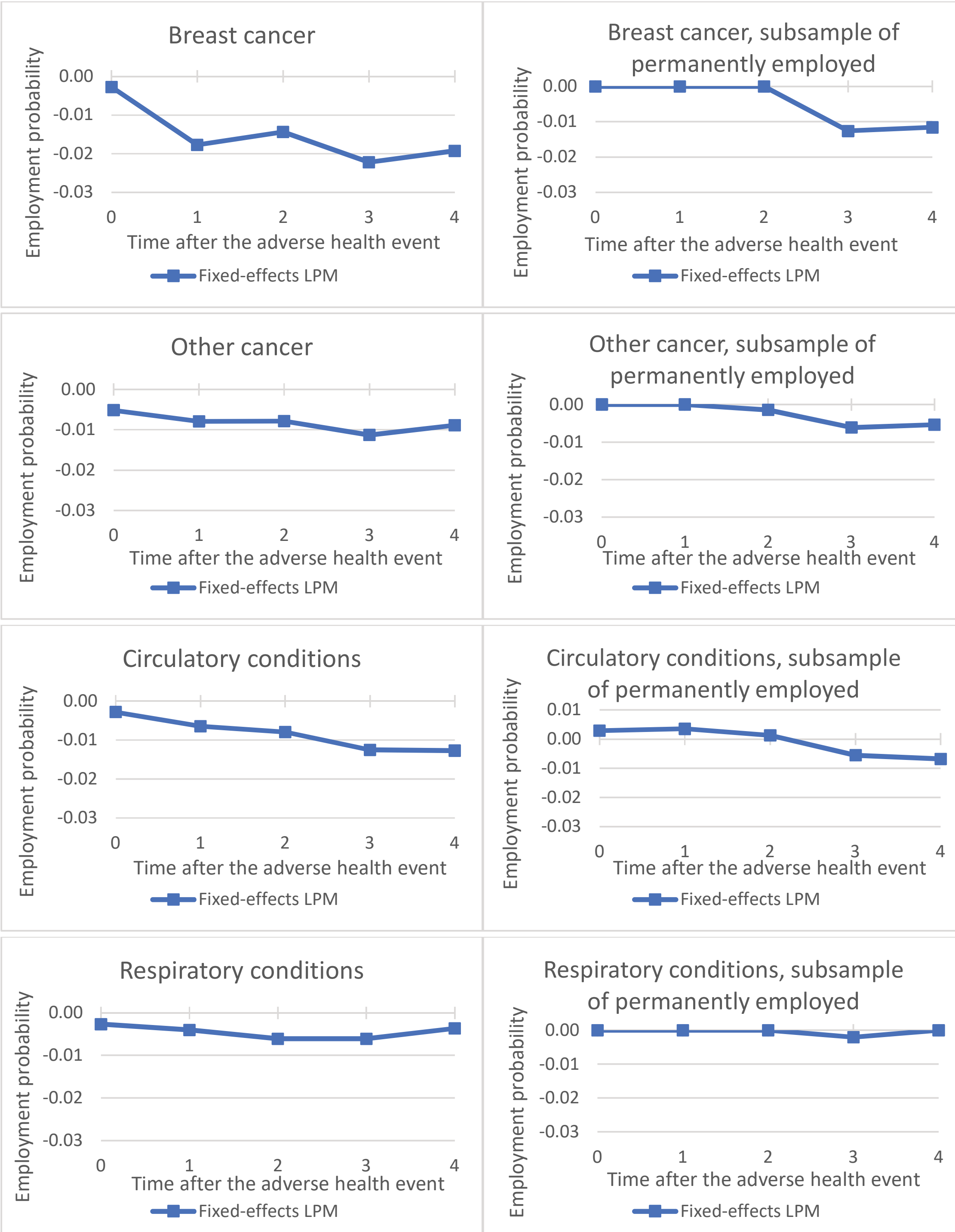
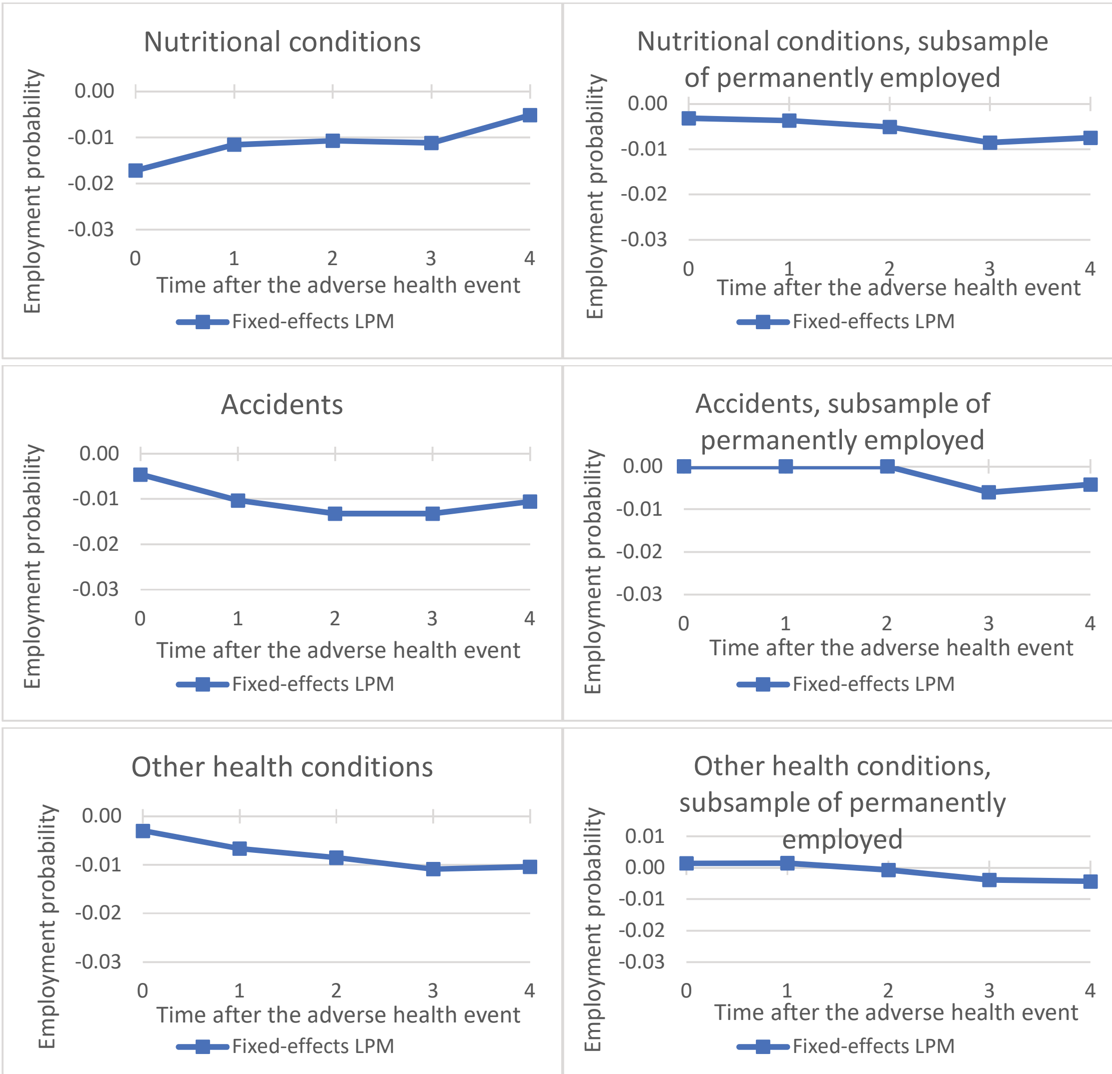
[25] In comparison, Ejrnaes and Kunze (2013) consider the impact of birth giving on the wage of the women when they return to work. They find a wage drop of 3 – 5.7 per cent.

[26] Studies that consider earnings, rather than the hourly wage and the working hours separately, find around 2% reductions in the earnings after an adverse health event (Halla and Zweimüller, 2013; García-Gómez et al., 2013).

Figure 2.4. Employment probability after an adverse health event by type of diagnosis

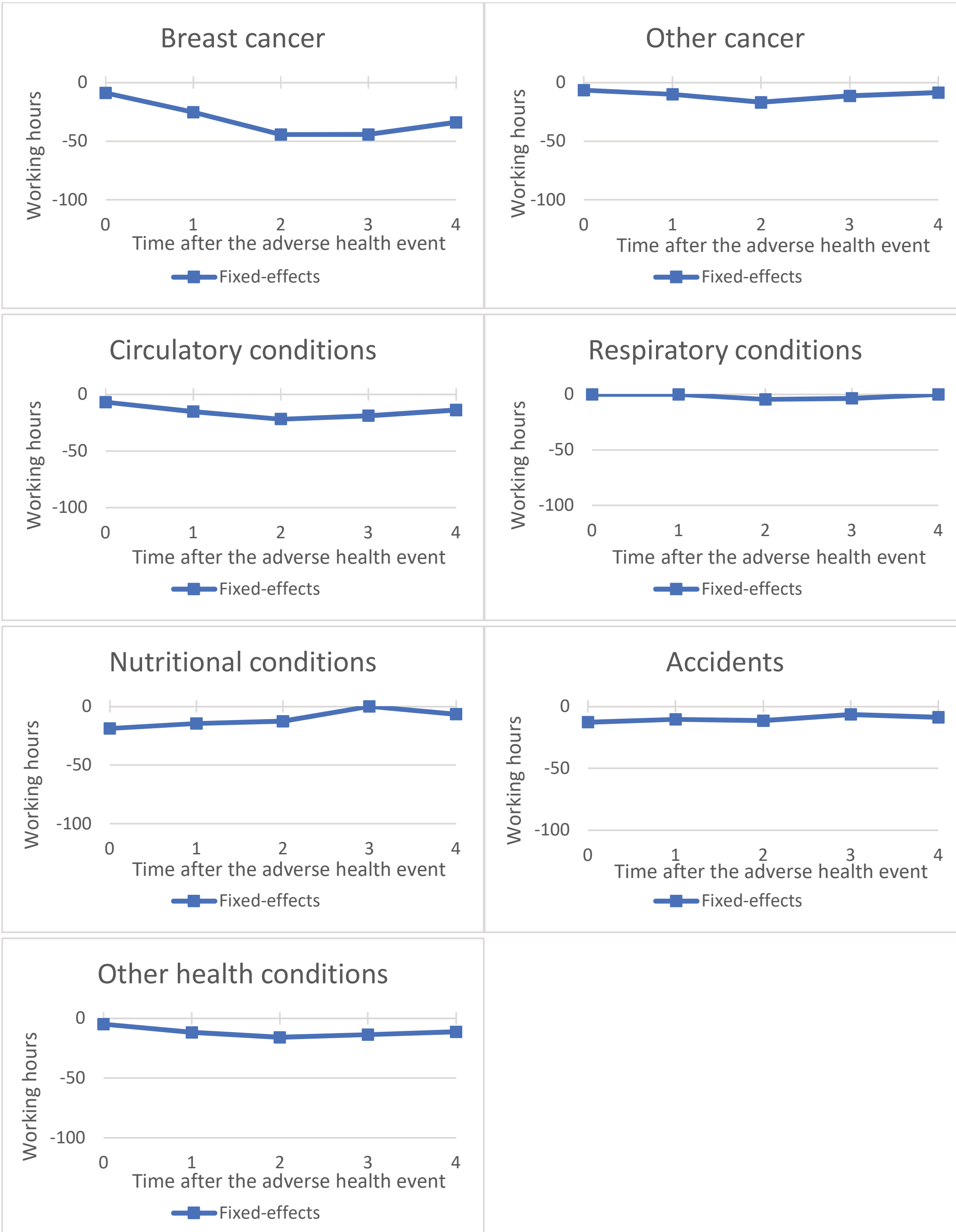




Notes: The underlying estimates can be found in Appendix 2.H. The left panels present Model 19 and the right panels Model 22.

Second, we consider whether women adjust their contractual working hours after each adverse health event (Figure 2.5). The strongest reduction of contractual working hours is observed in the group of women diagnosed with breast cancer (45 hours per year), followed by women with circulatory conditions (22 hours per year) and nutritional conditions (19 hours per year). However, the magnitudes of all adjustments are very small and may be considered economically insignificant. We observe comparable adjustments in the contractual working hours of the permanently employed women.

Figure 2.5. Working hours after an adverse health event by type of diagnosis

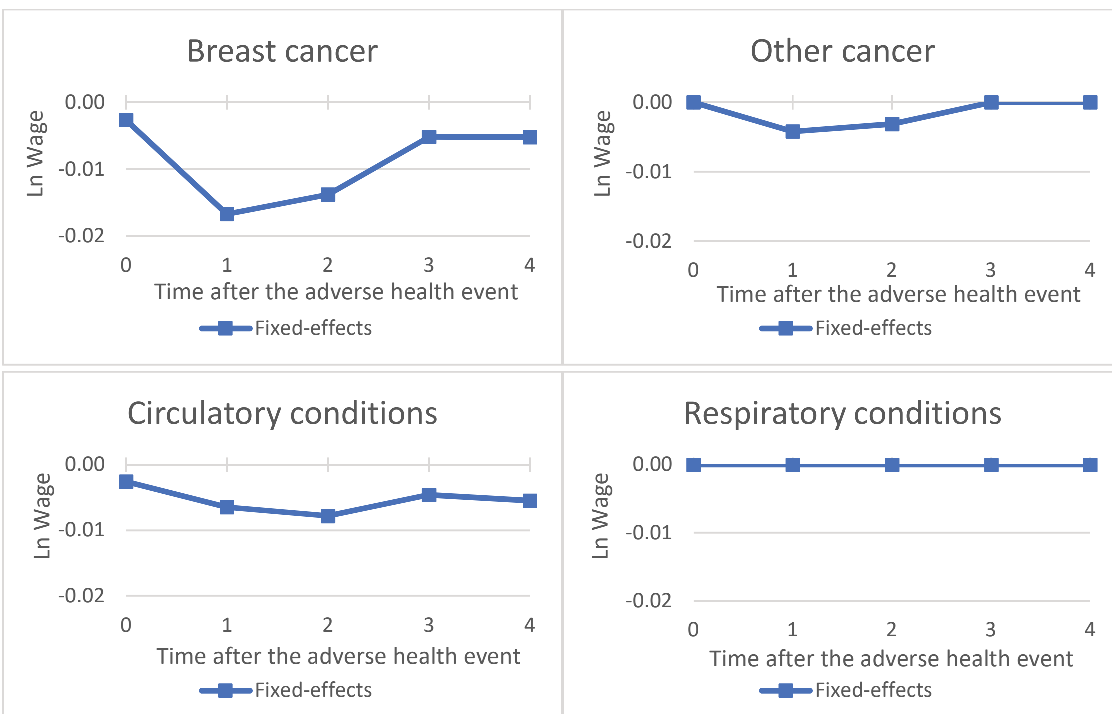


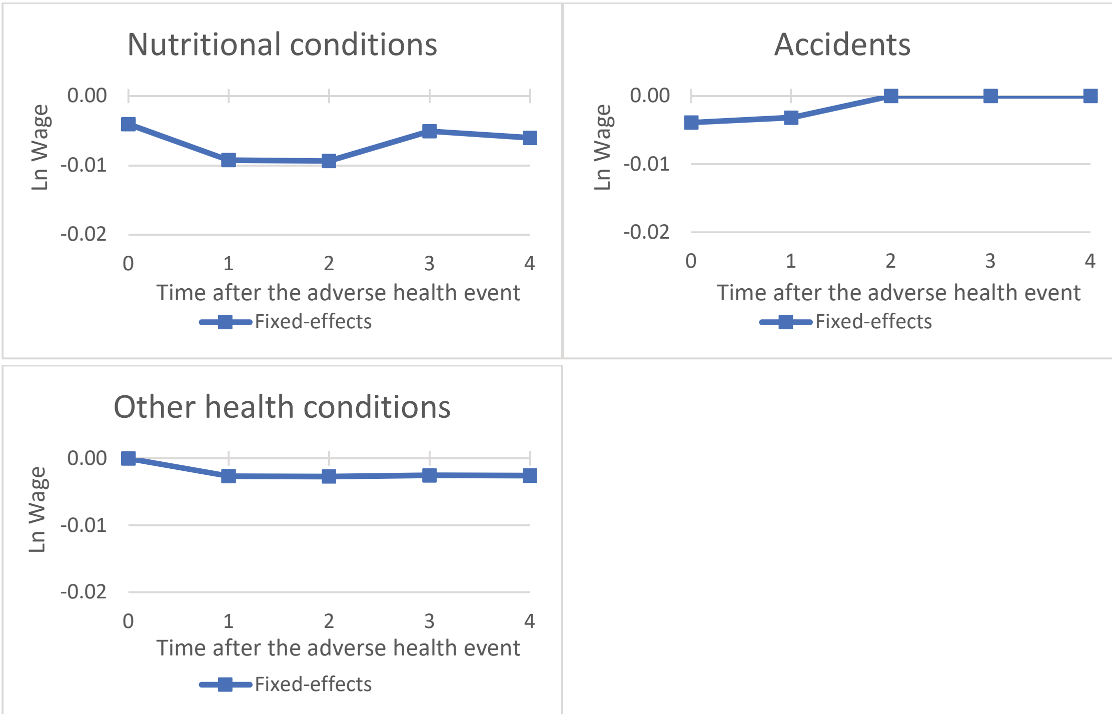
Notes: The underlying estimates can be found in Appendix 2.H. The panels present Model 20.

Last, we consider women's wage adjustments across the different types of adverse health events (Figure 2.6). We compare their wage profiles to the wage profiles of comparable healthy women. We found that the health conditions that women could recover from, such as cancer, are related to a temporary decrease in the wage profile followed by partial to full recovery of the wage profile. Then, the chronic and incapacitating health conditions, such as circulatory conditions, are related to long term reductions in the wage profile. With respect to the chronic and non-incapacitating health conditions we found two different patterns: after respiratory conditions there seems to be no change in the wage profile, while after nutritional conditions the wage profile is lower from the time of diagnosis up to and including the fourth year after the diagnosis. Lastly, we observe a lower wage profile during the first two years after an accident, followed by recovery of the wage profile in comparison to their healthy peers; and a minor long-term wage profile reduction after other health problems.

Permanently employed women experience similar adjustments in their wages, except for women diagnosed with chronic and non-incapacitating problems. We found that the women diagnosed with respiratory conditions and nutritional conditions have a lower wage in the year of diagnosis (0.34%, and 0.53% respectively), however the difference in the wage disappears in the following year.

Figure 2.6. Wage rate developments after an adverse health event by type of diagnosis





Notes: The underlying estimates can be found in Appendix 2.H. The panels present Model 21.

2.6. Robustness checks

As a first robustness check we randomly assigned to approximately five percent of the healthy women an adverse health event in a random year of the original period of observation, namely 2004 to 2012. The fraction of placebo diagnosis corresponds to the fraction of women who suffer from an adverse health event in the main analysis. We compared the labor market participation of the placebo diagnosed women and the other healthy women in the four years after the placebo diagnosis. The results are presented in Table 2.3. The first column shows the estimate of a linear probability model with fixed-effects. We do not observe any difference in the employment probability of the placebo diagnosed women and the healthy women in the four years after the placebo diagnosis. The second column reports the working hour estimates of a fixed-effect model. We do not observe any difference in the working hours of the placebo diagnosed women and the healthy women in the four years after the placebo diagnosis. Last, we compared the wage adjustments of the two groups by estimating a fixed-effect model. We do not observe any differences between the wage profiles of the two groups.[27] Based on these results, we can conclude that we capture the adverse health event in the main analysis.

Table 2.3. Placebo diagnosis

	Model 27 Employment	Model 28 Hours	Model 29 LnWage
Placebo diagnosis	-0.000447	1.248	-0.00122
	(0.00117)	(1.851)	(0.00124)
Placebo diagnosis T-1	0.00127	0.299	-0.000433
	(0.00131)	(2.083)	(0.00135)
Placebo diagnosis T-2	-0.000375	2.502	-0.00163
	(0.00136)	(2.129)	(0.00141)
Placebo diagnosis T-3	0.000670	2.412	-0.000458
	(0.00132)	(2.050)	(0.00137)
Placebo diagnosis T-4	0.000462	-0.529	5.32e-06
	(0.00115)	(1.863)	(0.00125)
Constant	0.791***	1,478***	3.099***
	(0.00115)	(1.842)	(0.00113)
Family controls	yes	yes	no
Age dummies	yes	yes	yes
Year dummies	yes	yes	yes
Observations	6,228,159	4,973,843	4,973,843
R-squared	0.004	0.036	0.075
Individuals	1,566,341	1,296,381	1,296,381

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Model 27, 28 and 28 are estimations of equations (1), (2), and (3.2), respectively.*

As a second robustness check, we perform a sub-analysis only on the sample of women who suffer from an adverse health event so that we can check whether those women have similar labor market participation before and after the adverse health event. [28] We estimated equations

[27] We performed for a second time this robustness check by giving a different random healthy group of women a placebo diagnosis. The results were the same: we did not observe any difference between the healthy and placebo diagnosed women.

[28] In the main analysis, women are part of the control group until the moment that they suffer from an adverse health event. As a result, the composition of the control group changes dynamically: in the comparison of the labor

(1), (2) and (3.2) using fixed-effect models, where the comparison point is the employment of the women before they receive a diagnosis. The results in Table 2.4 shows a lower employment probability from the time of diagnosis up to and including four years later, in comparison to the years before the diagnosis. We observe also a decrease in working hours and the wage profile. This robustness check supports our main findings that an adverse health event is related to a decrease in employment probability, minor decrease in working hours, and a decrease in the wage profile.

Table 2.4. Results of the sample of diagnosed women

	Model 30 Employment	Model 31 Hours	Model 32 LnWage
Diagnosis	-0.00203***	-4.774***	0.000862***
	(0.000268)	(0.441)	(0.000308)
Diagnosis T-1	-0.00598***	-11.51***	-0.00133***
	(0.000323)	(0.517)	(0.000350)
Diagnosis T-2	-0.00804***	-17.33***	-0.00136***
	(0.000362)	(0.574)	(0.000376)
Diagnosis T-3	-0.0113***	-15.11***	-0.000694*
	(0.000390)	(0.613)	(0.000407)
Diagnosis T-4	-0.0103***	-13.25***	-0.000886**
	(0.000393)	(0.626)	(0.000423)
Constant	0.895***	1,781***	2.105***
	(0.00202)	(3.262)	(0.00200)
Family controls	yes	yes	no
Age dummies	yes	yes	yes
Year dummies	yes	yes	yes
Observations	7,450,324	5,681,716	5,681,716
Individuals	1,040,761	869,507	869,507
R-squared	0.010	0.061	0.131

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Model 30, 31 and 32 are estimations of equations (1), (2), and (3.2), respectively.*

market participation after the adverse health event, we compare women who receive a diagnosis not only with women who would never receive an adverse health event, but also with women who will later receive a diagnosis. We compare the labor market participation trends of the two sub-groups that form the control group. Our results show parallel trends in labor market participation before the adverse health event. The results are presented in Appendix 2.J.

2.7. Discussion and conclusion

This chapter estimates the adjustments in employment status, working hours, and wage of women in the Netherlands after an adverse health event. Our findings show that women who experienced an adverse health event are likely to reduce their employment probability from the time of diagnosis up to four years later in comparison to their healthy peers, which is in line with previous studies (García-Gómez et al., 2013; Halla and Zweimüller, 2013; Jones et al., 2016). We observe about one percentage point reduction in employment probability in the fourth year after the diagnosis. To put this in perspective, the observed reduction is comparable to the additional observed mortality among this group of women over the same time period. Furthermore, our findings suggest that the employment adjustments after the adverse health event are related to the degree of job protection. For women who are in permanent employment and therefore cannot be laid off during the first two years after the onset of the health condition, we observe a reduction in their employment probability only after the protection period and to a lesser extent (0.44 percentage points). This result is in line with the idea that longer institutional employment protection provides the employee with more time to recover and as a result the health condition would have smaller impact on the employment probability of the individual. In line with Markussen et al. (2012), our result suggests that having a job to return to rather than looking for a job could be positive for the long-term employment of the individual.

For the women who stay in employment, we found that they are likely to work less hours contractually after an adverse health event, namely 4.5 hours a year in the year of diagnosis and 12 hours a year four years later in comparison to their healthy peers. These reductions, however, are negligible in economic terms. Furthermore, while we observe adjustments both in employment probability and contractual working hours during the first two years after the adverse health event, the adjustments are mainly in employment probability during the next two years. This result suggests that women adjust their contractual working hours only in the short-term. Nevertheless, our finding that the reduction in working hours was negligible suggests that employment exit was the main mechanism of labor market adjustment, which is in line with Jones et al. (2016). Women in temporary and permanent employment adjusted similarly their working hours.

Lastly, considering the hourly wage adjustments, we did not find differences between the women who were and were not diagnosed, which is in accordance with the findings of Jones et al. (2016). Interestingly, this was also the case for the women in permanent employment. However, we found some important differences in the wage adjustments when we considered the different types of adverse health events. First, we found that temporary health conditions were related to a temporary decrease in the wage profile: 1.7 percent reduction one year after the diagnosis for breast cancer patients, and 0.5 percent for other cancer patients, followed by partial wage recovery for the former and full wage recovery for the later by the fourth year after the diagnosis. Second, we found that the chronic and incapacitating conditions such as circulatory conditions are related to a long term decrease in the wage profile (approximately 0.5 percent). Third, we found two different patterns after chronic and non-incapacitating health conditions, namely no wage difference after respiratory conditions and continuously lower wage profile after nutritional conditions. Interestingly, the wage patterns were similar when we considered the permanently employed women, except for the women diagnosed with chronic and non-incapacitating health conditions. There we found an initially lower wage at the time of diagnosis, followed by a full wage recovery in the consequent year. While our results are in line with Pelkowski and Berger (2004) and point at the importance of considering the severity of the health condition when evaluating the consequent wage adjustments, they also show that the wage adjustments for the chronic and non-incapacitating health conditions are different between women with different degree of institutional job protection.

Disentangling the two effects – institutions and severity, could be beneficial for further understanding of the labor market adjustments after adverse health events, as well as for improvements in the social security system. It is important to note that we do not observe the individual preferences towards work before and after the diagnosis. As a result, we cannot disentangle if it is a personal choice to change the labor supply or the observed adjustments are a result of changes in the labor demand. Further research would be beneficial for answering this question. Furthermore, the labor maker adjustments after an adverse health event that we observe for women may not be similar for men. Therefore, future investigations into how men behave after an adverse health event would be helpful to understand whether there are differences between the two genders.

Appendix

2.A. LMR description and correction for data coverage

An individual is considered as suffering from a disease throughout the year if she has visited a hospital and the condition has been recorded as the main diagnosis. The coding of the diagnosis follows the 'Classification of Sicknesses, 1980' which is based on the International Statistical Classification of Diseases and Related Health Problems, 9 Revision, Clinical Modification. We divide the health conditions into the following groups: breast cancer; other type of cancer; circulatory conditions; diseases of the respiratory system; endocrine, nutritional and metabolic diseases; accidents; and other health conditions. In cases when the individual has been in the hospital for cancer therapy, such as radiotherapy, chemotherapy and/or immunotherapy, then this entry has been allocated to either breast cancer, other cancer, or to both based on the incidence of cancer up to three years before. Furthermore, we exclude hospital entries related to birth giving (1.36 % of the hospital entries).

The group Other health conditions consists of: infectious and parasitic diseases (1.02%); diseases of the blood and blood forming organs (1.07%); mental disorders (1.10%); diseases of the nervous system (4.72%); diseases of the sense organs (4.81%); diseases of the digestive system (14.77%); diseases of the genitourinary system (20.19%); diseases of skin and subcutaneous tissue (2.26%); diseases of musculoskeletal system and connective tissue (17.95%); congenital anomalies (0.68%); certain conditions originating in the perinatal period (0.02%); symptoms, signs and ill-defined conditions (16.63%); supplementary classification (19.65%). Since individuals can be diagnosed with more than one condition each year, the sum of all different diagnosis which are grouped in 'other health conditions' may exceed 100%. The distribution of other health problems reflects the Dutch health care system, where an individual first goes to the general practitioner before having access to a hospital (unless it is an emergency). Due to the 'gate-keeper' role of the general practitioners, we observe only a small fraction of mental health problems, for example, while the actual percentage is likely to be much higher across the Dutch population. Observing only hospital visits means that we observe mainly the more severe cases, which would have an impact on the work capabilities of the employee, and as such improves the validity of our results.

It is important to note that 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). Over all, according to Van der Laan (2013), the data provides record about approx. 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.

2.B. Mortality

We observe the employment patterns only for the women who survive. As such it is important also to consider the differences in the mortality rates among the women diagnosed with different health conditions. We distinguish between women who are: healthy (they have not had a health condition during the last four years) and diagnosed for a first time with: any health condition, breast cancer, other cancer, circulatory condition, respiratory condition, nutritional condition, other health condition or had an accident. Table 2.B.1 shows the four-year mortality rate from the time of diagnosis. We consider separately employed women (Panel A) and non-employed women at the time of diagnosis (Panel B), because they could have different mortality rates (Martikainen and Valkonen, 1996).[29]

First, we observe that initially employed women have consistently lower mortality than initially non-employed women, which is in line with the findings of Martikainen and Valkonen (1996). Second, we observe that unhealthy women have a higher mortality rate than the healthy one: the additional observed mortality among first-diagnosed women is 0.8 percentage points higher compared to healthy women in the group of initially employed women, and 1.6 percentage points higher in the group of initially non-employed women. Third, women

[29] Table 2.B.1 does not include the women who are diagnosed and die in the same calendar year. They are not considered in the empirical analysis, since we always observe employment on December 31st of the calendar year. For these mortality statistics, please see Appendix 2.C.

diagnosed with cancer have the highest mortality rate. However, while the mortality among women diagnosed with cancer decreases over time for the employed women, the one among the initially non-employed women does not seem to have a trend. Last, the lowest mortality is observed in the group of women who suffer from other health conditions (for the initially non-employed) and who have had an accident (for the initially employed).

Table 2.B.1. Four-year mortality statistics by employment status and type of diagnosis (in %)

Panel A: Employed women at the time of diagnosis

Year	Healthy	First diagnosed	Breast cancer	Other cancer	Circulatory conditions	Respiratory conditions	Nutritional conditions	Other health conditions	Accidents
2004	0.29	1.10	7.59	7.01	1.18	1.07	1.46	0.74	0.97
2005	0.28	1.10	6.81	6.69	1.16	1.03	1.23	0.88	1.00
2006	0.28	1.03	6.27	6.57	1.04	0.96	0.88	0.70	0.96
2007	0.28	0.99	5.79	6.80	1.06	1.11	1.39	0.62	0.90
2008	0.29	1.04	6.01	6.47	1.08	1.06	1.31	0.70	0.95

Panel B: Non-employed women at the time of diagnosis

Year	Healthy	First diagnosed	Breast cancer	Other cancer	Circulatory conditions	Respiratory conditions	Nutritional conditions	Other health conditions	Accidents
2004	0.70	2.27	10.31	11.51	2.85	3.97	4.41	3.03	2.12
2005	0.70	2.28	9.92	10.75	2.75	4.16	3.53	3.84	2.14
2006	0.71	2.28	9.88	10.78	2.66	4.47	4.17	3.18	2.12
2007	0.74	2.27	9.23	11.32	2.82	4.46	5.19	2.77	2.13
2008	0.74	2.32	8.54	11.73	2.87	4.99	3.59	3.15	2.25

Notes: The table reports the four-year mortality statistic in percentages per type of adverse health event. The top panel reports the mortality statistic for the women who are employed at the time of diagnosis, and the bottom panel reports the mortality statistic for the women who are not employed at the time of diagnosis.

2.C. Mortality up to the end of the calendar year

Since we observe most of the characteristics on 31st December (such as family situation, work and location), women must survive until then to be included in our sample. Table 2.C.1 shows the mortality rates before 31st December of women diagnosed with a specific type of disease in the corresponding calendar year. Comparing those with the four-year mortality statistics (Table 2.B.1), we observe similar trends: women diagnosed with cancer have the highest mortality probability; women who suffer from other health conditions and/or have had an accident have one of the lowest.

Table 2.C.1. Mortality statistics up to the end of the calendar year (in %)

Year	Breast cancer	Other cancer	Circulatory conditions	Respiratory conditions	Nutritional conditions	Other health conditions	Accidents
2004	3.07	7.34	2.41	1.28	1.58	0.70	0.81
2005	2.66	7.01	2.14	1.70	1.45	0.70	0.84
2006	2.95	6.89	2.06	1.63	1.50	0.67	0.65
2007	2.64	6.34	2.20	1.56	1.28	0.62	0.71
2008	2.96	6.19	1.87	1.72	1.47	0.64	0.52

Notes: The table reports the percentage of women who die before the end of the calendar year per type of adverse health event.

2.D. Simultaneous occurrence of adverse health events

Table 2.D.1. Simultaneous occurrence of adverse health events (in %)

Disease	Breast cancer	Other cancer	Circulatory problems	Respiratory problems	Nutritional problems	Accidents	Other health problems
Breast cancer		2.53	0.31	0.40	0.34	0.21	0.94
Other cancer	7.93		1.44	1.26	2.14	0.61	2.15
Circulatory	1.02	1.50		1.29	1.53	0.91	1.69
Respiratory	0.86	0.87	0.85		0.96	0.44	0.84
Nutritional	0.29	0.57	0.39	0.37		0.26	0.43
Accidents	0.26	0.24	0.34	0.25	0.38		0.70
Other	23.40	17.14	12.84	9.75	12.75	14.34	
Overlap	33.75	22.85	16.18	13.33	18.11	16.78	6.75
No overlap	66.25	77.15	83.82	86.67	81.89	83.22	93.25
Total number	36,307	113,789	118,860	78,155	30,425	44,381	905,554

Notes: The table reports the overlap of health conditions. Each column reports per type of health condition the percentage of woman who have been diagnosed with another type of health condition. The sum of the percentages and the percentage of women who did not receive another diagnosis is equal to 100%. The last row reports the total number of women who received the specific diagnosis.

2.E. Working hours

The first work indicator of interest is employment. An individual is considered as employed, if she had a job in the Netherlands for at least one day throughout the calendar year. For the employed individuals, we are interested in their intensive margin of labor market participation. Therefore, we construct a normalized measure, which is a continuous variable ranging from 0 (denoting working 0 hours throughout the year) to 1 (working full time all year long). The variable is composed as follows:

$$LMsupply = \frac{calendar\ days\ worked \text{ x } fte}{total\ calendar\ days\ per\ year}$$

Where *calendar days worked* stands for the calendar days the individual has had a job. The time span is corrected for job overlaps. *fte* denotes the weighted average of the full-time work equivalent from all the jobs the individual has had in that calendar year. It spans from 0, denoting no work, to 1, denoting full time work. The weighting is based on the length of the job. Lastly, *total calendar days per year* is equal to the actual length of the calendar year.

From this labor supply indicator, we can retrieve the number of hours the individual has worked throughout the year:

$$Hours\ worked = LMsupply \text{ x } 40 \text{ x } 52$$

where 40 is the number of hours in the work week and 52 denotes the number of weeks in the year. Therefore, our initial indicator ranging from 0 to 1, now spans from 0 to 2080 hours per year. From this information and the gross yearly income of the individual we can retrieve the average hourly wage:

$$Wage\ rate = \frac{cumulative\ gross\ yearly\ income}{hours\ worked}$$

2.F. Employment status, annual hours of work, and hourly wage rates by age

Figure 2.F.1. Employment status, annual hours of work, and hourly wage rates by age

Notes: Own calculations based on population data from Statistics Netherlands for the period 2004-2012.

2.G. Employment, working hours and wage estimates: no distinction between health conditions

Table 2.G.1. Employment, working hours and wage: no distinction between health conditions

Panel A: Model 1 to Model 6

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	RE	FE	Tobit	RE (fs)	RE (es)	FE
	Employment	Employment	Hours	Hours	Hours	Hours
Diagnosis	-0.00422***	-0.00237***	-7.34***	-9.282***	-8.016***	-4.523***
	(0.000249)	(0.000256)	(0.339)	(0.405)	(0.413)	(0.425)
Diagnosis T-1	-0.00812***	-0.00611***	-15.99***	-18.32***	-14.54***	-10.98***
	(0.000284)	(0.000293)	(0.350)	(0.462)	(0.460)	(0.478)
Diagnosis T-2	-0.0102***	-0.00795***	-21.81***	-24.92***	-19.68***	-15.87***
	(0.000302)	(0.000313)	(0.359)	(0.492)	(0.487)	(0.508)
Diagnosis T-3	-0.0134***	-0.0109***	-24.59***	-28.11***	-18.07***	-14.04***
	(0.000310)	(0.000321)	(0.367)	(0.502)	(0.493)	(0.516)
Diagnosis T-4	-0.0135***	-0.0106***	-24.04***	-27.53***	-16.44***	-11.90***
	(0.000300)	(0.000311)	(0.373)	(0.486)	(0.483)	(0.504)
Constant	0.944***	0.863***	1,942***	1,665***	1,782***	1,761***
	(0.000472)	(0.00101)	(1.503)	(0.982)	(0.835)	(1.620)
Family controls	yes	yes	yes	yes	yes	yes
Age dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	22,948,460	22,948,460	22,948,460	22,948,460	17,712,316	17,712,316
Individuals	3,804,345	3,804,345	3,804,345	3,804,345	3,109,970	3,109,970
R-squared	0.0756	0.011		0.1567	0.1647	0.067

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Model 1 and 2 are estimations of equation (1). Model 3 to Model 6 are estimations of equation (2). RE stands for a random effects specification. FE stands for fixed effects specification. Fs denotes full sample: both employed and non-employed women. Es denotes employed women only. Model 3 reports marginal effects of a random effect Tobit specification.*

Panel B: Model 7 to Model 9

VARIABLES	Model 7.1 Heckman 1	Model 7.2 Heckman 2	Model 8 RE	Model 9 FE
	Employment	LnWage	LnWage	LnWage
Diagnosis	-0.0587***	-0.00394***	-0.00402***	-0.000188
	(0.00311)	(0.000273)	(0.00029)	(0.000298)
Diagnosis T-1	-0.114***	-0.00665***	-0.00681***	-0.00273***
	(0.00318)	(0.000318)	(0.000319)	(0.00033)
Diagnosis T-2	-0.141***	-0.00724***	-0.00744***	-0.00308***
	(0.00323)	(0.000291)	(0.000334)	(0.000347)
Diagnosis T-3	-0.183***	-0.00701***	-0.00729***	-0.00272***
	(0.00328)	(0.000325)	(0.000341)	(0.000354)
Diagnosis T-4	-0.186***	-0.00701***	-0.00731***	-0.00244***
	(0.00332)	(0.000325)	(0.000335)	(0.000348)
Mills		-0.266***		
		(0.0165)		
Constant	2.734***	2.764***	2.505***	2.126***
	(0.0052)	(0.000556)	(0.000459)	(0.000985)
Family controls	yes	no	no	no
Age dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Observations	22,948,460	17,712,316	17,712,316	17,712,316
Number of id	3,804,345	3,109,970	3,109,970	3,109,970
R-squared		0.0128	0.0128	0.140

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Model 7.1. is an estimation of equation (3.1) and Models 7.2 to Model 9 are estimations of equation (3.2). RE stands for a random effects specification. FE stands for fixed effects specification. Model 7.1 reports random effect Probit estimates. Mills denotes the inverse Mills ratio. Model 7.2 has bootstrapped standard errors from 200 replications.*

Table 2.G.2. Employment, working hours and wage: no distinction between health conditions, subsample of permanently employed

Pannel A: Model 10 to Model 15

	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
	RE	FE	Tobit	RE (fs)	RE (es)	FE
	Employment	Employment	Hours	Hours	Hours	Hours
Diagnosis	0.00102***	0.00184***	0.00157	-0.655*	-2.052***	-0.241
	(0.000175)	(0.000176)	(0.3049471)	(0.368)	(0.458)	(0.474)
Diagnosis T-1	0.00117***	0.00206***	-2.306***	-3.178***	-5.829***	-3.535***
	(0.000206)	(0.000208)	(0.3172155)	(0.428)	(0.518)	(0.543)
Diagnosis T-2	-0.000873***	0.000122	-8.673***	-10.29***	-12.95***	-10.48***
	(0.000225)	(0.000227)	(0.326441)	(0.462)	(0.558)	(0.587)
Diagnosis T-3	-0.00476***	-0.00366***	-12.750***	-14.49***	-11.89***	-9.722***
	(0.000234)	(0.000237)	(0.3335866)	(0.473)	(0.556)	(0.587)
Diagnosis T-4	-0.00564***	-0.00439***	-14.132***	-15.71***	-12.61***	-10.60***
	(0.000223)	(0.000225)	(0.3380053)	(0.450)	(0.536)	(0.562)
Constant	0.754***	0.726***	1.621***	1.423***	1.982***	2.021***
	(0.00104)	(0.00120)	(3.195)	(2.192)	(2.458)	(3.405)
Family controls	yes	yes	yes	yes	yes	yes
Age dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	11,376,327	11,376,327	11,376,327	11,376,327	7,067,456	7,067,456
Individuals	2,545,482	2,545,482	2,545,482	2,545,482	1,588,830	1,588,830
R-squared	0.0265	0.019		0.0723	0.1803	0.068

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Model 10 and 11 are estimations of equation (1). Model 12 to Model 15 are estimations of equation (2). RE stands for a random effects specification. FE stands for fixed effects specification. Fs denotes full sample: both employed and non-employed women. Es denotes employed women only. Model 12 reports marginal effects of a random effect Tobit specification.*

Pannel B: Model 16 to Model 18

VARIABLES	Model 16.1 Heckman 1	Model 16.2 Heckman 2	Model 17 RE	Model 18 FE
	Employment	LnWage	LnWage	LnWage
Diagnosis	-0.0594***	-0.00470***	-0.00441***	-0.00145***
	(0.0068)	(0.000311)	(0.000334)	(0.000343)
Diagnosis T-1	-0.0742***	-0.00816***	-0.00778***	-0.00440***
	(0.00685)	(0.000334)	(0.000371)	(0.000384)
Diagnosis T-2	-0.163***	-0.00827***	-0.00727***	-0.00374***
	(0.00687)	(0.000382)	(0.000392)	(0.000407)
Diagnosis T-3	-0.296***	-0.00817***	-0.00615***	-0.00248***
	(0.00681)	(0.000366)	(0.000392)	(0.000408)
Diagnosis T-4	-0.308***	-0.00826***	-0.00613***	-0.00233***
	(0.00706)	(0.000369)	(0.000384)	(0.000398)
Mills		0.0186***		
		(0.000515)		
Constant	-0.516***	2.823***	2.601***	2.205***
	(0.00863)	(0.000714)	(0.00166)	(0.00215)
Family controls	yes	no	no	no
Age dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Observations	11,376,327	7,067,456	7,067,456	7,067,456
Number of id	2,545,482	1,588,830	1,588,830	1,588,830
R-squared		0.0388	0.0371	0.17

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Model 16.1. is an estimation of equation (3.1) and Models 16.2 to Model 18 are estimations of equation (3.2). RE stands for a random effects specification. FE stands for fixed effects specification. Model 16.1 reports random-effect Probit estimates. Mills denotes the inverse Mills ratio. Model 16.2 has bootstrapped standard errors from 200 replications.*

2.H. Employment, working hours and wage: distinction between health conditions

Table 2.H.1. Employment, working hours and wage: distinction between health conditions

	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
		Full sample			Permanently employed	
	Employment	Hours	LnWage	Employment	Hours	LnWage
BrCancerT	-0.00272**	-8.799***	-0.00265*	0.00103	-2.105	-0.00171
	(0.00133)	(2.203)	(0.00160)	(0.000933)	(2.317)	(0.00172)
BrCancerT-1	-0.0177***	-25.34***	-0.0167***	-0.000331	-10.78***	-0.0218***
	(0.00164)	(2.524)	(0.00192)	(0.00116)	(2.713)	(0.00200)
BrCancerT-2	-0.0144***	-44.38***	-0.0138***	-0.00217	-34.69***	-0.0185***
	(0.00181)	(2.946)	(0.00207)	(0.00133)	(3.357)	(0.00232)
BrCancerT-3	-0.0222***	-44.23***	-0.00518**	-0.0126***	-35.99***	-0.00691***
	(0.00202)	(3.164)	(0.00224)	(0.00157)	(3.517)	(0.00240)
BrCancerT-4	-0.0193***	-33.99***	-0.00522**	-0.0116***	-31.09***	-0.00754***
	(0.00206)	(3.233)	(0.00229)	(0.00153)	(3.556)	(0.00247)
OtherCancT	-0.00518***	-6.548***	1.72e-05	0.000424	-3.136**	-0.00186*
	(0.000769)	(1.266)	(0.000906)	(0.000532)	(1.347)	(0.000998)
OthCancT-1	-0.00792***	-9.953***	-0.00420***	0.000305	-7.857***	-0.00650***
	(0.000913)	(1.473)	(0.00105)	(0.000653)	(1.618)	(0.00120)
OthCancT-2	-0.00785***	-16.80***	-0.00313***	-0.00145*	-14.34***	-0.00492***
	(0.00100)	(1.636)	(0.00114)	(0.000742)	(1.837)	(0.00126)
OthCancT-3	-0.0113***	-11.36***	-0.000366	-0.00612***	-8.619***	-0.00256**
	(0.00108)	(1.706)	(0.00120)	(0.000822)	(1.839)	(0.00130)
OthCancT-4	-0.00890***	-8.410***	0.000524	-0.00536***	-8.619***	-0.000498
	(0.00108)	(1.741)	(0.00123)	(0.000798)	(1.857)	(0.00133)
CirculatT	-0.00283***	-6.824***	-0.00259***	0.00285***	-5.023***	-0.000700
	(0.000783)	(1.291)	(0.000938)	(0.000516)	(1.425)	(0.00104)
CirculatT-1	-0.00644***	-15.11***	-0.00650***	0.00352***	-8.492***	-0.00483***
	(0.000917)	(1.474)	(0.00107)	(0.000622)	(1.648)	(0.00118)
CirculatT-2	-0.00792***	-21.87***	-0.00781***	0.00126*	-19.06***	-0.00492***
	(0.00101)	(1.629)	(0.00116)	(0.000712)	(1.887)	(0.00130)
CirculatT-3	-0.0125***	-18.77***	-0.00461***	-0.00559***	-15.62***	-0.00235*
	(0.00107)	(1.701)	(0.00123)	(0.000779)	(1.894)	(0.00135)
CirculatT-4	-0.0127***	-13.78***	-0.00549***	-0.00680***	-12.17***	-0.00292**
	(0.00107)	(1.714)	(0.00123)	(0.000758)	(1.876)	(0.00130)
RespiratoryT	-0.00265***	-1.296	-0.000745	-0.000136	-3.441*	-0.00338***
	(0.000957)	(1.590)	(0.00108)	(0.000718)	(1.883)	(0.00130)
RespiratT-1	-0.00402***	-1.715	0.000369	0.000936	-4.927**	-0.00126
	(0.00109)	(1.792)	(0.00120)	(0.000840)	(2.191)	(0.00156)

RespiratT-2	-0.00606***	-4.431**	-0.000864	-0.00146	-5.458**	-0.000675
	(0.00116)	(1.891)	(0.00123)	(0.000950)	(2.341)	(0.00158)
RespiratT-3	-0.00607***	-3.512*	-0.000424	-0.00204**	-5.573**	-0.000297
	(0.00117)	(1.908)	(0.00126)	(0.000982)	(2.359)	(0.00162)
RespiratT-4	-0.00365***	-2.598	0.00129	-0.00124	-6.904***	-0.00134
	(0.00112)	(1.861)	(0.00122)	(0.000932)	(2.273)	(0.00159)
NutritionalT	-0.0172***	-18.76***	-0.00406**	-0.00312***	-9.775***	-0.00526**
	(0.00167)	(2.755)	(0.00196)	(0.00116)	(3.084)	(0.00207)
NutritionT-1	-0.0116***	-14.59***	-0.00923***	-0.00366***	-10.55***	-0.00379
	(0.00198)	(3.237)	(0.00225)	(0.00139)	(3.704)	(0.00246)
NutritionT-2	-0.0107***	-12.55***	-0.00936***	-0.00504***	-15.58***	-0.00393
	(0.00217)	(3.582)	(0.00244)	(0.00156)	(4.234)	(0.00291)
NutritionT-3	-0.0112***	-4.602	-0.00506**	-0.00850***	-10.65**	-0.00311
	(0.00231)	(3.683)	(0.00255)	(0.00162)	(4.208)	(0.00288)
NutritionT-4	-0.00519**	-6.625*	-0.00603**	-0.00748***	-12.03***	-0.000864
	(0.00232)	(3.788)	(0.00258)	(0.00161)	(4.157)	(0.00280)
AccidentsT	-0.00457***	-12.75***	-0.00390***	0.000506	-4.070*	-0.00262
	(0.00126)	(2.128)	(0.00146)	(0.000878)	(2.303)	(0.00168)
Accidents	-0.0103***	-10.54***	-0.00316*	-6.45e-05	-2.804	-0.00373**
T-1	(0.00147)	(2.439)	(0.00164)	(0.00107)	(2.668)	(0.00184)
Accidents	-0.0132***	-11.57***	-0.00106	4.64e-05	-8.933***	0.00176
T-2	(0.00161)	(2.644)	(0.00179)	(0.00120)	(3.092)	(0.00214)
Accidents	-0.0132***	-6.499**	-0.00200	-0.00607***	0.624	-0.000878
T-3	(0.00172)	(2.807)	(0.00191)	(0.00133)	(3.115)	(0.00226)
Accidents	-0.0106***	-8.825***	0.00277	-0.00423***	-2.788	-0.000403
T-4	(0.00168)	(2.797)	(0.00193)	(0.00127)	(3.152)	(0.00230)
OthHealthPr	-0.00300***	-4.779***	0.000146	0.00138***	-0.420	-0.00164***
	(0.000283)	(0.470)	(0.000327)	(0.000196)	(0.526)	(0.000377)
OthHProb	-0.00667***	-11.64***	-0.00266***	0.00147***	-3.814***	-0.00422***
T-1	(0.000327)	(0.533)	(0.000366)	(0.000234)	(0.609)	(0.000426)
OthHProb	-0.00854***	-15.76***	-0.00269***	-0.000660**	-10.13***	-0.00331***
T-2	(0.000353)	(0.573)	(0.000389)	(0.000257)	(0.661)	(0.000457)
OthHProb	-0.0109***	-13.66***	-0.00252***	-0.00381***	-9.572***	-0.00212***
T-3	(0.000365)	(0.588)	(0.000401)	(0.000269)	(0.671)	(0.000463)
OthHProb	-0.0104***	-11.19***	-0.00254***	-0.00429***	-10.09***	-0.00219***
T-4	(0.000360)	(0.583)	(0.000401)	(0.000259)	(0.651)	(0.000461)
Constant	-0.00272**	-8.799***	2.126***	0.00103	-2.105	2.204***
	(0.00133)	(2.203)	(0.000985)	(0.000933)	(2.317)	(0.00215)
Family controls	yes	yes	no	yes	yes	no
Age dummies	yes	yes	yes	yes	yes	yes

Year dummies	yes	yes	yes	yes	yes	yes
Observations	22,948,460	17,712,316	17,712,316	11,376,327	7,067,456	7,067,456
Individuals	3,804,345	3,109,970	3,109,970	2,545,482	1,588,830	1,588,830
R-squared	0.011	0.067	0.140	0.019	0.068	0.170

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.10 . Models 19 and 22 are estimations of equation (1). Models 20 and 23 are estimations of equation (2). Models 21 and 24 are estimations of equation (3.2). Models 22 to 24 are estimated on a subsample of permanently employed women. We use a fixed-effects specification for all estimates.*

2.I. Age gradient in the employment adjustment

It is likely that the employment adjustments after an adverse health event are different for younger and older women. To determine whether this is the case, we estimate equation (1) as a fixed-effects model where we allow for an interaction effect between age and the adverse health event. We divide the women into three age groups: 25 to 35; 36 to 45; and 46 to 55. The youngest group is used as a reference category.

Our results show that while women from all age groups reduce their employment, the magnitude of the reduction increases with age. The age heterogeneity is similar for the women in permanent employment; though, the adjustments for those women are smaller in magnitude, which is comparable to our main results. Furthermore, we observe the two-year job protection in the analysis of the permanently employed women, as we did in the main analysis.

Table 2.I.1. Age gradient in employment adjustments

Panel A: Model 25 – Full sample

	Model 25		
	Full sample		
	Employment		
Age:	Main effect	35-45	46-55
Diagnosis	-0.00104**	-0.00145**	-0.00262***
	(0.000500)	(0.000650)	(0.000627)
Diagnosis T-1	-0.00430***	-0.00173**	-0.00361***
	(0.000565)	(0.000720)	(0.000713)
Diagnosis T-2	-0.00563***	-0.00119	-0.00537***
	(0.000602)	(0.000757)	(0.000762)
Diagnosis T-3	-0.00569***	-0.00328***	-0.0107***
	(0.000618)	(0.000777)	(0.000786)
Diagnosis T-4	-0.00460***	-0.00345***	-0.0123***
	(0.000604)	(0.000766)	(0.000769)
Constant		0.863***	
		(0.00101)	
Family controls		yes	
Age dummies		yes	
Year dummies		yes	
Observations		22,948,460	
Individuals		3,804,345	
R-squared		0.011	

*Notes: Standard errors clustered by individual in parentheses. Fixed effects specification. *** p<0.01, ** p<0.05, * p<0.1*

Panel B: Model 26 – Permanently employed

	Model 26		
	Permanently employed		
	Employment		
Age:	Main effect	35-45	46-55
Diagnosis	0.00253***	-0.000754	-0.00106**
	(0.000469)	(0.000532)	(0.000526)
Diagnosis T-1	0.00331***	-0.00138**	-0.00177***
	(0.000539)	(0.000602)	(0.000608)
Diagnosis T-2	0.000711	-0.000173	-0.00128*
	(0.000578)	(0.00064)	(0.000656)
Diagnosis T-3	-0.000867	-0.00129**	-0.00497***
	(0.000586)	(0.000654)	(0.000674)
Diagnosis T-4	-0.00143**	-0.00110*	-0.00540***
	(0.000564)	(0.000636)	(0.000649)
Constant		0.726***	
		(0.0012)	
Family controls		yes	
Age dummies		yes	
Year dummies		yes	
Observations		11,376,327	
Individuals		2,545,482	
R-squared		0.019	

*Notes: Standard errors clustered by individual in parentheses. Fixed effects specification. *** p<0.01, ** p<0.05, * p<0.1*

2.J. Parallel trends in labor market participation before the adverse health event

As an additional robustness check, we perform a ‘weak’ test of the parallel trends in labor market participation of the women who will suffer from an adverse health event and those that would not suffer from an adverse health event. It is a weak test, because the composition of the control group changes dynamically, as explained in footnote 28: we compare the labor market participation of women who receive a diagnosis not only with women who would not suffer from an adverse health event in the time span that we observe, but also with women who will receive a diagnosis later in time.

To determine whether there are parallel trends, we estimate equations (1), (2) and (3.2) as fixed-effects models where we include variables denoting the future occurrence of an adverse health event, namely Diagnosis T+1, Diagnosis T+2 and Diagnosis T+3. Each of those is a binary variable which is equal to 1 if the woman suffers from an adverse health event in the respective future period (T+1, T+2, and T+3 respectively), and equal to 0 otherwise. The results of Model 33, presented in Table 2.J.1, show that the employment probability difference between the women who suffer from an adverse health event and those that do not is stable in the three years before the diagnosis, namely it is about 9 percentage points. This result suggests parallel trends in the employment probability of the two groups. With respect to the working hours, Model 34 show that the working hours on a yearly basis differ between the two groups with about 9.5 hours three years before the diagnosis and the gap increases to 13.5 hours in the year before the diagnosis. Even though those results are statistically significant, they are not economically significant. Lastly, with respect to the wage development, we observe a stable difference of about 0.2 percentage points throughout the three years before the adverse health event.

To sum up, we observe parallel trends in the labor market participation between women who will and will not suffer from an adverse health event in the three years before the event.

Table 2.J.1. Parallel trends before the adverse health event

	Model 33 Employment	Model 34 Hours	Model 35 LnWage
Diagnosis T+3	0.00872***	9.641***	0.00237***
	(0.000353)	(0.596)	(0.000425)
Diagnosis T+2	0.00941***	12.13***	0.00222***
	(0.000369)	(0.609)	(0.000418)
Diagnosis T+1	0.00861***	13.66***	0.00180***
	(0.000372)	(0.601)	(0.000408)
Diagnosis	0.00288***	2.816***	0.000893**
	(0.000371)	(0.595)	(0.000400)
Diagnosis T-1	-0.00110***	-3.998***	-0.00169***
	(0.000375)	(0.600)	(0.000406)
Diagnosis T-2	-0.00349***	-9.576***	-0.00211***
	(0.000369)	(0.593)	(0.000402)
Diagnosis T-3	-0.00707***	-8.632***	-0.00187***
	(0.000356)	(0.571)	(0.000391)
Diagnosis T-4	-0.00743***	-7.580***	-0.00176***
	(0.000329)	(0.534)	(0.000368)
Constant	0.858***	1,754***	2.125***
	(0.00103)	(1.648)	(0.00103)
Family controls	yes	yes	no
Age dummies	yes	yes	yes
Year dummies	yes	yes	yes
Observations	22,948,460	17,712,316	17,712,316
Individuals	3,804,345	3,109,970	3,109,970
R-squared	0.011	0.067	0.141

*Notes: Standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Model 33, 34 and 35 are estimations of equations (1), (2), and (3.2), respectively.*

Chapter 3: The effects of nationwide breast cancer screening on survival and employment after being diagnosed[30]

3.1. Introduction

Breast cancer is the most common type of cancer for women and the second deadliest in developed countries (GLOBOCAN, 2012). The Netherlands, the country analyzed in this chapter, ranks fourth in the incidence of breast cancer in 2012 after Belgium, Denmark and France (World Cancer Research Fund International), with one out of eight women being diagnosed with breast cancer at some point in her life (RIVM, 2014). This high incidence together with the high mortality rate of about 31%[31] among women who have been diagnosed with breast cancer, have led to the introduction in 1998 of a public health policy of nationwide breast cancer screening in the Netherlands.[32] This screening aims at early detection of breast cancer, which was expected to improve chances of survival. Otto et al. (2003) indeed find large mortality gains of nationwide breast cancer screening: compared with mortality rates before nationwide screening was introduced, breast-cancer mortality rates of women aged 55–74 years fell significantly after its introduction, reaching a 19.9 percent reduction in 2001. Likewise, Gelder (2012; p.114 and p.164) estimated that nationwide breast cancer screening in the Netherlands has reduced mortality among women diagnosed with breast cancer by 15.7 percent. An overview of European studies by Njor et al. (2012) show similar reductions in mortality rates of breast cancer screening across Europe. The reduced mortality among women diagnosed with breast-cancer together with an increase in the number of women diagnosed with breast cancer (Health Council of the Netherlands, 2014) has increased the number of breast cancer survivors.

While the abovementioned studies have identified positive survival effects of access to breast cancer screening, little is known about possible employment gains among breast cancer survivors. Such employment gains can be expected as several studies have shown a negative impact of breast cancer on the employment probability of women both in the short term

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[31] The age-adjusted (European standard population) incidence rate and mortality rate of women aged 35-85 in 1988 are respectively 181.9 per 100,000 women and 71.5 per 100,000 women (Otten et al., 2008).

[32] In 1989 the policy was introduced for women aged 50-69 and it was extended to women aged 70-75 in 1998 (Health Council of the Netherlands, 2014).

(Bradley et al., 2006; Bradley et al., 2005), as well as in the long term (Bradley et al., 2002; Heinesen and Kolodziejszyk, 2013); and, more importantly for our study, a stronger impact on employment at more advanced cancer stages (Thielen et al., 2015). These findings can be explained by the theoretical model developed by Grossman (1972), according to which individuals allocate their time between work and leisure, and if their health deteriorates need time to restore it. As a result, they have less time available for work and leisure. The necessary time for recovery is in turn related to the severity of the health condition – more severe health conditions require a longer recovery time. Therefore, there could be employment gains from breast cancer screening, as it facilitates diagnosis of breast cancer at an early stage of the disease. Obtaining insights in such employment gains is important as nationwide breast cancer screening requires a substantial monetary investment. The benefits for diagnosed women as well as for the society are, next to important survival gains, (economic) benefits in terms of higher employment, hence fewer disability insurance or sick leave benefits recipients among breast cancer survivors as a result of their improved health. The main aim of this chapter is, therefore, to quantify these employment gains among breast cancer survivors up to four years after the diagnoses. To the best of our knowledge, this is the first study to consider the effect of a nationwide breast cancer screening program on employment.

For the empirical analysis, we use Dutch administrative data from 2000 to 2012 that contain information on the age at diagnosis, mortality and employment. We focus on a sample of women diagnosed with breast cancer between the ages of 48 and 53 and we exploit the fact that the public health program of nationwide access to the breast cancer screening is for women aged 50 to 75. We find that access to breast cancer screening reduces the mortality rate by 30.8 percent in the first year after diagnosis, which is in line with previous research (Njor et al., 2012). A new empirical finding is that access to breast cancer screening leads to a 6.3 percent higher probability of employment in the first year after the diagnosis. Furthermore, these mortality and employment gains do not diminish during the four years after the diagnosis. A possible explanation for these findings is that as nationwide breast cancer screening program aims at early diagnosis, it improves the health among breast cancer survivors and they are therefore more likely to remain employed.

The remainder of the chapter is organized as follows: Section 3.2 outlines the theoretical framework. Section 3.3 describes the data and Section 3.4 the empirical methodology. Section 3.5 presents the empirical results and Section 3.6 the robustness checks. Last, Section 3.7 summarizes the main results and concludes.

3.2. Institutional setting and literature

3.2.1. Breast cancer and breast cancer screening program

Breast cancer is a life-threatening disease and women who are diagnosed have a five-year survival rate of 86 percent in the Netherlands (Dutch Cancer Registration, 2017). The average age at diagnosis is 61 years and at the time of diagnosis the tumor is in most cases already invasive (Health Council of the Netherlands, 2014). The occurrence of breast cancer, however, cannot be attributed purely to genetics, which have been shown to explain only 8-10 percent of the cases (Breastcancer.org, 2017). The risk factors for women, besides age, are related to life style factors such as higher education (Palme and Simeonova, 2015), 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 prompted in 1998 the public health initiative of a nationwide screening program in the Netherlands, which aims at early detection and improved chances of survival. The program targets women aged 50-75 and participation is free of charge. Women 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 second year until the age of 75.

Currently there are 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[33]. The Health Council of the Netherlands (2014) evaluated the screening program and found that it has high participation rate (82 percent in 2007 (highest); 80 percent in 2012); low referral rate (approximately 2.35 percent of screened women are referred for further diagnostic because of abnormal screening results); and reliable test performance (approximately 17.2 percent false positive results). Next to 50-75 year-old women who have access to the nationwide breast cancer screening program, also women under the age of 50 can ask to be screened for breast cancer if they have an increased risk for breast cancer, for example having a family member diagnosed with breast cancer.

3.2.2. Health, health care, mortality, and employment

Grossman (1972, 2000) considers ‘good health’, or the health stock, as a commodity which individuals demand, as sick days bring them a disutility. While the health stock depreciates with age, the individual could invest in it to restore it to a certain extent. One of the possible

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

investments that the individual can make is the utilization of medical care (Grossman, 2000). Of course, ultimately, if the health stock is below a certain threshold, the individual dies. In that line of thought screening for breast cancer can be seen as an investment into maintaining good health. Besides considering health as a consumption commodity, Grossman (1972) argues that it is also an investment commodity: the higher the health stock the more time the individual has for work and leisure. Therefore, health conditions, which reduce the health stock, also reduce the time available for work and leisure.

The existing literature finds indeed that the investment in maintaining good health through breast cancer screening increases the survival chances of the individual. In a meta study of European findings, Njor et al. (2012) found that breast cancer screening results in 26 percent (95 percent confidence interval: 13 – 36 percent) reduction in mortality, evaluated at 6 to 11 years after the diagnosis[34]. In line with these estimates, the Health Council of the Netherlands (2014) evaluated a reduction of 34 percent in the age-standardized breast cancer mortality in 2012, when breast cancer screening was available, in comparison to the period 1986 – 1988, before the nationwide screening program started. They attribute more than half of this decrease to the early detection of the disease; while the rest of it to the improvements in the breast cancer treatment.

Differently than Njor et al. (2012) and the Health Council of the Netherlands (2012), we observe the access to breast cancer screening rather than women actually being screened. In a meta study, Broeders et al. (2012) find that while the reduction in mortality for the women who are actually screened is 38 to 48 percent, for the ones who are invited for screening it is 25 to 31 percent, suggesting that considering access to screening, rather than actual breast cancer screening, would provide with a lower estimate than the true effect of screening. Given the findings about mortality gains from access to breast cancer screening and the previous literature, we expect to find differences in the mortality rates of women who have been diagnosed before and after they could participate in the nationwide breast cancer screening program in the Netherlands.

A different strand of literature touches upon Grossman's (1972) argument that reductions in the health stock have a negative effect on the time available for work. For example, Heinesen and Kolodziejszyk (2013) use administrative Danish data and follow women for three years after a breast cancer diagnosis. They find that the diagnosed women are 4.4 percentage

[34] For more details on the empirical evidence from breast cancer screening see Health Council of the Netherlands, 2014, chapter 5.

points less likely to be employed after the diagnosis in comparison to a control group. Furthermore, this effect increases over time and three years after the diagnosis the difference between the employment of the diagnosed women and the control group is 6.7 percentage points. In a similar manner, Bradley et al. (2002) follow women diagnosed with breast cancer in the US for seven years (on average) and finds that they are seven percentage points less likely to be employed in comparison to women who do not have breast cancer. A follow-up study of Bradley et al. (2005) shows that the negative effect of breast cancer on employment is present even six months after the diagnosis. Additionally, as Grossman (1972) treats health as a stock variable, a later diagnosis would imply a larger reduction in the health stock which requires a longer recovery period. Indeed, Thielen et al. (2015) find that, compared to an early diagnosis of breast cancer, a later diagnosis has a stronger negative effect on the employment probability three years after the diagnosis. Since breast cancer screening facilitates an early detection of the disease, we expect that women that have been diagnosed when the breast cancer screening is available are more likely to stay employed in comparison to women who have been diagnosed without screening.

Lastly, the labor market institutions could affect the way women adjust their employment after the breast cancer diagnosis. García-Gómez (2011) finds that health shocks have a negative effect on the probability of employment, however the magnitude differs across nine European countries and part of the difference could be explained by the social security arrangements. The author shows that in countries where the disability policies have lower integration dimension[35] (such as Ireland), individuals reduce more their labor market activity in comparison to individuals in countries where the integration dimension is higher (such as Denmark and the Netherlands). Likewise, Bradley et al. (2013) relate the eligibility to health insurance in the USA to the employment probability of women who survive breast cancer. The authors find that women who are not eligible for health insurance through their husbands are less likely to leave their job in order to keep their eligibility for health insurance.

In the Netherlands, the employees have the opportunity of two years sick leave after an adverse health event which leads to a reduced work capacity (Wet uitbreiding loondoorbetalingsplicht bij ziekte, 1996; Wet verlenging loondoorbetalingsverplichting bij

[35] The integration dimension consist of employment and rehabilitation measures: “coverage consistency, assessment structure, employer responsibility for job retention and accommodation, supported employment programme, subsidized employment programme, sheltered employment sector, vocational rehabilitation programme, timing of rehabilitation, benefit suspension regulations and additional work incentives” (García-Gómez, 2011).

ziekte, 2003). During this time the employee cannot be dismissed and is entitled to her salary (a total of 170% of her last yearly salary spread over a two-year period). If she is on a temporary labor contract which ends during this period, she still receives the financial support, but the company is not obliged to extend her contract. Thus, the employee has the opportunity to spend time to recover from her health condition without being at risk of losing her job. Should the employee not recover her work capacity, she can apply for disability benefits. Furthermore, to improve the work re-integration of the employee, the law obliges the employers to draft a reintegration plan and find a suitable job for the work capacity of the employee during this job protection period.

Based on this institutional setting, we expect that most women would continue being employed during the first two years after the breast cancer diagnosis and that a stronger reduction in employment would be observed after the two-year protection period.

3.3. Data

We use individual level administrative Dutch data, provided by Statistics Netherlands (CBS), for the period 2000 to 2012. The information has been retrieved from four different sources. First, the information about employment spells has been retrieved from the Social Statistical Dataset on Jobs (Sociaal Statistisch Bestand, SSB-banen, 2000-2012; Bakker et al., 2014). Second, personal and family information has been retrieved from the Municipality Registry (Gemeentelijke Basisadministratie, GBA, 2000-2012; CBS, 2015). Third, we use income information from the Integrated Personal Income data set (Integraal Persoonlijk Inkomen, 2003-2012; CBS, 2016a), which has been collected by the tax authorities. Fourth, the medical information, in the form of hospital entries, is retrieved from the National Medical Registration (Landelijke Medische Registratie, LMR, 2000-2012; CBS, 2016b), which was provided to Statistics Netherlands by the foundation for Dutch Hospital Data (DHD). In addition, we make use of age specific annual population mortality rates that have been retrieved from the Human Mortality Database (2004-2012; Human Mortality Database, 2017).

3.3.1. Sample selection

We select women who are diagnosed with breast cancer in the time span 2004 to 2008. We are interested in the women who are diagnosed for a first-time, however the hospital data does not contain information about that. Therefore, and following Chapter 2, we consider the history of hospital visits to identify the onset of the health condition: If a woman has not received a breast cancer diagnosis during the last four years, a breast cancer diagnosis is considered a new diagnosis. We focus on the sample of 9,310 women who are diagnosed for a first time between the age of 48 and 53, that is just before having access to national wide screening at ages 48 and 49 and when having access to it at ages 50-53. Depending on age, one expects differences in the stage of the disease. Because of nationwide access to the screening program from age 50 onwards, women diagnosed from age 50 onwards are more likely to have an early diagnosis than women diagnosed before age 50.

Further cleaning of the data results in leaving out 84 (0.90 percent) women due to missing information on one or more of the covariates: employment, personal income, having a partner, income of the partner, number and age of the children, and adults living in the household. Then we leave out 186 (1.99 percent) women because we do not have information about them in one of the time periods and we could not confirm that they are deceased. This results in a panel of 9,040 women, which we follow from the year before they receive a breast cancer diagnosis to four years thereafter.

3.3.2. Descriptive statistics

Table 3.1 shows the distribution of new breast cancer cases by age at diagnosis. More women receive a diagnosis at the ages of 50 and 51 than at other ages. This corresponds to the beginning of the screening period for a cohort. At the time a cohort starts to be screened, there are relatively more diagnosis than just before or after, since both the women who would have been diagnosed without screening are diagnosed, as well as the women who otherwise would have been diagnosed in the future. In the next age groups – age groups 52 and 53, we observe that the numbers of diagnosed are much lower but still somewhat above the numbers prior to when the screening is available. We assume that women diagnosed when screening is available are likely to have an earlier diagnosis due to the possibility of being screened. Since the women diagnosed at the age of 50 are invited for screening for a first time, it is likely that some of the diagnosed women would have more advanced stages of breast cancer, while others would 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.

The last three columns of Table 3.1 describe the employment history, health and family status of the women diagnosed with breast cancer in the year before diagnosis. First, employment history combines employment information from the previous four years. It ranges from 0 to 1, and is equal to 1 for four years of employment; 0.75 for three years; 0.50 for two years; 0.25 for one year; and 0 if the woman has not been employed in any of the previous four years. We choose for this long-term measure rather than for employment status in the previous year in order to have a more robust measure of labor force attachment. We observe that younger women have, on average, a higher labor force attachment than older women (0.74 vs. 0.66). Second, the health status in the year before the diagnosis is captured by a binary variable, which is equal to 1 if the woman received a diagnosis for any health condition other than breast cancer. We observe that the younger women have fewer other health conditions than the older women. Especially women diagnosed at the age of 53 have substantially more often other health conditions than the younger ones, namely 14 percent. Lastly, Table 3.1 does not show any strong differences in the probability of having a partner between the various ages.

Table 3.1. Descriptive statistics at the year before diagnosis

Age at diagnosis	Number of women	Employment history	Other health conditions (%)	Partner (%)
Diagnosed at 48	1,209	0.74	10.50	80.07
Diagnosed at 49	1,298	0.70	12.33	78.35
Diagnosed at 50	1,912	0.70	11.04	80.07
Diagnosed at 51	1,812	0.68	11.92	79.25
Diagnosed at 52	1,466	0.68	11.26	78.92
Diagnosed at 53	1,343	0.66	14.07	79.30
Total	9,040	0.69	11.81	79.36

Notes: Age at diagnosis denotes the age of the woman in the year of diagnosis. Number of women is a cumulative number of women diagnosed at each age 48 to 53 for the whole sample. Employment history ranges from 0 to 1 and denotes the employment probability based on information from the four years before the diagnosis. Other health conditions is equal to 1 if the woman receive another diagnosis in the year before the breast cancer diagnosis; and 0 otherwise. Partner is equal to 1 if the woman has a partner in the year before the diagnosis; and 0 otherwise.

Mortality is measured by a binary variable, which is equal to 1 if the woman dies during the calendar year, and 0 if she survives. Table 3.2 shows the mortality probabilities in the years following diagnoses per age at diagnosis. The last column shows the probability of survival four years after diagnosis. We observe that women who have been diagnosed at the ages of 50 and 51 have the highest overall survival probability after four years, namely 92 percent. The lowest survival probability is observed in the oldest group of women. With respect to the changes in mortality over time since diagnosis, Table 3.2 does not show any clear trends.

In a similar manner we measure employment as a binary variable – 0 denotes no employment in that calendar year; 1 denotes employment. The probability of employment, given survival, up to four years after diagnosis is depicted in Table 3.3. First, we observe that younger women are more likely to be employed in every time period than the older women. The raw difference in the employment rate of women aged 48 and 53 is about ten percentage points. Furthermore, for all age groups, the probability of employment decreases over time since diagnosis.

Table 3.2. Mortality over time since diagnosis and four-year survival probability

Age at diagnosis T	Mortality at T %	Mortality at T+1 %	Mortality at T+2 %	Mortality at T+3 %	Mortality at T+4 %	Survival at T+4 %
Diagnosed at 48	0.74	2.00	2.04	2.26	1.78	91.48
Diagnosed at 49	1.62	2.35	1.84	2.53	1.68	90.37
Diagnosed at 50	0.94	1.48	1.82	1.97	1.73	92.31
Diagnosed at 51	0.83	2.00	1.93	1.74	1.59	92.16
Diagnosed at 52	1.91	1.53	2.19	2.53	1.70	90.52
Diagnosed at 53	2.23	2.51	2.58	2.41	1.73	89.05
Total	1.34	1.94	2.05	2.19	1.69	91.12

Notes: The mortality rate is conditional on the individual being alive in the previous period. The survival rate is measured based on the individuals being alive before the diagnosis. The information is retrieved from the Municipality Registry (2000-2012).

Table 3.3. Employment per age at diagnosis over time since diagnosis

Age at diagnosis T	Employment at T %	Employment at T+1 %	Employment at T+2 %	Employment at T+3 %	Employment at T+4 %
Diagnosed at 48	73.92	72.53	72.92	70.96	70.98
Diagnosed at 49	69.38	68.00	67.48	65.80	64.96
Diagnosed at 50	68.27	66.29	66.87	64.70	64.48
Diagnosed at 51	65.05	63.32	63.69	61.58	60.78
Diagnosed at 52	65.72	63.28	61.66	59.41	57.42
Diagnosed at 53	63.21	60.63	60.06	57.52	56.44
Total	67.38	65.46	65.30	63.17	62.36

Notes: The employment rate is measured based on the individuals who are alive in the corresponding period. The information is retrieved from the Social Statistical Dataset on Jobs (2000-2012).

Other covariates for our empirical analysis are personal income, income of the partner, number and age of children, and number of other people living in the household (see Table 3.4 for summary statistics). They are all measured in the year before the diagnosis.

Table 3.4. Summary table of covariates

Variable	Obs.	Mean	Std. Dev.
Personal income	6,183	20,511	15,689.78
Partner's income	7,089	44,910	31,575.02
Permanent employment	9,040	0.5162[36]	0.4998
Adults in household	9,040	2.3364	0.9047
Age of children	9,040	5.6182	7.3836
Number of children	9,040	0.5822	0.8573

Notes: Personal income denotes the personal income of the women who are employed. It is measured in euros. Partner's income denotes the income of the partner for the women who have a partner and the partner is employed. It is measured in euros. Permanent employment is equal to 1 if the woman has a permanent employment contract, and 0 otherwise. Adults in household denotes the number of people older than 18 who live in the household. Age of children denotes the average age of all the children under 18 living in the household. Number of children denotes the number of children under 18 living in the household. All variables are measured in the year before the diagnosis.

3.3.3. Labor market transitions

In the year before diagnosis women could be employed or not, and in the subsequent years they can either stay in employment, leave employment or die. The row percentages in Table 3.5 are transition probabilities given the employment state in the year before diagnosis. We find similar short and long run trends for both groups – diagnosed with and without screening. First, there is path dependence in employment: initially employed women are more likely to stay employed after the diagnosis and initially non-employed women are more likely to stay in non-employment after the diagnosis, respectively. Second, initially non-employed women have a higher mortality rate after the diagnosis than initially employed women.

[36] Since the average employment rate in the year before the diagnosis is 68.40%, this implies that 75% of the employed women are in permanent employment.

Table 3.5. Labor market transitions

Panel A: Diagnosed at age 48 and 49

States at T-1	State at T+1 (short term)			State at T+4 (long term)			
	Employed	Non-Employed	Dead	Employed	Non-Employed	Dea d	Total (n)
Employed	91%	7%	2%	80%	12%	8%	100% (1,812)
Non-Employed	8%	86%	6%	13%	74%	13%	100% (695)
Total	68%	29%	3%	62%	29%	9%	100% (2,507)

Notes: The row percentages denote the transition probabilities from the state in period T-1 to period T+1, and respectively period T+4. The row percentages are equal to 100%.

Panel B: Diagnosed at age 50 to 53

States at T-1	State at T+1 (short term)			State at T+4 (long term)			
	Employed	Non-Employed	Dead	Employed	Non-Employed	Dead	Total
Employed	90%	8%	2%	78%	15%	7%	100% (4,371)
Non-Employed	5%	90%	5%	8%	80%	12%	100% (2,162)
Total	62%	35%	3%	55%	36%	9%	100% (6,533)

Notes: The row percentages denote the transition probabilities from the state in period T-1 to period T+1, and respectively period T+4. The row percentages are equal to 100%.

3.3.4. Population mortality and employment rate

To ensure that we account for the cohort and year specific trends in mortality and employment of the female population in the Netherlands, we will benchmark our model by using a population cohort and year specific statistics. The cohort specific annual mortality rate is available from the Human Mortality Database (HMD, 2017)[37]. However, there is no officially reported

[37] For a summary table of the HMD mortality rates, please see Appendix 3.A.

employment rate on a cohort level for each calendar year. Therefore, we calculate it based on the population data provided by Statistics Netherlands[38].

3.4. Empirical strategy

We estimate the effect of access to breast cancer screening on the mortality and employment probabilities. The probability of dying conditional on being alive the year before (i.e. a discrete time proportional hazard rate) is modelled as follows:

$$P(M_{i,t} = 1) = HMD_{a_i t}\, exp\big(\gamma_0 + \gamma_1 SCREENING_i + \eta_0 V_t^0 + \textstyle\sum_{k=2}^{4} \eta_k V_t^k + \delta_0 SCREENING_i \text{ x } V_t^0 + \textstyle\sum_{k=2}^{4} \delta_k SCREENING_i \text{ x } V_t^k + \boldsymbol{X}_i \boldsymbol{\mu}'\big) \qquad (1)$$

where $M_{i,t}$ is equal to 1 if individual *i* dies in period *t*, and 0 otherwise. $SCREENING_i$ is equal to 1 if individual *i* is diagnosed at or after the age of 50 when nationwide screening is available, and 0 otherwise. V_t^k stands for the time since diagnosis and *k* denotes the (full) years from the time of diagnosis up to four years later. $HMD_{a_i t}$ denotes the annual population mortality rate of individuals aged a_i in year *t* and in this way, we can flexibly control for an age gradient; the time effects (e.g., due to medical advances); and different age, and time effects across cohorts (see Kalwij, 2018). The vector $\boldsymbol{X}_i$ comprises of the following socioeconomic background variables: log of personal income, having a partner, log of income of the partner, number and age of the children, log of adults living in the household, other diagnoses and employment history. We control for the socioeconomic status of the women as previous research has shown a socioeconomic gradient in the health status of the individual (Cutler, Lleras-Muney and Vogl, 2011), as well as in the labor market response to an adverse health event (Torp et al., 2013; Heijnen, Hassink and Plantenga, 2014). Indeed, we also see in Table 3.5 that non-employed women have higher mortality rate after breast cancer diagnoses than employed women. The socioeconomic background variables are measured in the year before diagnosis and are included in deviations from their sample means.

The proportionality assumption imbedded in equation (1) implies that the mortality rates of women diagnosed with breast cancer are modelled relatively to the population mortality rates.

[38] A comparison between self-computed mortality rates, using the data available at Statistics Netherlands, and the HMD mortality rates shows a correlation of 0.93, thus suggesting that our self-calculated population values are representative for the true population values. Moreover, the empirical results when using these computed rates are similar to when using the ones from the HMD (see Appendix 3.A).

That is, we use as a baseline the annual population mortality rate in equation (1) which is age and year specific, $HMD_{a_i t}$, in order to net out the general population mortality trends.

The coefficient corresponding to one of the variables in the exponent function of equation (1) is interpreted as follows: the exponent of the coefficient minus one (when multiplied with 100) is the percentage change in the mortality rate due to a one unit change in this variable[39]. The coefficient γ_0 captures how the mortality rate of the women aged 48 and 49 in the first year after being diagnosed with breast cancer without having access to the nationwide breast cancer screening program (and with average values of $\boldsymbol{X}_i$ that are by construction equal to zero), differs from the population mortality rates of women with the same age and in the same year. If γ_0 is equal to zero, then these women will have the same mortality rates as women in the general population; if it is positive (negative), then it shows by how much the mortality rates of these women increase (decrease) compared to average women of the same age in the population.

The parameter γ_1 captures the difference in mortality rates between women diagnosed with and without access to the nationwide breast cancer screening program. We expect γ_1 to be negative, since the aim of the breast cancer screening is early diagnosis, which has been shown to result in lower mortality (Njor et al., 2012). The parameters η_k (k= {0, 2, 3, 4}) capture the changes in mortality over time since the diagnosis. Since the year of diagnosis as a time period is half the size of the other periods[40], we use the year after the diagnosis (k=1) as a reference period in the empirical specification. We also allow these changes to be affected by the access to screening by including an interaction term between screening and time since diagnosis, captured by the parameters δ_k. Lastly, the vector $\boldsymbol{\mu}$ contains the effects related to the socio-economic variables. If all parameters are equal to 0, women diagnosed with breast cancer would face the same mortality rate as women with the same age and in the same year who are not diagnosed with breast cancer.

Next, and similarly to equation (1), we model the effects of access to breast cancer screening on the probability of employment, conditional on survival, as follows:

$$P(E_{i,t} = 1|M = 0) = PER_{a_i t} \exp\big(\beta_0 + \beta_1 SCREENING_i + \omega_0 V_t^0 + \textstyle\sum_{k=2}^4 \omega_k V_t^k + \tau_0 SCREENING_i \text{ x } V_t^0 + \textstyle\sum_{k=2}^4 \tau_k SCREENING_i \text{ x } V_t^k + \boldsymbol{X_i \iota'}\big) \qquad (2)$$

[39] For binary variables. For continuous variables, it is the coefficient itself.

[40] If we assume that women have an equal probability for diagnosis throughout the calendar year, on average the year of diagnosis lasts six months after diagnosis.

where $E_{i,t}$ is equal to 1 if individual i is employed in time t; and 0 otherwise, PER_{a_it} denotes the age and year specific population employment rate of individuals with age a_i in year t. The structure of the employment model is similar to the mortality model. We use as a benchmark a population annual employment rate which is age and year specific in order to net out the year, cohort and age specific employment effects.

The parameter β_0 relates to the difference in the employment rate between the general population and women who have been diagnosed with breast cancer without having access to breast cancer screening (*ceteris paribus*). Previous literature finds that that breast cancer is a welfare disease and as such is more likely in the higher educated population (Palme and Simeonova, 2015). Therefore, we expect that women diagnosed with breast cancer, on average, are more likely to be working at the time of diagnosis and have higher career aspirations than the general population, which suggests that β_0 would be positive.

The parameter β_1 captures the employment differences between women diagnosed with breast cancer, when nationwide screening is and is not available. We expect β_1 to be positive, as screening leads to early diagnosis which would lead to less severe treatment and a shorter time to recover (Grossman, 1972) and, therefore, a higher likelihood of being employed. We also allow for employment changes after the diagnosis, captured by ω_k. We expect that the employment after diagnosis decreases with time: in the beginning there is the institutional protection, so less women are likely to leave the work place (see Section 3.2.2). Furthermore, in the empirical specification we use as a reference period the year after diagnosis (k=1) to have consistency between the mortality and employment models. The parameters τ_k allow the employment changes over time to differ between the women who have been diagnosed if they have and have not access to nationwide breast cancer screening. If all $\tau_{i,k}$ are equal to zero, the employment patterns after being diagnosed are the same for diagnosed women with and without access to breast cancer screening. In addition, $\boldsymbol{\iota}$ contains the parameters related to the socio-economic control variables. In the cases that all parameters are equal to 0, this would imply that women diagnosed with breast cancer face the same employment rate as an average woman.

3.4.1. Estimation and identification

We estimate the following mortality model by Nonlinear Least Squares:

$$M_{i,t} = HMD_{a_it}\, exp\big(\gamma_0 + \gamma_1 SCREENING_i + \eta_0 V_t^0 + \textstyle\sum_{k=2}^{4} \eta_k V_t^k + \delta_0 SCREENING_i \text{ x } V_t^0 + \textstyle\sum_{k=2}^{4} \delta_k SCREENING_i \text{ x } V_t^k + \boldsymbol{X}_i \boldsymbol{\mu}'\big) + \nu_{i,t} \quad (3)$$

where the specification in the argument of the exponent function is identical to that of equation (1). υ_{it} is an idiosyncratic error term. Next, we estimate the following employment model by Nonlinear Least Squares:

$$E_{i,t} = PER_{a_it} \exp\big(\beta_0 + \beta_1 SCREENING_i + \omega_0 V_t^0 + \textstyle\sum_{k=2}^{4} \omega_k V_t^k + \tau_0 SCREENING_i \text{ x } V_t^0 + \textstyle\sum_{k=2}^{4} \tau_k SCREENING_i \text{ x } V_t^k + \boldsymbol{X_i \iota'}\big) + \sigma\lambda_{i,t} + \varepsilon_{i,t} \quad (4)$$

where the specification in the argument of the exponent function is identical to that of equation (2) and ε_{it} is an idiosyncratic error term.

$\lambda_{i,t}$ is the inverse Mills ratio to take into account that employment is conditional on survival and that, therefore, the error terms in equations (3) and (4) can be correlated and $E(\varepsilon_{i,t}|M_{i,t} = 0) \neq 0$, which implies survival bias, or more generally an endogenous sample selection bias, in the employment estimates (Bradley et al., 2002). This bias may occur as we observe the employment status of women at a certain age who have been diagnosed with breast cancer conditional on them being alive at the end of the calendar year and it may be that women who survive have different employment behavior than the unobserved employment probability of the women who do not survive. Indeed, Table 3.5 shows that employed women have a lower mortality rate in comparison to women who are non-employed before the diagnosis; as well as a path dependency in employment. The inverse Mills ratio is a function of the variables and parameters of equation (3) (Greene, 2012; Heckman, 1979) and the standard errors of the estimation results of equation (4) are bootstrapped to take this into account.[41]

Furthermore, equations (3) and (4) are identified by the inclusion of a population age and year-specific employment statistic in equation (4) and the population age and year-specific mortality statistic in equation (3).

Lastly, as shown above, σ is the correlation between the error terms in the mortality and employment equations. We expect it to be negative if, as suggested by the literature (see, e.g., Martikainen and Valkonen, 1996), women who are more likely to be employed are less likely to die.

[41] $E\big(\varepsilon_{i,t}|M_{i,t} = 0\big) = -\sigma\lambda_{i,t}$, $\lambda_{i,t}(a) = \frac{-f(a)}{F(a)}$ if truncation is $< a$ (Greene, 2012; Theorem 19.2). One additional assumption needed for this sample selection correction is joint normality of the added error terms to the equations when estimating these with Nonlinear Least Squares, hence f denotes the standard normal density function and F denotes the standard normal cumulative distribution function of the predicted values of the mortality equation.

3.5. Results

We examine the effects of availability of nationwide breast cancer screening program on the mortality and employment probabilities of women after they have been diagnosed with the disease. Table 3.6 presents our main results.

The estimates from the mortality model (column 1 of Table 3.6) show that availability of the nationwide breast cancer screening program leads to a 30.8 percent ((exp(-0.368)-1)x100%) lower mortality rate for women in the first year after the diagnosis. This result is in line with the estimate of the official evaluation of the Dutch screening program by the Health Council of the Netherlands (2012), namely they report a 34 percent reduction in mortality, as well as the previous studies of survival gains of breast cancer screening (Njor et al., 2012; Broeders et al., 2012). The finding that in the year of diagnosis ("Zero years"), the mortality rate of the diagnosed women is 37.9 percent less than the mortality rate in the year after the diagnosis is likely the results of the fact that a cancer diagnosis can be received at any point of time during that year, which means the period on average lasts half of a regular year. In the second and third years after diagnosis women have similar mortality rates to the mortality rates in the year after the diagnosis. Four years after the diagnosis, their mortality rate is slightly less than half (to be exact, 41.9 percent) of the observed mortality in the year after the diagnosis. Nevertheless, a joint test of significance shows that, overall, the time since breast cancer diagnosis have no significant effect on the mortality rate (p-value is 0.13). Lastly, we consider whether women who are diagnosed when the nationwide breast cancer screening program is available have different mortality rates in each year after the diagnosis. The interaction terms between diagnosis and time since diagnosis are not individually significant, nor jointly. This suggests that the mortality rates of the diagnosed women change in a similar manner in the time after the diagnosis, in other words the trend in the mortality rates is similar irrespective of the availability of screening.

Overall, our results suggest that nationwide access to breast cancer screening leads to a reduction in the mortality rate of women diagnosed with breast cancer and that this reduction does not strengthen or weaken during the years after the diagnosis.

The second column of Table 3.6 presents the second-stage results, namely the employment results. The estimates show that women diagnosed with breast cancer when the nationwide breast cancer screening program is available have 6.3 percent higher employment probability in the year after the diagnosis. This result is similar to the findings of Thielen et al. (2015) that Danish women with earlier breast cancer diagnosis are more likely to be employed. It is also in line with Grossman's (1972) argument that more severe health problems have a

Table 3.6. Mortality and employment after screening

Coefficient	Model 1A Mortality	Model 1B Employment
Intercept	2.270***	-0.309***
	(0.151)	(0.056)
Screening	-0.368**	0.0610***
	(0.177)	(0.006)
Years after the diagnosis:		
Zero years	-0.477**	0.0200***
	(0.243)	(0.004)
Two years	-0.261	-0.0102**
	(0.214)	(0.005)
Three years	-0.219	-0.0333***
	(0.201)	(0.006)
Four years	-0.544**	-0.0331***
	(0.226)	(0.007)
F-test[a]	1.80	69.25
p-value	0.1256	0.0000
Screening x zero years	0.361	0.00286
	(0.287)	(0.005)
Screening x two years	0.117	0.00583
	(0.254)	(0.005)
Screening x three years	0.0634	0.000753
	(0.244)	(0.008)
Screening x four years	0.0631	-0.00127
	(0.270)	(0.008)
F-test[b]	0.43	2.16
p-value	0.7844	0.7059
Inverse Mills ratio		-0.194***
		(0.026)
Observations	43,651	42,848

*Notes: Standard errors clustered by individual in parentheses. Model 1B has bootstrapped standard errors from 200 iterations. All models include controls for: personal income, partner, income of the partner, number and age of the children, adults living in the household, other health conditions and employment history in the year before diagnosis. *** p<0.01, ** p<0.05, * p<0.10*

[a] The null hypothesis of the F-test is that the effects on mortality and employment rate, respectively, are the same in the years after the diagnosis.

[b] The null hypothesis of the F-test is that the effects on mortality and employment rate, respectively, are the same in the years after the diagnosis between the women who have and have no access to the nationwide

stronger negative effect on employment. Nevertheless, we find as well that women reduce their employment after a breast cancer diagnosis. This result is in line with individuals reducing their employment after a severe health problem (Bradley et al., 2002; Heinesen and Kolodziejszyk, 2013). The strong drop in the employment probability two years after diagnosis is, arguably, likely to be related to the institutional setting in the Netherlands (see Section 3.2.2), which provides job protection for two-years after an adverse health event, unless the employee has a temporary contract which expires during that period. In the latter occasion the employer is not obliged to extend the employee's contract, which could as well explain the initial decrease in employment after the breast cancer diagnosis. Interestingly, the interaction terms between screening and time since diagnosis are not individually statistically significant, nor jointly. This implies that nationwide breast cancer screening does not affect the trends in employment after diagnosis.

Lastly, the estimate of the coefficient on the inverse Mills ratio shows that there is a statistically significant negative correlation between the error terms in the mortality and employment equations which underlines the importance of jointly modelling the mortality and employment probabilities.[42] This finding is in line with Martikainen and Valkonen (1996) who show that unemployed women have a higher mortality rate; and the statistics in Table 3.5 which show path dependency in employment.

3.6. Robustness checks

We perform three robustness checks. The results are presented in Table 3.7. First, we include binary variables for each year of diagnosis. Since there have been medical developments in the time span we consider, it could be that women diagnosed in the earlier years receive different treatment than those diagnosed towards the end of the time span. In the mortality model, Model 2A, the years of diagnosis are not individually significant, nor jointly, which suggests that the possible improvements in treatment in the period 2004 to 2008 did not impact the mortality of the women. In Model 2B, the estimates of the year effects are negative, which suggests possible compositional differences, namely that the women diagnosed with breast cancer have a lower employment probability than their healthy peers. The estimates of the impact of the national availability of breast cancer screening on the mortality rate and the probability of employment are similar to the ones in Table 3.6.

Second, besides dividing the women into two groups based on the availability of breast cancer screening, we also include their age at diagnosis as separate binary variables (see Table 3.1, Section 3.3.2 for the proportion of women diagnosed at each age). The reference group for

[42] Nevertheless, we also estimated the employment equation without correcting for survival bias (see Model 1D, Appendix 3.A) and the results were similar to Model 1B. Thus, it seems that correcting for survival bias is not essential for our model.

the women who do not have access to nationwide breast cancer screening program is the group of women diagnosed at the age of 49; and the reference group for the women who have access to the screening program is the group of women diagnosed at the age of 51. Model 3A, Table 3.7, shows that the women who were diagnosed when breast cancer screening was available have a lower mortality rate in comparison to women who were diagnosed when the screening program was not available, which is in line with our main results. Furthermore, the model shows that the mortality gains from availability of the screening program are similar across the women diagnosed at age 50 to 53. Additionally, there is no statistical difference in the mortality rate of the women diagnosed at age 48 and 49, for whom the nationwide screening is not yet available. With respect to the employment probability, Model 3B shows that women who were diagnosed when the screening program was available are more likely to be employed. While there is no statistical difference in the employment probability of the women, for whom the program was not available (i.e. diagnosed at age 48 and 49), we observe that the employment gains of the screening availability are increasing with the age of diagnosis: while women diagnosed at the age of 50 are 2.4 percent less likely to be employed in comparison to the women diagnosed at the age of 51, the women diagnosed at the age of 52 are 3.6 percent more likely to be employed and the women diagnosed at age 53 are 7.8 percent more likely to be employed that the women diagnosed at the age of 51. These results clearly show the positive impact of nationwide breast cancer screening availability on employment and support our main results. The change of the mortality rates and employment probability over time since the diagnosis are similar to the results in Table 3.6.

Third, we considered whether there are differences between the diagnosed women related to the institutional setting. According to the labor laws in the Netherlands, employees in permanent employment cannot be laid-off during the first two years after a severe health condition. Therefore, in Model 4A and Model 4B (Table 3.7), we included an interaction term between the screening availability variable and a variable capturing whether the woman has a permanent employment contract in the year before the diagnosis. The variable is measured in deviations from the sample mean so that the definition of the intercept and the screening coefficient are consistent across models. The results show that while women in permanent employment benefit similarly to the other women from the nationwide availability of breast cancer screening in terms of mortality gains, they benefit more when it comes to the probability of being employed. This result is in line with our expectations based on the institutional setting. Furthermore, we still observe a positive impact of availability of screening on mortality and on employment, which is in line with our main results.

Table 3.7. Robustness checks of mortality and employment results

Coefficient	Model 2A Mortality	Model 2B Employment	Model 3A Mortality	Model 3B Employment	Model 4A Mortality	Model 4B Employment
Intercept	2.370***	-0.0439	2.236***	-0.125*	2.291***	-0.272***
	(0.168)	(0.062)	(0.161)	(0.064)	(0.150)	(0.052)
Screening	-0.360**	0.0651***	-0.428**	0.0480***	-0.408**	0.0502***
	(0.180)	(0.005)	(0.206)	(0.008)	(0.175)	(0.009)
Years after the diagnosis:						
Zero years	-0.494**	0.0172***	-0.495**	0.0178***	-0.478**	0.0197***
	(0.244)	(0.004)	(0.243)	(0.004)	(0.241)	(0.004)
Two years	-0.282	-0.00866*	-0.260	-0.00882**	-0.252	-0.00990**
	(0.216)	(0.005)	(0.215)	(0.004)	(0.211)	(0.004)
Three years	-0.277	-0.0291***	-0.229	-0.0294***	-0.197	-0.0327***
	(0.203)	(0.006)	(0.202)	(0.005)	(0.199)	(0.006)
Four years	-0.571**	-0.0286***	-0.539**	-0.0285***	-0.521**	-0.0324***
	(0.228)	(0.007)	(0.226)	(0.006)	(0.224)	(0.007)
F-test[a]	1.91	59.14	1.82	62.04	1.76	69.75
p-value	0.1066	0.0000	0.1221	0.0000	0.1337	0.0000
Year of diagnosis:						
Year 2005	-0.192	-0.0284***				
	(0.118)	(0.008)				
Year 2006	-0.0235	-0.0504***				
	(0.118)	(0.008)				
Year 2007	-0.0495	-0.0864***				
	(0.120)	(0.008)				
Year 2008	-0.274**	-0.0938***				
	(0.131)	(0.008)				
F-test[b]	1.65	228.73				
p-value	0.1587	0.0000				
Age at diagnosis:						
Age 48			0.0913	-0.00526		
			(0.149)	(0.008)		
Age 50			0.119	-0.0240***		
			(0.130)	(0.007)		

Age 52			0.0724	0.0359***		
			(0.133)	(0.009)		
Age 53			0.173	0.0755***		
			(0.133)	(0.010)		
F-test[c]			0.56	128.99		
p-value			0.6923	0.0000		
Permanently employed					0.176	0.00758
					(0.170)	(0.015)
Screening x Permanently					-0.271	0.0395**
employed					(0.171)	(0.017)
F-test[d]					1.26	20.78
p-value					0.2827	0.0000
Inverse Mills ratio		-0.319***		-0.299***		-0.205***
		(0.037)		(0.038)		(0.025)
Observations	43,651	42,848	43,651	42,848	43,651	42,848

*Notes: Standard errors clustered by individual in parentheses. Model 2B, Model 3B and Model 4B have bootstrapped standard errors from 200 iterations. All models include interaction terms between screening and number of years since diagnosis. Since those are all statistically insignificant, they have been excluded from the table for the sake of brevity. All models include controls for: personal income, partner, income of the partner, number and age of the children, adults living in the household, other health conditions and employment history in the year before diagnosis. *** p<0.01, ** p<0.05, * p<0.1*

[a] The null hypothesis of the F-test is that the effects on mortality and employment rate, respectively, are the same in the years after the diagnosis.

[b] The null hypothesis of the F-test is that the effects on mortality and employment rate, respectively, are the same in the calendar years after the diagnosis.

[c] The null hypothesis of the F-testis that the effects on mortality and employment rate, respectively, are the same between the women diagnosed at different ages in the time after the diagnosis.

[d] The null hypothesis of the F-test is that the effects on mortality and employment rate, respectively, are the same in the years after the diagnosis between women with and without permanent employment contracts.

Overall, the results in Table 3.6 are robust to the checks performed in Table 3.7.[43]

[43] For an estimation of the employment models without correcting for survival bias see Appendix 3.A. The results are similar to Model 2B, Model 3B and Model 4B, respectively.

3.7. Summary and conclusions

This chapter has investigated the mortality and employment gains of access to breast cancer screening in the Netherlands. We found that women who are diagnosed with breast cancer when nationwide breast cancer screening is available are 30.8 percent less likely to die and 6.3 percent more likely to be employed in the first year after the diagnosis in comparison to women who are diagnosed when nationwide breast cancer screening is not available. Our mortality results are in line with the previous literature, which argues that access to breast cancer screening reduces the mortality of the women diagnosed with the disease, as it facilitates early diagnosis. Additionally, our employment results are consistent with the findings of Thielen et al. (2015) that women with earlier breast cancer diagnosis are more likely to be employed. Furthermore, we found that the mortality rates of the diagnosed women are similar in the four years after the diagnosis, while the employment rate of the diagnosed women decreases in this time period. The latter findings are consistent with the literature on the negative impact of health conditions on employment. Additionally, we found that the decrease in employment is strongest after the second year, which could be related to the institutional job protection system in the Netherlands during the first two years after an adverse health event. Lastly, we found that those mortality and employment patterns over the time since diagnosis are not affected by the access to screening, in other words the mortality and employment gains of screening do not diminish in the four years after the diagnosis.

However, it is important to note that the mortality benefits after screening could be difficult to evaluate in the short term. Since breast cancer screening leads to early diagnosis, the death that is prevented by screening would have not happened until a few years later. Therefore, the mortality gain that we estimate may be an underestimation of the impact of the screening program. Further research can address this issue when data over a longer time span are available.

In conclusion, our results show that the nationwide breast cancer screening program in the Netherlands has next to the mortality gains for which it was designed, also employment gains for those who survive. This finding suggests that the importance of the program is not limited only to the health benefits but has also a positive spillover effect on the labor market. Better work re-integration of the increasing number of breast cancer survivors is important for their own well-being, as well as it could reduce the burden on the public subsidies (such as sick leave payments and disability payments, among others). Such a result could stimulate other countries to consider the adoption of nationwide breast cancer screening, as the potential employment gains could outweigh the costs of providing the program.

Appendix

3.A. Further robustness checks

To check the validity of our self-calculated employment measure, we calculated on the same data a mortality measure similar to the one reported by the Human Mortality Database. Table 3.A.1 shows the average value of the mortality rate for each age group considered in the analysis and the corresponding years in which we observe each of those age groups. The general trend is that the population mortality rate increases with age: while it is on average 0.22 percent for 48 year old women in the considered period, it reaches 0.42 percent for 57 year old women.

Table 3.A.1. Age and year specific mortality rate from the HMD

Age	Mortality rate (%)	From Year	To Year
Age 48	0.22	2004	2008
Age 49	0.23	2004	2009
Age 50	0.26	2004	2010
Age 51	0.28	2004	2011
Age 52	0.30	2004	2012
Age 53	0.32	2004	2012
Age 54	0.35	2005	2012
Age 55	0.38	2006	2012
Age 56	0.40	2007	2012
Age 57	0.42	2008	2012
Total	0.31	2004	2012

Notes: The numbers are based on information from the Human Mortality Database (2017).

Model 1C in Table 3.A.2 shows the results of the main mortality model estimated with a dependent variable the self-computed cohort year specific mortality rate. The results are quantitatively similar to the main mortality results.

Then we estimated the employment models without correcting for survival bias. Model 1D, Model 2 C, Model 3C and Model 4C in Table 3.A.2 show the results. The estimates are similar to the models where we correct for survival bias.

Table 3.A.2. Robustness checks of dependent variable and correcting for survival bias

	Model 1C	Model 1D	Model 2C	Model 3C	Model 4C
Coefficient	Mortality	Employment	Employment	Employment	Employment
Intercept	2.335***	-0.804***	-0.754***	-0.805***	-0.785***
	(0.151)	(0.026)	(0.027)	(0.026)	(0.026)
Screening	-0.364**	0.0598***	0.0632***	0.0479***	0.0471***
	(0.177)	(0.007)	(0.007)	(0.010)	(0.010)
Years after the diagnosis:					
Zero years	-0.479**	0.0244***	0.0241***	0.0244***	0.0244***
	(0.242)	(0.005)	(0.005)	(0.005)	(0.005)
Two years	-0.258	-0.0136**	-0.0136**	-0.0136**	-0.0135**
	(0.214)	(0.005)	(0.005)	(0.005)	(0.005)
Three years	-0.233	-0.0428***	-0.0429***	-0.0428***	-0.0427***
	(0.201)	(0.007)	(0.007)	(0.007)	(0.007)
Four years	-0.551**	-0.0439***	-0.0444***	-0.0438***	-0.0437***
	(0.227)	(0.008)	(0.008)	(0.008)	(0.008)
Year of diagnosis:					
Year 2005			-0.0277***		
			(0.010)		
Year 2006			-0.0492***		
			(0.010)		
Year 2007			-0.0873***		
			(0.010)		
Year 2008			-0.0918***		
			(0.010)		
Age at diagnosis:					
Age 48				-0.00306	
				(0.010)	
Age 50				-0.0228**	
				(0.009)	
Age 52				0.0344***	
				(0.010)	
Age 53				0.0714***	
				(0.011)	
Permanently employed					0.00708
					(0.016)

Screening x Permanently employed					0.0428**
					(0.020)
Observations	43,651	42,848	42,848	42,848	42,848

*Notes: Standard errors clustered by individual in parentheses. The dependent variable of Model 1C is calculated based on the CBS data. It is a robustness check of Model 1A. Model 1D, Model 2C, Model 3C and Model 4C are robustness checks of Model 1B, Model 2B, Model 3B and Model 4B. They are not corrected for survival bias. All models include interaction terms between screening and years since diagnosis. Since those are all insignificant, they have been excluded from the table for the sake of brevity. All models include controls for: personal income, partner, income of the partner, number and age of the children, other health conditions and employment history in the year before diagnosis. *** p<0.01, ** p<0.05, * p<0.1*

Chapter 4: Husband's employment adjustments after their wife receives a breast cancer diagnosis [44]

4.1. 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.[45] 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

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

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).

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 chapter 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 allowed by law hours 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 when 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 chapter is as follows. Section 4.2 presents the theoretical framework and the institutional setting. Section 4.3 describes the data and Section 4.4 the method. Results are presented in Section 4.5, robustness checks in Section 4.6 and conclusions in Section 4.7.

4.2. Economic framework

4.2.1. 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; Bradley et al., 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.

4.2.2. 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.

4.2.3. 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.[46] 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).[47]

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

[47] For further insights into the impact of the breast cancer screening program on the survival and employment of women in the Netherlands, please see chapter 3.

4.3. 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 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 4.A for further details).

4.3.1. 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. In 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.

4.3.2. 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[48]; 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 4.1 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.

[48] 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.

Table 4.1. 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

Notes: 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.

4.3.3. 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 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.[49]

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.

4.3.4. Descriptive statistics

Table 4.2 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.

[49] A comparison table per matching covariate is available in Appendix 4.B. It shows that the two groups are comparable based on their observed characteristics.

Table 4.2. 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

Notes: 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.

4.3.5. 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:

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

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. $\upsilon_{i,t}$ 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.[50]

4.3.6. 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.[51] 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 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.

4.3.7. 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

[50] The estimates of equation (1) and the corresponding F-statistics are presented in Appendix 4.C.

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

employment of the wives of the treated and controls are equally likely to be employed before the treatment.

In table 4.3 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 4.3. 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 [a]	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

Notes: 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.

[a] *It is measured during the last 12 months*

4.4. 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:

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

where $\boldsymbol{G}$ 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 $\boldsymbol{G}$.

4.5. Empirical results

First, we considered the estimates of equation (2) (see Panel A of Table 4.4). 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 left side of Panel B of Table 4.4 shows the estimation results of equation (2) for the husbands whose wives were not employed before the diagnosis, and the right side of Panel B of Table 4.4 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.

Table 4.4. Estimates of equation (2)

Panel A: Full sample

Specification	Full sample			
	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00705**	0.00172	-0.0377	-0.00369
	(0.00286)	(0.00228)	(0.0503)	(0.00308)
Observations	638,523	515,907	515,907	515,907
R-squared	0.0067	0.0223	0.0017	0.0071
Individuals	17,293	14,881	14,881	14,881

Panel B: Selection based on employment of the wife

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00332	0.00401	-0.100	-0.00412	-0.00864***	0.000844	-0.0126	-0.00350
	(0.00567)	(0.00469)	(0.0964)	(0.00553)	(0.00328)	(0.00258)	(0.0589)	(0.00370)
Observations	194,269	142,586	142,586	142,586	444,254	373,321	373,321	373,321
R-squared	0.0071	0.0201	0.003	0.0058	0.0067	0.0234	0.0015	0.0079
Individuals	5,265	4,182	4,182	4,182	12,028	10,699	10,699	10,699

*Notes: The parameter estimates of the interaction term $\beta_1$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*

In Table 4.5, 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.[52] 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 4.5 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 4.5 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 4.5 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 4.5 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,[53] 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.

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

[52] 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 chapter.

[53] 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.

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).[54]

The fifth row of Table 4.5 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.

Table 4.5. 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

*Notes: 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*

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

4.6. Robustness checks[55]

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.[56] 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.[57] 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.

4.7. Conclusion

This chapter 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

[55] The estimates are presented in Appendix 4.F.

[56] The crosstabulation is presented in Appendix 4.C.

[57] See Appendix 4.E for a summary table and t-test comparison based on the wife's employment.

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 in 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 in 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.

Appendix

4.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.

4.B. Matching covariates of the cleaned sample

Table 4.B.1. Post-matching variables, after cleaning the data

Variable	Non-Treated		Treated					
	Mean	Std Dev	Mean	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

Notes: 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.

4.C. Common trends

Table 4.C.1. 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

*Notes: 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.

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

Table 4.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

Notes: 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.

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

Table 4.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

Notes: 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 4.E.2. Subsample of husbands whose wife is between 48 and 53 years old

Variable	Wife is not employed Mean	Std Dev	Wife is employed 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

Notes: 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.

4.F. Robustness checks

Table 4.F.1. AR(1): estimates of equation (2)

Panel A: Full sample

Specification	Full sample			
	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00370**	0.000554	-0.0788**	-0.00538**
	(0.00146)	(0.00158)	(0.0328)	(0.00256)
Observations	621,230	501,026	501,026	501,026
R-squared	0.00104	0.0142	0.00399	0.0191
Individuals	17,293	14,838	14,838	14,838

Panel B: Selection based on employment of the wife

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00415	0.00224	-0.0595	-0.00140	-0.00352**	0.000116	-0.0830**	-0.00614**
	(0.00274)	(0.00311)	(0.0647)	(0.00501)	(0.00173)	(0.00183)	(0.038)	(0.00296)
Observations	189,004	138,404	138,404	138,404	432,226	362,622	362,622	362,622
R-squared	0.00125	0.0197	0.00324	0.0269	0.00105	0.022	0.0022	0.029
Individuals	5,265	4,164	4,164	4,164	12,028	10,674	10,674	10,674

*Notes: 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 4.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

*Notes: 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 4.F.3. Four periods: estimates of equation (2)

Panel A: Full sample

Specification	Full sample			
	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00505	0.00410	-0.112	-0.00475
	(0.00354)	(0.00339)	(0.0716)	(0.00483)
Observations	69,014	55,696	55,696	55,696
R-squared	0.0098	0.0390	0.0021	0.0136
Individuals	17,293	14,797	14,797	14,797

Panel B: Selection based on employment of the wife

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	0.00465	0.0102	-0.102	0.00311	-0.00923**	0.00175	-0.113	-0.00763
	(0.00702)	(0.00748)	(0.140)	(0.00953)	(0.00407)	(0.00370)	(0.0832)	(0.00558)
Observations	20,998	15,381	15,381	15,381	48,016	40,315	40,315	40,315
R-squared	0.0102	0.0331	0.002	0.0126	0.01	0.0421	0.0023	0.0142
Individuals	5,265	4,151	4,151	4,151	12,028	10,646	10,646	10,646

*Notes: 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 4.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

*Notes: 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 4.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

Notes: 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 4.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

*Notes: 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 4.F.7. Wife Age 48 to 53: estimates of equation (2)

Panel A: Full sample

Specification	Full sample			
	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00598**	0.00241	-0.0272	-0.00214
	(0.00301)	(0.00245)	(0.0540)	(0.00327)
Observations	563,415	453,015	453,015	453,015
R-squared	0.0069	0.0224	0.0021	0.0067
Individuals	15,260	13,075	13,075	13,075

Panel B: Selection based on employment of the wife

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00353	0.00393	-0.127	-0.00641	-0.00708**	0.00178	0.0126	-0.000472
	(0.00590)	(0.00508)	(0.103)	(0.00598)	(0.00347)	(0.00277)	(0.0633)	(0.00390)
Observations	175,366	128,136	128,136	128,136	388,049	324,879	324,879	324,879
R-squared	0.0074	0.0197	0.0034	0.0055	0.0069	0.0239	0.0018	0.0075
Individuals	4,753	3,755	3,755	3,755	10,507	9,320	9,320	9,320

*Notes: 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 4.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

*Notes: 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 4.F.9. Husband Age below 60: estimates of equation (2)

Panel A: Full sample

Specification	Full sample			
	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00701**	0.00191	-0.00285	-0.00203
	(0.00281)	(0.00230)	(0.0478)	(0.00296)
Observations	610,585	504,062	504,062	504,062
R-squared	0.0051	0.0232	0.0012	0.0087
Individuals	16,534	14,448	14,448	14,448

Panel B: Selection based on employment of the wife

Specification	Wife is not employed				Wife is employed			
	Employment	LnHWage	Working hours	LnMonthly income	Employment	LnHWage	Working hours	LnMonthly income
Basic model	-0.00488	0.00434	-0.0652	-0.00315	-0.00794**	0.000990	0.0230	-0.00157
	(0.00571)	(0.00475)	(0.0912)	(0.00532)	(0.00319)	(0.00260)	(0.0562)	(0.00354)
Observations	183,810	139,231	139,231	139,231	426,775	364,831	364,831	364,831
R-squared	0.0062	0.0208	0.0023	0.0072	0.0048	0.0244	0.0010	0.0096
Individuals	4,980	4,055	4,055	4,055	11,554	10,393	10,393	10,393

*Notes: 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 4.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

*Notes: 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*

Chapter 5: Conclusion

This dissertation contributes to the research of the changes in labor market participation after a female adverse health event. The focus of the three core chapters is on the relation of elements of the Dutch institutional setting to the impact of adverse health on employment. The second chapter provides a general overview of the employment adjustments of women who have suffered from an adverse health event. The analysis considers the differences in employment adjustments among women who have different job protection coverage after the adverse health event. The third chapter analyses the employment gains of the nationwide breast cancer screening program, which is a health policy aimed at early diagnosis of breast cancer. The fourth chapter researches the difference in spillover effects after a breast cancer diagnosis on the spouse's employment among families with different coverage of the sick leave policy.

The overarching question researched in the three chapters is whether the labor market consequences of a female adverse health event could be affected by the institutional setting. To answer this question, each chapter provides an answer to one of the following sub-questions:

- ❖ Does the job protection policy in the Netherlands mitigate the negative effect of an adverse health on employment? (Chapter 2)
- ❖ To what extent can the change in employment after an adverse health event be explained by the job protection policy and/or the severity of the health condition? (Chapter 2)
- ❖ Does the nationwide breast cancer screening program, which aims at reducing the severity of the health condition by providing early checks, result in productivity gains? (Chapter 3)
- ❖ Can the income replacement during sick leave after a breast cancer diagnosis be related to the provision of caregiving by the spouse? (Chapter 4)

5.1. Results and contributions

5.1.1. Women's labor market participation after an adverse health event

Chapter 2 analyses the employment adjustments of women after an adverse health event. It provides an empirical analysis of administrative Dutch data which follows women aged 25 to 55 during four years after an adverse health event. The chapter is based on Grossman's (1972) theory that after an adverse health event, individuals need to take time off work so that they can spend time on recovering their health. According to Grossman's theory the reduction in employment should be highest immediately after the adverse health event and the effect should decrease over time. However, this is not the pattern observed in reality: the negative effect of adverse health on employment increases over time (Halla and Zweimüller, 2013; García-Gómez, Van Kippersluis, O'Donnell and Van Doorslaer, 2013). Thus, this chapter analyses whether this pattern can be explained by the institutional setting, namely sick leave and job protection, and/or the type of health condition; and whether the magnitude of the negative effect of health on employment differs in relation to the coverage of the institutional setting and/or the type of health condition.

The results show that women who experienced an adverse health event are likely to leave their employment from the time of diagnosis up to four years later, which is in line with previous studies. The observed reduction in employment of 1.06 percentage points in the fourth year after the diagnosis is comparable to the additional observed mortality among this group of women over the same time period. For the women who stay in employment, I found that they are likely to work less hours after an adverse health event, namely 4.5 hours a year in the year of diagnosis and 12 hours a year four years later. For women who are in permanent employment and therefore cannot be laid off during the first two years after the onset of the health condition, the job separation is likely to happen only after the initial protection period and to a lesser extent (0.44 percentage points). Lastly, considering the wage adjustments, I did not find differences between the women who were and were not diagnosed, which is in accordance with the findings of the rest of the literature. Interestingly, this was also the case for the women in permanent employment. However, I found some important differences in the wage adjustments when I considered the different types of adverse health events. First, I found that temporary health conditions were related to a temporary decrease in the wage profile: 1.7 percent reduction one year after the diagnosis for breast cancer patients, and 0.5 percent for other cancer patients, followed by partial wage recovery for the former and full wage recovery for the later by the fourth year after the diagnosis. Second, I found that the chronic and incapacitating conditions such as circulatory conditions are related to a long term decrease in the wage profile (approximately 0.5 percent). Third, I found two different patterns after chronic and non-incapacitating health conditions, namely no wage difference after respiratory conditions and continuously lower wage profile after nutritional conditions.

Chapter 2 has the following contributions:

- An empirical analysis has been performed, which considers simultaneously the degree of institutional protection for women suffering from an adverse health event and the severity of their health condition and as a result disentangles the effect of both on the labor market participation.
- It has been found that diagnosed women aged 25 to 55 gradually decrease their working hours during the years of institutional protection; while after the institutional protection, women are likely to leave their employment rather than reduce their working hours.
- It has been shown that the labor market participation of women after an adverse health event is related to the type of their work contract, and thus the degree of institutional protection. Diagnosed women in permanent employment reduce their employment 41.4% less in comparison to the population of diagnosed women.
- The empirical analysis of different types of health conditions (namely, temporary health conditions; chronic and incapacitating health conditions; chronic and non-incapacitating health conditions) which is performed in the chapter shows that there are reductions in employment after all adverse health events. However, the changes in the wage profile could be related to the type of health condition.

5.1.2. The effects of nationwide breast cancer screening on survival and employment after being diagnosed

Chapter 3 analyses the mortality and employment gains from the Nationwide breast cancer screening program in the Netherlands. It provides an empirical analysis based on Dutch administrative data which compares the mortality and employment of women who are covered by the program with women who are not covered by the program. The aim of the breast cancer screening program is early diagnosis which is expected to lead to lower mortality. As a result, the mortality gains have been widely researched before. The potential impact on employment, however, has not been considered before in the literature. Following Grossman (1972) an early diagnosis would imply less severe health shock and as such it is likely to require less recovery time and thus lead to less reduction in employment.

In chapter 3 I find that access to breast cancer screening reduces the mortality rate by 30.8 percent in the first year after diagnosis, which is in line with previous research (Njor et al., 2012). Next, I found that access to breast cancer screening leads to 6.3 percent higher probability of employment in the first year after the diagnosis. Furthermore, while I did not find changes in the mortality rate related to the time since diagnosis, I found that women's employment probability decreases during the four years after the diagnosis. Additionally, I found that the decrease in employment is strongest after the second year, which could be related to the institutional job protection system in the Netherlands during the first-two years after an adverse health event. However, these patterns were not affected by providing breast cancer screening nationwide.

Chapter 3 has the following contributions:

- A new empirical model has been specified which corrects the mortality equation for the cohort specific population mortality trends. The employment equation has been specified in a similar manner and further expanded with the inverse Mills ratio, which has been calculated based on the mortality equation, to correct for the improved survival probability of the breast cancer survivors from the nationwide breast cancer screening program.
- It has been found that women who have access to the nationwide breast cancer screening in the Netherlands have 6.1% higher employment probability in the year after the diagnosis in comparison to women who have been diagnosed with breast cancer when the program was not available.

5.1.3. Husband's employment adjustments after their wife receives a breast cancer diagnosis

Chapter 4 analyses the effect of an adverse health event on the employment of the spouse, the so-called spillover effects. Based on administrative Dutch data I follow the husbands of women who have been diagnosed with breast cancer for two years after the diagnosis and compare their employment to husbands whose wives were not diagnosed with breast cancer. According to Berger (1983) the spillover effects are dependent on the tasks that the spouse needs to compensate for, thus a reduction in employment in case the unhealthy spouse was specialized in home production; and respectively increase in employment in case the unhealthy spouse was working. Chapter 4 takes a novel approach in considering the spillover effects by looking at the opportunity for replacement income from sick leave. As such the analysis disentangles the caregiving and income effects.

Chapter 4 finds that husbands are 0.71 percentage points less likely to be employed after their wives' health deteriorates. While husbands whose wives were employed before the diagnosis have a 0.86 percentage points lower employment probability after she is diagnosed, the employment probability of husbands whose wives were not employed did not decrease.

Such a result could be explained by the replacement income during the sick leave, which reduces the financial loss for the family and could aid the husband to spend more time with his wife. I considered as well whether differences in the severity of the diagnosis of the wife and the family composition could be related to the employment adjustments of the husband. While I found that later diagnosis, widowhood, and older age of the husband are not related to a different employment probability of the husband, I did find differences related to having children in the household. In general, husbands were likely to have a higher employment probability when there were children in the household, and especially in the households where the wife was not employed before the diagnosis. These results can be related to a stronger financial constraint in the presence of children in the household.

Chapter 4 has the following contributions:

- It has been found that husbands reduce their employment to provide caregiving even though they could take caregiving leave, thus suggesting that the legally allowed caregiving leave may not be sufficient.
- A new social phenomenon has been found in the comparison of the employment of husbands whose wives were diagnosed with breast cancer. Caregiving is observed only in the families where the wife was working before the breast cancer diagnosis and there is income replacement during the sick leave period.
- It has been found that there is no effect of the access to the nationwide breast cancer screening program, whether the husband is a widower, nor the husband being older than 60 years old, on the employment of the husband after the breast cancer diagnosis of his wife.
- The empirical analysis performed in the chapter shows that in the families where the wife was not employed before the diagnosis, the husband increased his employment probability with 3.4 percentage points when there were children in the family in comparison to the families without children. This result is not present in the families where the wife was employed before the diagnosis and is likely to be related to financial constraints.

5.2. Back-of-the-envelope calculation of employment probability gains and losses

This section attempts to combine the results from the three content chapters. Each chapter focuses on a specific situation where adverse health could have a negative impact on employment. I found that while there could be a negative effect on working hours and wage rate, the dominant effect of adverse health is on employment probability. The chapters focus on two policies – sick leave and nationwide breast cancer screening program, which could affect this negative effect. Chapter 2 looks extensively at the effect of different sick leave schemes on the labor market participation of women, irrespective of the adverse health event, as well as it considers specific health events. Chapter 3 and 4 focus on the employment consequences of breast cancer. While chapter 4 considers the impact of the sick leave policy on the spillover effects, thus the employment of the husband, chapter 3 considers the impact of breast cancer screening as a policy aiming at earlier diagnosis, thus having the potential to bring employment gains.

In terms of coverage of the period after the diagnosis, chapter 2 and 3 consider a time span of 4 years, and chapter 4 considers a time span of 2 years. To keep the back-of-the-envelope calculations of employment probability gains (and losses) consistent as much as possible, the calculations below are performed with the point estimates of the second year after the diagnosis.

In chapter 2, I found that there is increase in employment probability from the sick leave regulation. I considered the employment changes of women after an adverse health event and I compared women based on their employment contract. I found that women who are in permanent employment, thus have a job protection during the first two years after the adverse health, are more likely to stay employed in the long term. (In this case all women receive the sick leave, however some women have a job to come back to, and other women do not).

A back-of-the-envelope calculation shows that the 2-year job protection leads to 4.42 percentage points higher employment probability two years after a breast cancer diagnosis, and 2.86 percentage points higher employment probability four years after a breast cancer diagnosis.[58]

[58] The calculation is based on 67.44% women in permanent employment at the time of the diagnosis, and 32.56% in temporary employment. Estimated decrease of employment probability for all women in the second year of the diagnosis of 1.44 percentage points and no change for the women in permanent employment, thus suggesting 4.42 percentage points decrease of employment for women in temporary employment. Similarly, four years after the diagnosis, the estimates show a 1.93 percentage points decrease of employment probability for the full sample,

In chapter 4 I considered the impact of the presence of sick leave for the spillover effects of breast cancer on the employment of the husband. I found that in the families where the wife was employed, thus she is entitled to income replacement during her sick leave, the husband is likely to reduce his employment probability by 0.86 percentage points during the two years after the diagnosis. While in the families, where the wife was not employed before the diagnosis, thus she is not eligible for sick leave and is likely that the husband is the only bread winner in the family, I did not observe a change in his employment probability in the two years after the breast cancer diagnosis. From these results it follows that the sick leave policy leads to 0.86 percentage points lower employment probability of the spouse.

Thus, combining the two results, the job protection/sick leave policy in the Netherlands is likely to lead to an increase of 3.56 percentage points (4.42 percentage points - 0.86 percentage points) in overall employment probability after breast cancer.

In chapter 3, I considered the employment differences between women covered by the national breast cancer screening program and women not covered by it. The aim of the program is early detection of the disease. I found that the program leads to 30.8% mortality gains and 6.3% employment gains in the second year after the diagnosis. Combining those two results leads to overall gains in employment probability of 1.94%. Since the average employment probability at the time of diagnosis is 67.38%, this implies that the gains in employment probability are 1.31 percentage points.

Overall, the combination of the current sick leave policy and nationwide breast cancer screening leads to increase of 4.87 percentage points (3.56 percentage points + 1.31 percentage points) in employment probability measured in the second year after the breast cancer diagnosis.

The overall increase in productivity suggests that besides the social aspect of providing the sick leave policy and the national breast cancer screening program (which is provided for free to women in the Netherlands), there is also an economic aspect: both policies lead to a higher overall productivity. Thus, when evaluating the costs of those programs and whether they should be implemented or not, the decision should also include the productivity gains from the enrollment in those programs.

The policy relevance of this dissertation is two-fold. First, with respect to the institutional setting in the Netherlands, my results suggest that the employment probability, and in general the productivity, of women on temporary contracts is likely to benefit from them

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and 1 percentage point decrease for the women in temporary employment, thus suggesting a 3.86 percentage points decrease of employment for temporary employed women.

being able to return to their employer when they recover from an adverse health event. Thus, extending the coverage of the sick leave policy to provide temporary employees with the opportunity to return to work is likely to lead to productivity gains. Second, from a global policy perspective, my results show that the benefits of the nationwide breast cancer screening program are related not only to mortality gains, but also to productivity gains. Given the fact that very few countries provide a nationwide breast cancer screening program, my results suggest that when a government considers implementing such a program, they should also take into account the positive effect on productivity in order to make a more accurate cost-benefit analysis of implementing the program.

5.3. Limitations and further research

A few limitations of the analysis are worth mentioning. First, the analysis in this dissertation is performed on high quality administrative data. While such data is very powerful for econometric analysis, it provides limited insights into some of the underlying adjustment mechanisms. Namely, I find that there is a reduction in employment after an adverse health event, however from the analysis it is not clear whether women change their preferences for work and thus decide to reduce their employment; or whether the change in employment results from health-related discrimination from their employer. Further analysis on qualitative data would be beneficial for understanding the reasons for the adjustments.

Second, while I observe the employment probability, working hours and wage of the women, I do not observe their work tasks. Thus, it is not clear which tasks women can and cannot perform during and after their recovery. Further research focusing on feasibility of specific work would be beneficial in understanding whether by changing the tasks that women have to perform, their re-integration back in the work force can be improved.

Third, the analysis is based on situations where the woman suffers from an adverse health event. Further analysis considering situations where a man receives a diagnosis would be beneficial for understanding whether there are gender differences in the augmenting effect of the institutions on the effect of the adverse health event on employment.

Fourth, while this thesis considers individual employment patterns, further research into the labor supply of the entire household could be beneficial. As employment decisions are likely to be join decisions in the household, modeling the employment of the two spouses simultaneously could provide further insights into the total effect of adverse health on employment.

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Nederlandstalig samenvatting

Motivatie en doel

Verbeteringen in medische behandelingen hebben ertoe geleid dat relatief meer mensen in de werkende leeftijd volledig kunnen herstellen van levensbedreigende ziekten, waardoor ze in staat zijn om betaalde werkzaamheden te hervatten. Een deel van de overlevenden keert echter niet terug naar de oude werksituatie van vóór de ziekte: ze worden minder actief op de arbeidsmarkt, gaan met pensioen of raken gedeeltelijk arbeidsongeschikt (García-Gómez, 2011). Bij een vergrijzende bevolking en het met leeftijd toenemende risico op ernstige gezondheidsproblemen zal het aantal mensen met ernstige gezondheidsproblemen waarschijnlijk toenemen (Loisel en Anema, 2013). Behalve dat dit de economie kan belasten, heeft het een negatief inkomenseffect op degenen die hersteld zijn van de ziekte (Halla en Zweimüller, 2013; García-Gómez, Van Kippersluis, O'Donnell en Van Doorslaer, 2013); bovendien kan het arbeidsaanbod van andere gezinsleden worden beïnvloed (García-Gómez et al., 2013; Jeon en Pohl, 2017).

Het doel van dit proefschrift is om een bijdrage te leveren aan kennis over de arbeidsmarktprestaties van individuen in hun reactie op gezondheidsproblemen van vrouwen. Onderzocht wordt hoe onderdelen van de Nederlandse institutionele context aan deze uitkomst kunnen worden gerelateerd. Een gezondheidsprobleem is hierbij het gevolg van een medische diagnose tijdens een ziekenhuisopname (klinisch of dagopvang). Aangezien er waarschijnlijk medische verschillen zijn tussen mannen en vrouwen, richt dit proefschrift zich op situaties waarin vrouwen geconfronteerd worden met gezondheidsproblemen.

Voor de beantwoording van de overkoepelende vraag, behandelt elk hoofdstuk een andere dimensie en beantwoordt een van de volgende deelvragen:

- ❖ Vermindert de Nederlandse werkgelegenheidsbescherming het negatieve effect van een gezondheidsprobleem op werkgelegenheid? (Hoofdstuk 2)
- ❖ In hoeverre kan een verandering in het arbeidsaanbod na een gezondheidsprobleem worden verklaard door het beleid inzake werkgelegenheidsbescherming en/of de ernst van de gezondheidsprobleem? (Hoofdstuk 2)
- ❖ Resulteert het landelijk borstkanker-onderzoek, dat gericht is op het verminderen van de ernst van de gezondheidsprobleem, in productiviteitswinsten door vroege controles aan te bieden? (Hoofdstuk 3)

- ❖ Kan de inkomensvervanging tijdens ziekteverlof na een diagnose van borstkanker worden gerelateerd aan het verlenen van mantelzorg door de echtgenoot? (Hoofdstuk 4)

Structuur van het proefschrift

Dit proefschrift draagt bij aan het onderzoek naar de veranderingen in de arbeidsmarktparticipatie na een negatieve gezondheidssituatie bij vrouwen. Het bevat een introductie, drie kernhoofdstukken en een conclusie. De focus van de drie kernhoofdstukken betreft de impact van gezondheidsproblemen op de werkgelegenheid in relatie tot onderdelen van Nederlandse arbeidsmarktinstituties. Hoofdstuk 2 geeft een algemeen overzicht van de aanpassingen van werkgelegenheid van vrouwen die geconfronteerd worden met een gezondheidsprobleem. De analyse belicht hierbij de reacties van vrouwen met een verschillende mate van werkgelegenheidsbescherming. Hoofdstuk 3 analyseert de werkgelegenheidswinsten door het landelijk bevolkingsonderzoek borstkanker, dat gericht is op een vroege diagnose van borstkanker. Hoofdstuk 4 richt zich op de invloed van een diagnose van borstkanker bij vrouwen op het arbeidsaanbod van hun partner. Hierbij wordt er een relatie gelegd met van de mogelijkheid tot ziekteverzuim bij een betaalde baan van de gediagnosticeerde vrouwen.

Hoofdstuk 2: Arbeidsmarktparticipatie van vrouwen na een gezondheidsprobleem

Hoofdstuk 2 beschrijft de uitkomsten van een onderzoek naar de werkgelegenheidsaanpassingen van vrouwen nadat er bij hen een gezondheidsprobleem is vastgesteld. De analyse legt een relatie tussen de aanpassing van werkgelegenheid aan de werkgelegenheidsbescherming en de ernst van het gezondheidsprobleem. De analyse is gebaseerd op Nederlandse administratieve gegevens over de periode 2004 - 2012, waarbij vrouwen van 25 tot 55 jaar gedurende vier jaar na de medische diagnose zijn gevolgd. Er wordt hierbij gebruik gemaakt van informatie over hun werkgelegenheid, de omvang van hun arbeidsaanstelling en hun uurloon.

Uit de empirisch resultaten blijkt dat vrouwen die een gezondheidsprobleem hebben gehad hun baan zullen verlaten vanaf het moment van diagnose tot vier jaar later, wat een bevestiging is van eerdere studies. De gevonden daling van de werkgelegenheid van 1,06 procentpunten in het vierde jaar na de diagnose is vergelijkbaar met de hogere mortaliteit bij deze groep vrouwen in dezelfde periode. Verder wordt gevonden dat de vrouwen die aan het werk blijven, minder uren werken na een gezondheidsprobleem. Er is een daling van 4,5 uur per jaar in het jaar van diagnose tot 12 uur per jaar vier jaar later. Voor vrouwen die in vaste dienst zijn en daarom niet ontslagen kunnen worden gedurende de eerste twee jaar na het begin van de gezondheidsprobleem, zal de een baanverandering banen met name plaatsvinden na de initiële beschermingsperiode (0,44 procentpunten). Ten slotte zijn er met betrekking tot mogelijke aanpassingen van het uurloon geen verschillen tussen de vrouwen die wel of niet gediagnosticeerd waren, wat in overeenstemming is met de bevindingen van de rest van de literatuur. Interessant genoeg was dit ook het geval voor de vrouwen in vaste dienst.

Er zijn belangrijke verschillen in de loonaanpassingen tussen de verschillende soorten gezondheidsproblemen. Ten eerste zijn tijdelijke gezondheidsproblemen gerelateerd aan een tijdelijke verlaging van het uurloon: 1,7 procent reductie een jaar na de diagnose voor borstkankerpatiënten en 0,5 procent voor de overige kankerpatiënten, hetgeen gevolgd wordt door een gedeeltelijk herstel van het loon voor de eerste groep en een volledige loonterugval voor de tweede groep in het vierde jaar na diagnose. Ten tweede zijn de chronische en invaliderende gezondheidsproblemen, zoals circulatoire problemen, gerelateerd aan een langdurige daling van het uurloon (ongeveer 0,5 procent). Ten derde zijn er twee verschillende patronen na chronische en niet-invaliderende gezondheidsproblemen, namelijk geen loonverschil na respiratoire problemen en een permanent lager loon na voedingsproblemen.

Hoofdstuk 3: De effecten van bevolkingsonderzoek borstkanker op overleving en werk na de diagnose borstkanker

Hoofdstuk 3 gaat over het verschil in de werkgelegenheid van vrouwen die gediagnosticeerd worden op borstkanker op basis van de ernst van hun diagnose. Het vergelijkt het arbeidsaanbod van vrouwen bij wie de diagnose is gesteld toen zij toegang hadden tot het Nederlandse bevolkingsonderzoek borstkanker met vrouwen die geen toegang hadden tot het programma. De empirische analyse wordt uitgevoerd aan de hand van Nederlandse administratieve gegevens van 2000 tot 2012 die informatie bevatten over de leeftijd van de vrouwen tijdens de diagnose, hun sterfte en werkgelegenheid. Het richt zich op een steekproef van 9040 vrouwen die een borstkanker diagnose tussen 48 en 53 hebben gekregen en maakt gebruik van het feit dat de toegang tot het bevolkingsonderzoek borstkanker begint op de leeftijd van 50.

Uitkomst van het empirische analyse is dat de toegang tot het bevolkingsonderzoek borstkanker het sterftecijfer met 30,8 procent verlaagt in het eerste jaar na diagnose, wat in lijn is met eerder onderzoek (Njor et al., 2012). Bovendien wordt gevonden dat toegang tot het bevolkingsonderzoek borstkanker leidt tot een 6,3 procent hogere kans op werk in het eerste jaar na diagnose. Hoewel er geen veranderingen in de mortaliteit zijn gevonden die verband houden met de verstreken tijd sinds de diagnose van borstkanker, blijkt uit de schattingen dat kans op arbeid van deze groep vrouwen afneemt in de vier jaar na de diagnose. Daarnaast wordt gevonden dat de daling van de werkgelegenheid na het tweede jaar verklaard kan worden door het institutionele systeem van werkgelegenheidsbescherming in Nederland gedurende de eerste twee jaar na een gezondheidsprobleem. Deze patronen worden echter niet beïnvloed door het bevolkingsonderzoek borstkanker.

Hoofdstuk 4: Arbeidsmarktaanpassingen van mannen nadat bij hun partner de diagnose borstkanker is gesteld

Hoofdstuk 4 richt zich op de indirecte kosten van een borstkankerdiagnose bij vrouwen op de arbeidsmarktparticipatie van hun echtgenoot. Na een diagnose zijn er twee tegengestelde effecten die kunnen leiden tot veranderingen in de arbeidsparticipatie van de echtgenoot. Zorg aan de partner leidt tot een afname van het arbeidsaanbod van de mannen, terwijl het ook kan leiden tot een toename van het arbeidsaanbod om de gederfde inkomsten van hun partner op te vangen.

Op basis van individuele administratieve gegevens voor de periode 2006 tot 2011, gebruikt het hoofdstuk een combinatie van Coarsened Exact Matching en een difference-in-difference schattingsstrategie om gezinnen te vergelijken waarbij er voor de vrouw de diagnose borstkanker is gesteld en gezinnen waar dat niet het geval is.

Uit de schattingen blijkt dat mannen een 0,71 procentpunten lagere kans op werk hebben nadat borstkanker is gediagnosticeerd bij hun partner. Het maakt daarbij een verschil of de vrouwen een betaalde baan hadden vóór de diagnose. In het geval een betaalde baan neemt de kans op werk van mannen af met 0,86 procentpunt, terwijl er geen effect wordt gevonden bij vrouwen die geen betaalde baan hebben. Dit resultaat kan worden verklaard door het vervangingsinkomen tijdens het ziekteverlof, waardoor het financiële verlies voor het gezin wordt verminderd en de man en vrouw meer tijd samen kunnen doorbrengen. Bovendien wordt geanalyseerd of de verschillen in de ernst van de diagnose van de vrouw en/of de gezinssamenstelling gerelateerd kunnen worden aan het arbeidsaanbod van de echtgenoot. Hoewel latere diagnose, weduwschap en hogere leeftijd van de man geen verband houden met het arbeidsaanbod van de mannen, was er wel een verschil met betrekking tot thuiswonende kinderen. Over het algemeen hadden mannen een hogere kans op werk na diagnose als er kinderen in het huishouden waren, en vooral in de huishoudens waar de vrouw vóór de diagnose niet in dienst was. Deze resultaten kunnen verband houden met een sterkere financiële beperking in de aanwezigheid van kinderen in het huishouden.

Impact van borstkanker op werkgelegenheid en verdere beleidsimplicaties

Op basis van de empirische bevindingen in elk hoofdstuk voer ik een tentatieve berekening uit de effecten van verzuim op het arbeidsaanbod. De conclusie hieruit is dat de combinatie van het huidige ziekteverzuimbeleid en het bevolkingsonderzoek borstkanker leidt tot een toename van 4,87 procentpunt van de werkgelegenheid in het tweede jaar na een diagnose borstkanker.

De algemene productiviteitsverhoging duidt erop dat naast het sociale aspect van het bieden van het ziekteverzuimbeleid en het bevolkingsonderzoek borstkanker (dat kosteloos aan vrouwen in Nederland wordt verstrekt), er ook een economisch aspect is: beide vormen van beleid leiden tot een hoger algemene productiviteit. Bij een evaluatie van de kosten van deze programma's behoort deze productiviteitswinst te worden meegenomen.

De beleidsrelevantie van dit proefschrift is tweeledig. Ten eerste suggereren de resultaten dat, gezien de institutionele situatie in Nederland, de kansen op werk, en in het algemeen de productiviteit, vrouwen met een tijdelijk contract zullen profiteren van het feit dat zij naar hun werkgever kunnen terugkeren als zij herstellen van een gezondheidsprobleem.

Het uitbreiden van de dekking van het ziekteverzuimbeleid om werknemers met een tijdelijk dienstverband de kans te geven om weer aan het werk te gaan, zal kunnen leiden tot productiviteitswinst. Ten tweede laten de resultaten vanuit het oogpunt van het mondiale beleid zien dat de voordelen van het bevolkingsonderzoek borstkanker niet alleen verband houdt met de afname van sterfte, maar ook met winsten in de productiviteit. Gezien het feit dat maar heel weinig landen een bevolkingsonderzoek borstkanker hebben, suggereren de resultaten dat wanneer een overheid overweegt een dergelijk programma in te voeren, zij ook rekening moeten houden met het positieve effect op de productiviteit om een meer accurate kosten-batenanalyse te maken van de uitvoering van het programma.

Bijdragen van dit proefschrift

Hoofdstuk 2 'Arbeidsmarktparticipatie van vrouwen na een gezondheidsprobleem' bevat de volgende bijdragen:

- Er is een empirische analyse uitgevoerd, waarin de mate van institutionele bescherming wordt gerelateerd aan de ernst van de gezondheidstoestand bij vrouwen die aan een gezondheidsprobleem leiden. De interactie daartussen kan een effect hebben op de arbeidsmarktparticipatie.

- Het is gebleken dat gediagnosticeerde vrouwen van 25 tot 55 hun arbeidstijd geleidelijk afnemen in de jaren van institutionele bescherming van ziekteverzuim. Na deze periode verlaten vrouwen hun baan eerder dan dat ze hun werktijden verkorten.
- Er is aangetoond dat de arbeidsmarktparticipatie van vrouwen na een gezondheidsprobleem gerelateerd is aan het type arbeidsovereenkomst, en daarmee de mate van institutionele bescherming. Gediagnosticeerde vrouwen in vaste dienst verminderen hun baan met 41,4% minder in vergelijking met de populatie van gediagnosticeerde vrouwen.
- De empirische analyse van gezondheidsproblemen die ontstaan zijn vanuit diverse medische diagnoses (namelijk tijdelijke gezondheidsproblemen, chronische en invaliderende gezondheidsproblemen, chronische en niet-invaliderende gezondheidsproblemen) die in het hoofdstuk worden uitgevoerd, toont aan dat er na alle gezondheidsproblemen vermindering in werkgelegenheid zal zijn. De veranderingen in het uurloon kunnen echter verband houden met het soort gezondheidsprobleem.

Hoofdstuk 3 ‘De effecten van bevolkingsonderzoek borstkanker op overleving en werk na de diagnose borstkanker’ heeft de volgende bijdragen:

- Er is een nieuw empirisch model gespecificeerd dat de mortaliteitsvergelijking corrigeert voor de cohortspecifieke trends in populatiesterfte. De werkgelegenheidsvergelijking is op een vergelijkbare manier gespecificeerd en verder uitgebreid met de inverse Mills-ratio, die is berekend op basis van de mortaliteitsvergelijking, om te corrigeren voor de verbeterde overlevingskans van de overlevenden van borstkanker uit het bevolkingsonderzoek borstkanker.
- Er is geconstateerd dat vrouwen die toegang hebben tot het bevolkingsonderzoek borstkanker in Nederland een 6.1% hogere werkgelegenheidswaarschijnlijkheid hebben in het jaar na de diagnose in vergelijking met vrouwen bij wie de borstkanker diagnose werd gesteld toen het programma niet beschikbaar was.

Hoofdstuk 4 ‘Arbeidsmarktaanpassingen van mannen nadat bij hun partner de diagnose borstkanker is gesteld’ heeft de volgende bijdragen:

- Er is gebleken dat echtgenoten hun werk verminderen om zorg te bieden, ook al kunnen ze zorgverlof opnemen, wat suggereert dat het wettelijk toegestane zorgverlof niet voldoende zou zijn.
- Een nieuw sociaal fenomeen is gevonden in de vergelijking van de arbeidsaanbod van mannen wier vrouwen werden gediagnosticeerd met borstkanker. Zorg wordt alleen waargenomen in de families waar de vrouw werkte voorafgaand aan de borstkanker diagnose. Tijdens de periode van ziekteverlof is er dus sprake van inkomensvervanging.
- Er is vastgesteld dat er geen effect is van toegang tot het bevolkingsonderzoek borstkanker op het arbeidsaanbod van de man nadat bij zijn vrouw de borstkanker diagnose is gesteld voor weduwnaars of voor echtgenoot die ouder zijn dan 60 jaar,
- Uit de empirische analyse blijkt dat in de gezinnen waar de vrouw niet vóór de diagnose betaalde arbeid verrichte, de kans op werk van de man toenam met 3,4 procentpunten in het geval dat er kinderen in het gezin waren in vergelijking met de gezinnen zonder kinderen. Dit resultaat is niet aanwezig in de families waar de vrouw vóór de diagnose betaalde arbeid verrichtte. Dit duidt er op dat het arbeidsaanbod gerelateerd is aan financiële beperkingen.

De resultaten en bijdragen van dit proefschrift zijn georganiseerd en verspreid via drie wetenschappelijke artikelen. De eerste is gepubliceerd in de peer reviewed boekenserie Research in Labour Economics. De tweede en derde maken deel uit van de discussiepapierreeks van U.S.E. en in het proces van worden voorgelegd aan peer-reviewed tijdschriften.

- Kambourova, Z., Hassink, W., & Kalwij, A. (2019). Women's employment adjustments after an adverse health event. In S. Polachek & K. Tatsiramos (Eds.), *Health and Labor Markets* (pp. 25-70). *Research in Labor Economics*, Vol. 47, Emerald Publishing Limited
- Kambourova, Z., & Kalwij, A. (2019). The effects of nationwide breast cancer screening on survival and employment after being diagnosed. U.S.E. Working Paper Series (nr:19-09).
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Curriculum Vitae

Zornitza Kambourova was born in Sofia, Bulgaria in 1990. She graduated cum laude from the National Bank and Trading Highschool in Sofia, in 2009. Thereafter she moved to Utrecht, the Netherlands, where she followed the Economics and Business Economics Bachelor Program in Utrecht University as an honors student. She was awarded the Utrecht Excellence Scholarship for the period of her bachelor's degree. She received her bachelor's diploma also cum laude in 2012. As part of the program, she spent one year in Rome, where she studied Strategic Management at LUISS Guido Carly University. During her time in Utrecht she was an active member of the student organization ECU'92 and while in Rome, she was part of ESN Roma Luiss. Zornitza was then accepted in the two-year Multidisciplinary Economics Reseach Master at Utrecht University in 2012, for which she was awarded the Utrecht Sylff Scholarship. During her master's education, Zornitza was a teaching assistant for the courses Economic Growth, Corporate Finance and Mathematics. After completing successfully her master's degree, Zornitza became a PhD candidate at Utrecht University School of Economics. During her appointment, she presented her work at numerous scientific conferences. Zornitza was a member of the LEG PhD Council from 2015 to 2017. As part of her appointment at U.S.E., she was teaching assistant in the courses Empirical Economics, Statistics, Mathematics and the Summer School Introductory Econometrics. She received the ECU'92 Teacher Talent Award in 2017 as a recognition for her work from her students. Since April 2018, Zornitza has been working as a consultant at Quint Wellington Redwood.

Zornitza married Thomas van Hellemondt in 2017 and became a Dutch citizen in 2019.

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