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The Effects of Nationwide Breast Cancer Screening on Survival and Employment after Being Diagnosed

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Abstract
This paper uses Dutch administrative data to evaluate the survival and employment gains of a nationwide breast cancer screening program in the Netherlands for women who have been diagnosed with breast cancer. This program is a public health policy that targets women aged 50 – 75 and aims at early diagnosis to reduce mortality among women who are diagnosed with breast cancer. The sample consists of 9040 women aged 48 to 53 who are diagnosed with breast cancer and these are followed for four years after being diagnosed. The empirical analysis exploits that women aged 48 and 49 are not covered by the nationwide breast cancer screening program and women aged 50 – 53 are covered. The empirical findings show that nationwide screening for breast cancer reduces mortality with 31 percent and increases employment with 6 percent in the years after being diagnosed. The mortality and employment gains do not diminish during the four years after the diagnosis. From a policy perspective, these findings suggest substantial health and employment benefits of a nationwide breast cancer screening program.

Keywords: Breast cancer, screening, women, mortality, employment, the Netherlands

JEL classification: I12, I18, J21

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1. Introduction

Breast cancer is the most common type of cancer for women and the second deadliest in developed countries (GLOBOCAN, 2012). The Netherland, the country analyzed in this paper, 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%[1] 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.[2] 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 (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

[1] 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).

[2] 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).

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 paper 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 paper is organized as follows: Section 2 outlines the theoretical framework. Section 3 describes the data and Section 4 the empirical methodology. Section 5 presents the empirical results and Section 6 the robustness checks. Last, Section 7 summarizes the main results and concludes.

2. Institutional setting and literature

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[3]. 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.

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 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

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

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[4]. 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 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

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

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[5] (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 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

[5] 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).

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. 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).

3.1. 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 Kambourova, Hassink and Kalwij (2019), 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.

3.2. Descriptive statistics

Table 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 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 1 does not show any strong differences in the probability of having a partner between the various ages.

Table 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 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 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 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 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: 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 4 for summary statistics). They are all measured in the year before the diagnosis.

Table 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[6]	0.4998
Adults in household	9,040	2.3364	0.9047
Age of children	9,040	1.3492	1.7736
Number of children	9,040	1.2020	1.7353

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. 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 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.

[6] 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 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	Dead	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.

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.

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)[7]. However, there is no officially reported employment rate on a cohort level for each calendar year. Therefore, we calculate it based on the population data provided by Statistics Netherlands[8].

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

[8] 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 A).

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:

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

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 if 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 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. 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[9]. 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

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

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[10], 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:

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

where $E_{i,t}$ is equal to 1 if individual i is employed in time t; and 0 otherwise, $PER_{a_i t}$ 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

[10] 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.

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 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.

4.1. Estimation and identification

We estimate the following mortality model by Nonlinear Least Squares:

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

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:

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

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 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.[11]

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.

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 6 presents our main results.

The estimates from the mortality model (column 1 of Table 6) show that availability of the nationwide breast cancer screening program leads to a 30.8 percent 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

[11] $E(\varepsilon_{i,t} | M_{i,t} = 0) = -\sigma\lambda_{i,t}$, $\lambda_{i,t}(a) = \frac{-f(a)}{F(a)}$ 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.

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 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 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 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.[12] 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 5 which show path dependency in employment.

6. Robustness checks

We perform three robustness checks. The results are presented in Table 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 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 1, Section 3.2 for the proportion of women diagnosed at each age). The reference group for 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 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

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

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 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 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.

Overall, the results in Table 6 are robust to the checks performed in Table 7.[13]

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

Table 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 breast cancer screening program.*

Table 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 employed					-0.271	0.0395**
					(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.*

7. Summary and conclusions

This paper 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.

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Appendix 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 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 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

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

Model 1C in Table 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 A.2 show the results. The estimates are similar to the models where we correct for survival bias.

Table 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*