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*Jon H. Fiva, Torbjørn Hægeland and Marte Rønning*

# Health Status After Cancer
## Does It Matter Which Hospital You Belong To?

**Abstract:**
Survival rates are widely used to compare quality of health care. In this paper we introduce post-illness employment as a supplemental indicator of successful treatment of serious diseases. Utilizing rich register based data on cancer patients we document substantial differences across Norwegian hospital catchment areas with respect to employment five years after diagnosis. Conventional quality indicators based on survival rates indicate smaller differences. The two sets of indicators are only weakly correlated, suggesting that they capture different parts of the quality distribution, and that using only one of them may be insufficient.

**Keywords:** Quality indicators, health sector, survival, employment, cancer

**JEL classification:** I11, I12, J21

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**Address:** Jon H. Fiva, Department of Economics, University of Oslo. E-mail: j.h.fiva@econ.uio.no

Torbjørn Hægeland, Statistics Norway, Research Department. E-mail: thd@ssb.no

Marte Rønning, Statistics Norway, Research Department. E-mail: mro@ssb.no

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# 1 Introduction

Health care expenditures have grown dramatically over time in most industrialized countries, and currently account for on average 9 percent of GDP across OECD countries (OECD, 2007). The functioning of the health care system has large welfare implications, and it is important to evaluate how these resources are spent. If there are substantial quality differences across health institutions, this is worrisome both from efficiency and equity perspectives.

The existing literature on quality differences across health institutions and regions relies primarily on survival rates as proxies for successful treatment of diseases such as cancer and pneumonia (e.g. Iezzoni et al. 1996, Farrow et al. 1996, Gowrisankaran and Town, 1999, Geweke et al. 2003, Kravdal, 2006, OECD, 2007). That survival of the patients is an important quality dimension of health care, is beyond dispute. In many circumstances, however, survival rates may miss important aspects of quality of care. Even for many serious diagnoses, survival rates are high, and due to advances in medical technology, several illnesses that used to be lethal only a few decades ago now give patients a fair chance to survive, see e.g. Cutler (2008).

With death as a less likely outcome, assessment of health care solely based on differences in survival rates is less adequate if health status given survival may be affected by the treatment given. Quality indicators reflecting patients' long-term health status should therefore be considered.

The main contribution of this paper is to introduce post-diagnosis employment as a measure of successful treatment, and to compare quality indicators using survival and employment as outcome measures. We do not argue that the two sets of indicators are alternative quality measures. Rather, they may be complementary, as they focus on differences between health institutions at different points in the patient outcome distribution. To the extent that "health care quality" is not a one-dimensional phenomenon, i.e. that indicators based on different outcome measures yield different results, it is necessary either to use several indicators or to construct an outcome measure that assigns values on the same scale to different outcomes.

Our application is based on individual level data from the Norwegian Cancer Registry. The data contains information on disease characteristics, timing of diagnosis and time of death, and cover close to all cancer incidents in Norway. Furthermore, the cancer data contain a personal identifier allowing them to be merged with data on socio-economic background characteristics and labor market outcomes from administrative registers.

Several studies document that cancer may have a negative impact on employment and the ability to work. Based on survey data from the US, Bradley et al. (2005) find that 12 percent of women employed prior to breast cancer diagnosis appeared to move out of the labor force. Similarly, Short et

al. (2005) find that 13 percent of cancer survivors had quit working for cancer-related reasons within four years after diagnosis. The existing evidence on the relationship between cancer and labor market outcomes is dominated by studies based on a small set of patients,[1] but there are some exceptions. Syse et al. (2008) document that individuals surviving cancer are less likely to be employed in comparison to the cancer-free population in Norway. Taskila et al. (2005, 2007) come to slightly different conclusions using Finnish register data. A meta-analysis by de Boer et al. (2009) shows that patients often regard returning to work as an indicator of recovery, and that employment is also associated with a higher quality of life.

A majority of the papers assessing quality differences across health institutions perform their analysis at the hospital level. A key challenge for these studies of quality of health care is to account for selection of patients across hospitals. Systematic differences across hospitals with respect to observed patient characteristics can be controlled for in the analysis. However, if hospitals differ with respect to unobserved patient characteristics, and these characteristics are correlated with the outcome measure used, quality indicators will be biased. Most studies of health care quality ignore this issue (e.g. Farrow et al. 1996, Iezzoni et al. 1996, Paulsen et al., 2006). Important exceptions are Gowrisankaran and Town (1999) and Geweke et al. (2003) who show that selection issues are empirically relevant in the case of hospital quality indicators.

In this paper we exploit an institutional feature of the Norwegian health care system to handle the selection problem. Although cancer patients may receive treatment from more than one hospital, all patients are initially allocated to a local hospital strictly based on their residential address. We therefore, in our empirical analysis, assign patients to the hospital they belong to rather than to the hospital(s) they were actually treated at. Quality differences between hospital catchment areas may be due to differences in the quality of local hospital treatment, but also to differences with respect to sending patients to other hospitals with specialized competences, and regional differences in the quality of general practitioners. From the view of the patients, such a quality measure may be just as relevant.[2]

We document substantial differences across Norwegian hospital catchment areas with respect to employment five years after diagnosis. Quality indicators based on survival indicate smaller differences. The correlation between the two sets of indicators is modest, which suggest that they capture different part of the quality distribution. Conventional quality indicators based on differences in survival rates may therefore not reveal the full picture of quality differences in care across units.

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[1] Spelten (2002) offers a review of the small scale studies.

[2] Our analysis is related to Kravdal's (2006) investigation of regional variation in cancer survival in Norway. He documents differences in survival rates across Norwegian regions, even when controlling for a limited set of individual and regional characteristics. We extend upon Kravdal's analysis by utilizing a much richer set of patient characteristics, as well as considering other outcome measures.

# 2 Institutional settings

All Norwegian citizens are covered by the public health care system. Treatment, including highly specialized services, is mostly provided free of charge. In the period we study, responsibility of health care services was shared between the regional (county) and local (municipality) level of government. Local governments (n=440) had (and still have) the responsibility for primary health care (first and foremost provided by general practitioners (GP)), including both preventive and curative treatment. Counties (n=19) had the responsibility for somatic hospitals and specialized treatment. In 2002, the responsibility for somatic hospitals was transferred to the national government. Both municipalities and counties are multi-purpose authorities primarily financed through regulated income tax and block grants from the central government. Prior to the 2002 reform, health care accounted for about two-thirds of the expenditures of the counties (Carlsen, 1994).[3]

Until 2001, when free hospital choice was introduced, assignment dependent on residential address. Hence for a given address, patients could not freely choose in which hospital to be treated. In 2000, 55 such catchment areas existed.[4] To receive hospital treatment, except for emergency care, all citizens have to be referred by a GP. In the need for more specialized or intensive treatment, patients are referred to or transferred to hospitals outside their catchment area (either by the local hospital or by the GP).[5]

Norway is sparsely populated. Together with ambitious regional policy this implies that somatic hospitals in Norway vary a lot in terms of size, so does the size of the hospital catchment areas. The number of patients each catchment is responsible for varies from about 13,000 to about 507,000, with an average of about 90,000. In most cases, hospital catchment areas do not span more than one county. Appendix Figure A1 offers maps of hospital catchment areas and counties.

[3] To coordinate hospital planning the 19 counties have been grouped into five health regions (four after 2002) headed by health committees with county representatives. Cooperation among counties within health regions was voluntary up to 1999 when cooperation was made mandatory. In each health region there is a teaching hospital. Teaching hospitals are owned by the county where they are located, except for The National Hospital of Norway (Rikshospitalet) and The National Cancer Hospital (Radiumhospitalet), which were under the responsibility of the central health authorities. For a more thorough description of the Norwegian health care sector we refer the reader to Van den Noord et al. (1998) and Aakvik and Holmås (2006).

[4] Nine catchments have more than one local hospital. These catchments have one main hospital and one to three smaller units typically offering specialized treatment of other diseases than cancer.

[5] We cannot offer any evidence on the extent of treatment received outside catchment areas. In our data set, hospitals are made anonymous. Kravdal (2006) notes that patients that are referred to a hospital outside their own health region, usually receive treatment by one of the two national hospitals.

# 3 Data and descriptive statistics

The core data source in this analysis is individual level data from The Norwegian Cancer Registry. Reporting to the Cancer Registry is mandatory (and done by clinicians and pathologists), and the completeness of registration for solid tumors is close to 100 percent (Cancer Registry of Norway, 2008, Larsen et al., 2009). The Cancer Registry includes information on date of diagnosis; location of the tumor (cancer type); characteristics of the tumor (determined by specialists at hospital); and the date the death certificate was issued (if the patient has died).

Patients are identified in the Cancer Registry by a unique personal identification number. This allows us to merge in data on socio-economic background characteristics, local government of residence and labor market outcomes from different administrative registers. Data from the Cancer Registry is available since the 1950s, we use however on the period 1987 to 2000, because we do not have complete labor market data before 1987. Between 1987 and 2000, 236,234 individuals were diagnosed with cancer for the first time.

This analysis relies on two different criteria to assess the quality of health services: survival and employment, both measured five years after diagnosis. Clearly, employment is not a relevant indicator of wellness for all cancer patients. We exclude patients that are older than 59 years (approaching retirement) and younger than 21 (less likely to have entered the labor force) on the date of diagnosis. More than 70 percent of the total number of cancer patients is excluded from the analysis due to this restriction.

During the period 1987 to 2000, the hospital catchment structure was relatively stable. Most of the changes in the catchment structure were driven by catchment areas being merged (the total number of catchment areas decreased from 63 to 55 from 1987 to 2000). In our analysis, we rely on the catchment area structure that existed in 2000. We drop patients living (at the time of diagnosis) in local governments that did not belong to the same catchment the entire period (18 local governments). This implies dropping less than 2 percent of all patients. Our final sample consists of 46,720 cancer patients in 55 hospital catchment areas and 19 counties.

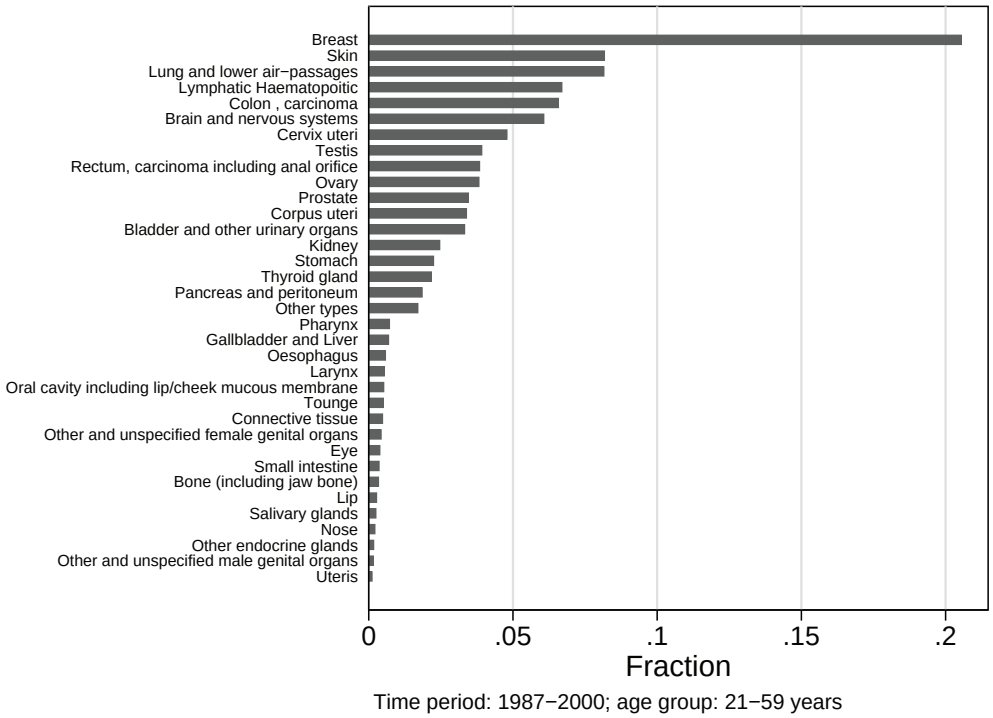
## 3.1 Characteristics of the disease

Cancer is a disease characterized by abnormal growth of cells. The severity of the illness depends in particular on where the tumor is located (cancer type) and whether the cancer has spread to other locations or not (metastasis).

Figure 1 shows the prevalence of different cancer types in our sample. The most common cancer type in our sample is breast cancer (22 percent). The second and third most prevalent cancer

types are lung cancer (8 percent) and skin cancer (8 percent).[6] In the regression analysis, we include dummy variables for cancer type according to the most detailed ICD7 classification. 211 different cancer types are represented in the sample.

**Figure 1: The distribution of the different cancer types (ICD7 classifications)**




On average, 65 percent of the cancer patients in our sample are alive five years after diagnosis and 39 percent are employed (see Table 1). These results mask considerable differences across cancer types. While about 80 percent of patients diagnosed with breast cancer are alive five years after diagnosis, only 13 percent of lung cancer patients are. The data reveal even larger discrepancies for employment. About 50 percent of breast cancer patients are employed five years after diagnosis, in comparison to only 5 percent of lung cancer patients. Figure 2 illustrates these results in detail for all cancer types, for survival after five years (upper panel) and employment after five years (bottom panel).

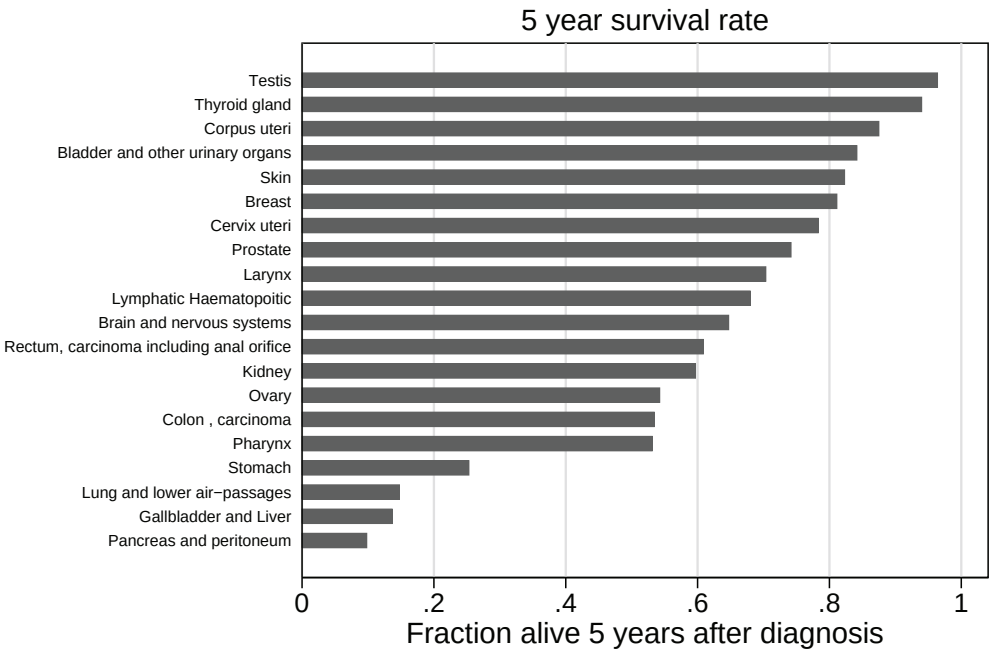
**Table 1: Success measures: means**

| Success measures | |
|---|---|
| Five year survival rate | 0.65 |
| Five year employment rate | 0.39 |

N=46,720 individuals

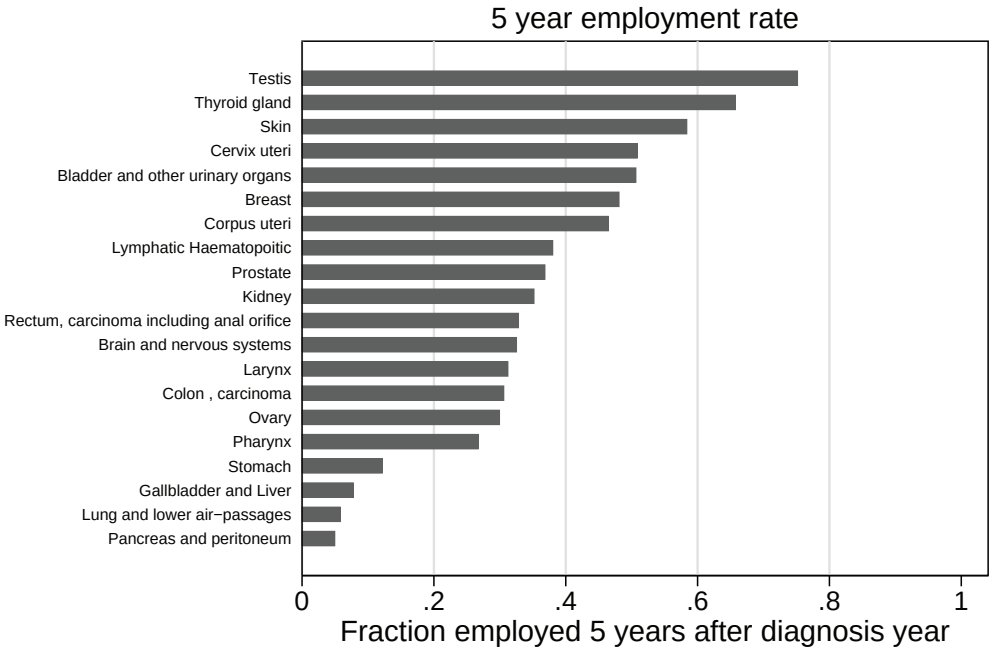
[6] The prevalence of different cancer types in the general population is slightly different from our sample. E.g. prostate cancer account for about ten percent of cancer in the general population, but only three percent in our sample. Appendix Figure A2 shows prevalence of different types of cancer for the whole cancer population (all age groups).

**Figure 2: Health status after cancer, by cancer type (ICD7 classifications)**




Time period: 1987−2000

20 most common cancer types (21−59 years) are included




Time period: 1987−2000

20 most common cancer types (21−59 years) years are included

Table 2 reports that 43 percent of the cancer patients had a localized tumor on the date of diagnosis (i.e., the tumor is located only in the originated tissue). 34 percent had a distant tumor (i.e. the malignant tumor has spread to other lymph nodes or organs). These can be divided into two subcategories: regional cancer (spread to nearby lymph nodes, 18 percent of the sample) and distant cancer (spread to other organs or lymph nodes farther away, 16 percent of the sample). For 24 percent of the patients, specialists are not able to determine degree of metastasis (these are therefore reported in the data to have unknown degree of metastasis on the date of diagnosis). The correlation between the type of the tumor and the chances of surviving is high. The average five year survival rate are is 83 percent for those with a localized tumor, 61 percent for those with regional spread and only 14 percent for those with distant cancer, as shown in Table 3. Patients with localized cancer are also more likely to be employed. Five years after the year of diagnosis, 52 percent of these individuals are employed. The corresponding numbers for patients with regional and distant cancer are 34 percent and 7 percent, respectively. In the regression analysis, we include dummy variables for the different types of metastasis.

**Table 2: Metastasis at the time of diagnosis, summary statistics**

| Metastasis | Mean |
|---|---|
| Localized | 0.43 |
| Regional | 0.18 |
| Distant | 0.16 |
| Unknown | 0.24 |

N=46,720 individuals

**Table 3: Relation between metastasis and success measures**

| Metastasis | Survival | Employment |
|---|---|---|
| Localized | 0.83 | 0.52 |
| Regional | 0.61 | 0.34 |
| Distant | 0.14 | 0.07 |
| Unknown | 0.70 | 0.31 |

N=46,720 individuals, reported are mean values

## 3.2 Other control variables

There may be considerable variation across different demographic and socioeconomic groups with respect to both severeness of a given disease and response to treatment. If this is the case, and there is systematic variation across hospital catchment areas with respect to socioeconomic characteristics of patients, failing to control for this will attribute (un)favorable patient or disease characteristics to hospitals. To minimize the chances of getting biased estimates of quality of care we include a rich battery of control variables capturing patient characteristics, such as gender, age, education and marital status.

Successful labor market outcomes do not only depend on quality of care, but also on local labor markets and previous employment history of the patients. A strength of our analysis is that we include control variables capturing labor market status of the patients before diagnosis, i.e. employment, working hours and dummies for industry affiliation (41 dummies). We consequently can net out local labor market characteristics that do not vary over time. Labor market status before diagnosis may also proxy for other unobserved patient characteristics, such as the patient's general health status. A descriptive overview of these variables is found in Appendix Table A1.

# 4 Empirical approach

The main aim of the paper is to investigate whether there are differences across hospital catchment areas with respect to post-diagnosis outcomes like survival and employment, taking into account differences in patient characteristics. Following Gowrisankaran and Town (1999) we base our analysis on the following model:

$$y_{ijt} = \text{Disease}_i\beta + \text{Patchar}_i\alpha + z_j\eta + \theta_t + \varepsilon_{ijt} \qquad (1)$$

$y_{ijt}$ is an outcome measure which takes value one if patient *i* who is a resident in hospital catchment area *j* is alive/working five years after being diagnosed with cancer for the first time on date *t*. $Disease_i$ is a vector consisting of variables describing the characteristics of the diseases such as cancer type and degree of metastasis at the time of diagnosis, $Patchar_i$ is a vector containing variables describing the patients' demographic and socioeconomic status (age, education level, gender, marital status and labor market and industry affiliation the year prior to diagnosis). Our parameters of interest are $\eta$. $\eta$ is a vector of hospital catchment specific effects denoting the effect on $y_{ijt}$ of being a resident of hospital catchment area *j*. Since quality of care is measured at the catchment area level, the estimated $\eta$ will capture differences in quality of care stemming from differences in local hospital quality, differences in the quality of general practitioners and differences with respect to sending patients to other hospitals with specialized competences. In order to capture general time trends, we also include a vector of year dummies, $\theta_t$. Finally, $\varepsilon_{ijt}$ is an error term assumed to be independent and identically distributed.

All control variables that we include in our model are discrete, and as Angrist (2001) points out, a linear probability model is then appropriate. We consequently estimate Equation (1) with Ordinary Least Squares (OLS).[7] When estimating Equation (1) with a linear probability model, the

[7] We have also experimented with a logit specification and the results are similar.

estimated η can be interpreted as quality of health care in hospital catchment area *j*, if catchment area *j* is faced with an average disease and patient composition.

Although patients in Norway are attached to a hospital based on residential address, they may still be transferred to hospitals outside their catchment area if sufficient treatment is not provided by their local hospital. The practice of transferring patients to other hospitals is based on both more or less formal rules and subjective judgments, and is in any case not fully codifiable. Hence relating patients to the hospital(s) they were actually treated at is problematic because we will then need to assume that patients that are transferred to other hospitals than their home hospital are similar to other patients (conditional on disease and patient characteristics). If this is not the case, e.g. if patients are transferred from smaller to larger hospitals for more specialized treatment, and these patients suffer from more severe diagnoses (that we do not observe or can control for), the results will be biased towards finding well performing small hospitals and poor performing larger hospitals. In addition, even though free hospital choice was not introduced in Norway in the period covered by our analysis, one cannot exclude the possibility that some patients had knowledge of which hospitals that provided better treatment, and was able to be referred or transferred to these hospitals. In general, however, the sign of the bias is not known.[8] In a related study to ours, Gowrisankaran and Town (1999) find that quality differences across hospitals are magnified when the selection problem is accounted for in a study of pneumonia patients in California. They use the distance from each patient's address to any given hospital as instrumental variables for hospital choice.

Assigning patients to the hospital they belong to minimize the chances of selection biases, although we cannot rule out that sorting of patients across hospital catchment areas takes place. Such sorting could in principle exist and be either explicit; e.g. patients with (unobserved) poorer health status may migrate to well performing hospital catchment areas (Tiebout, 1956); or implicit in the sense that moves across catchment areas are correlated with, but not motivated by the quality of health care offered in the catchment area. For $\hat{\eta}$ to be unbiased, and hence be given an interpretation as quality indicators (conditional differences in outcomes across hospital catchment areas), we need to assume that the $z_j$ are exogenous, i.e. there is conditional random assignment to hospital catchment areas. The conditional random assignment assumption implies that we assume that patients are not sorted across hospitals catchment areas based on factors that we do not control for and which simultaneously affect $y_{ijt}$.

[8] Another related methodological challenge is that patients sometimes receive treatment at more than one hospital (approximately 40 percent of the patients in our sample receive treatment at more than one hospital). It is not obvious how one should weight each hospital's contribution to treatment. The most straightforward solution would be to give each hospital equal weight. However, in many cases this is an unreasonable assumption, e.g. when patients gets immediately transferred from one hospital to another, or if patients get transferred from one hospital to another only to receive palliative care.

In the empirical analysis we rely on a very rich and comprehensive dataset, containing not only detailed information on diagnoses, but also detailed characteristics of patients with respect to socioeconomic characteristics and labor market status before illness. Our identifying assumption may nonetheless fail to hold if, conditional on all control variables, there is systematic variation across catchment areas in e.g. the extent patients suffer from comorbidities or the extent patients comply with medical protocols. To empirically investigate this possibility, we check whether $\hat{\eta}$ are sensitive to the inclusion of our rich set of patient characteristics. If they are insensitive to relevant observable characteristics, they are unlikely to change much if we could control for potentially relevant unobservable characteristics. For a more formal discussion of this argument, see Altonji et al. (2005).

# 5 Results

## 5.1 The estimated hospital catchment area fixed effects, $\hat{\eta}$

In our analysis we focus both on unconditional estimates, which we refer to as unadjusted indicators, and estimates based on the full set of control variables that we have available, which we refer to as adjusted indicators. As explained above, the predicted catchment area fixed effects can be considered as quality of health care in hospital catchment area, if catchment area is faced with an average disease and patient composition. For both success measures, the F-test strongly rejects the null hypothesis of no regional variation in quality of care. For employment the relevant p-value is 0.000 for both unadjusted and adjusted indicators. For survival the relevant p-value is 0.000 for unadjusted and 0.032 for adjusted indicators.

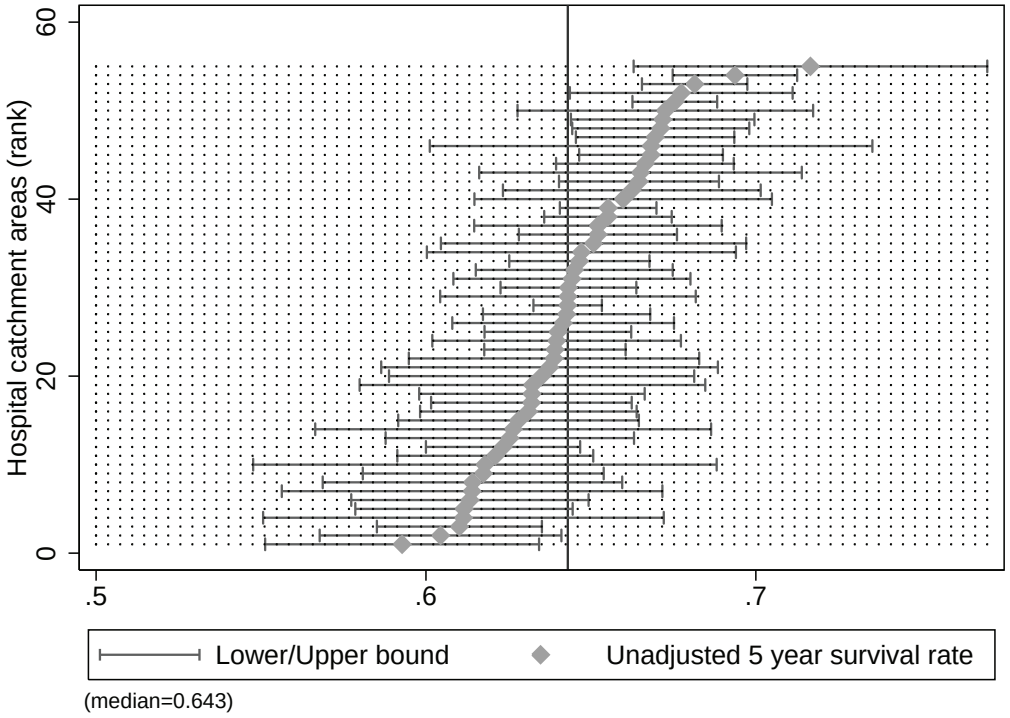
Table 4 reports summary statistics of unadjusted and adjusted survival and employment rates. The point estimates of the adjusted catchment area fixed effects vary from 0.595 to 0.686 for survival and from 0.332 to 0.442 for employment. The variation across catchment areas is larger for employment rates than for survival rates. Comparing unadjusted to adjusted indicators, we find that the variation based on unadjusted indicators is slightly larger, an issue which we return to below.

**Table 4: Performance measures – descriptive statistics**

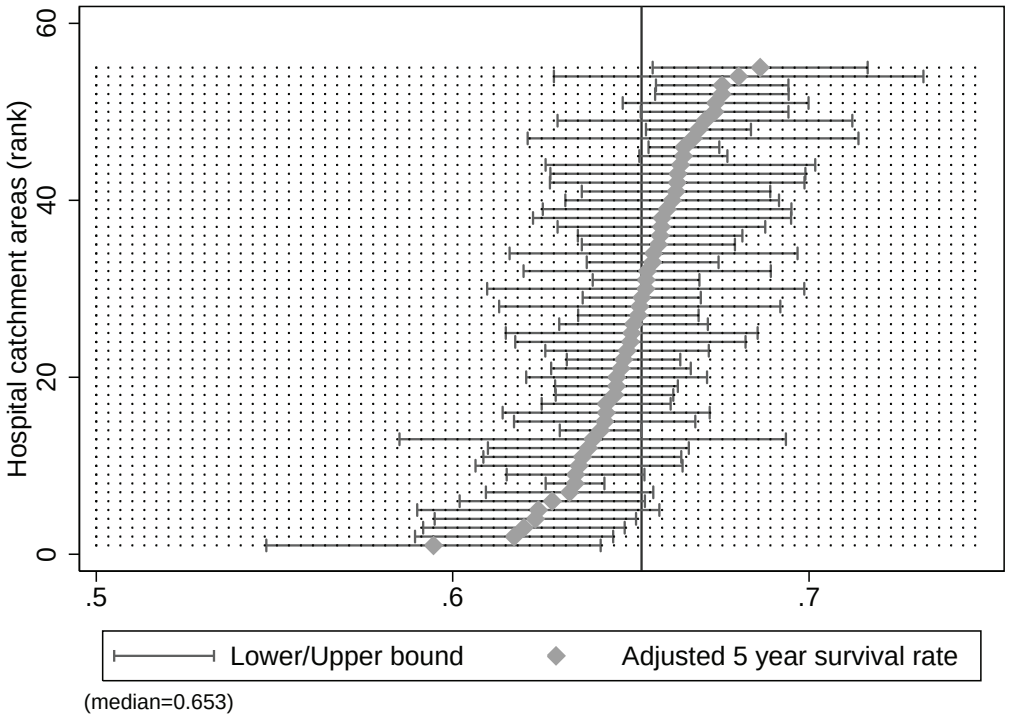
| | Mean | Median | St.dev | Min | Max | Coeff. of var |
|---|---|---|---|---|---|---|
| Unadjusted survival rate | 0.644 | 0.643 | 0.024 | 0.593 | 0.717 | 0.038 |
| Adjusted survival rate | 0.651 | 0.653 | 0.017 | 0.595 | 0.686 | 0.026 |
| Unadjusted employment rate | 0.377 | 0.370 | 0.040 | 0.294 | 0.479 | 0.107 |
| Adjusted employment rate | 0.388 | 0.387 | 0.025 | 0.332 | 0.442 | 0.065 |

N=55 hospital catchment areas.

**Figure 3: Unadjusted and adjusted survival rates and corresponding 90 percent confidence intervals – catchment areas**

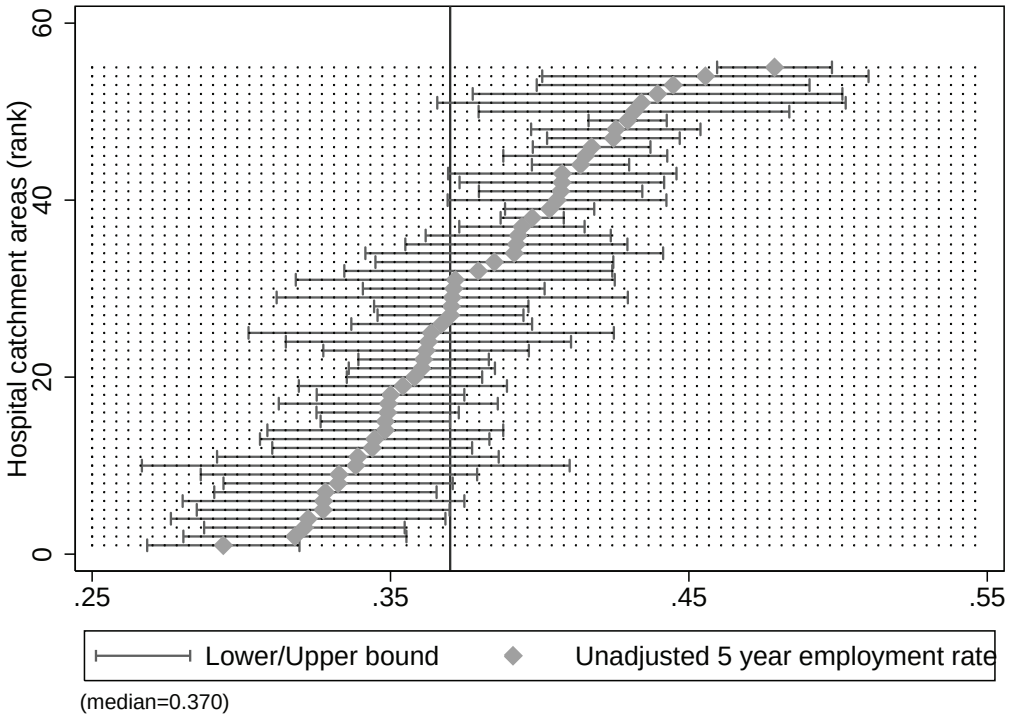



(median=0.643)




(median=0.653)

**Figure 4: Unadjusted and adjusted employment rates and corresponding 90 percent confidence intervals – catchment areas**



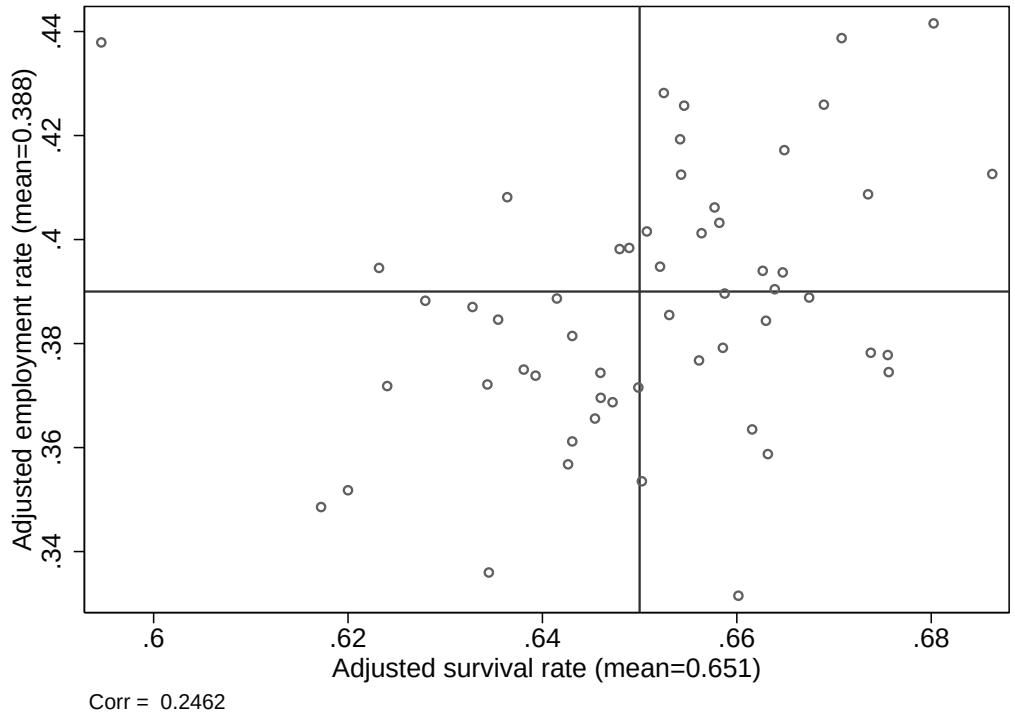

(median=0.370)


median=0.387

Taken at face value, the estimates imply that there are substantial differences between hospital catchment areas with respect to both survival and employment after cancer. However, the quality indicators are estimated with considerable uncertainty, which has to be taken into account. The uncertainty related to each point estimate of health care quality is illustrated in Figures 3 (survival) and 4 (employment) which report 90 percent confidence intervals for unadjusted (upper panel) and adjusted indicators (lower panel). For both survival and employment, we find that 12 confidence intervals out of 55 (22 percent) do not contain the point estimate of the median performing catchment area. This is similar to the finding of Gowrisankaran and Town (1999) who report that 28 percent of the hospitals in their sample have 90 percent confidence intervals that do not include the national mean.

To further clarify to what extent differences in estimated quality of care are statistically significant, we test all 1485 pairwise combinations of catchment areas under the null hypothesis of no quality differences. At the ten percent significance level, we find that 15.1 percent of the unadjusted survival rates and 11.7 percent of the adjusted survival rates are significantly different from each other. For employment we find that 39.4 percent of the unadjusted rates and 23.2 percent of the adjusted rates are significantly different from each other.

**Figure 5: Relation between adjusted survival and employment rate – catchment areas**




In Figure 5 we document the relation between adjusted quality indicators based on our two different success criteria. As is apparent in the figure, the correlation between the two sets of

indicators is modest. The correlation coefficient is only 0.26. This strongly suggests that conventional quality indicators based on differences in survival rates may not reveal the full picture of quality differences in health care across units. Our understanding is that the two outcome measures capture different observable points of a continuous latent health status distribution.

## 5.2 The importance of controlling for patient characteristics

To what extent is there systematic variation across catchment areas with respect to disease and patient characteristics, and how does controlling for them affect estimated quality indicators? This is an important question for two reasons. Most important, if patient characteristics that matter for a successful outcome vary across catchment areas (selection on observables), simple indicators based on unadjusted survival or employment rates may give a distorted picture of quality of care. Second, the importance of selection on observables may indicate to what extent selection on unobservables is likely to bias our hospital catchment area fixed effects (Altonji et al., 2005).

Obtained results from estimating Equation (1) is reported in Table 5 and 6. Table 5 shows results when survival after five years serves as the dependent variable, whereas Table 6 shows results where the dependent variable is participation in the labor market after five years. In both tables we add control variables in four steps. We start with including year dummies only (specification 1), this is our 'unadjusted specification'. We then add variables capturing metastasis and cancer type (specification 2) and covariates capturing age and sex (specification 3). Educational background and marital status is added in the next step (specification 4). Finally, we include information on labor market status (employment, weekly working hours and industry dummies) the year prior to diagnosis (specification 5). This is our 'adjusted specification'.

The control variables that we include generally have the expected relationship with our measure of successful treatment, and most of them are highly significant. As seen from column 1 in the two tables, year dummies and hospital catchment area fixed effects alone explain less than one percent of the variation in successful treatment, according to the $R^2$ measure. Characteristics of the disease are the major explanatory factors of survival and employment according to our estimates. Having a metastatic tumor on the date of diagnosis lowers the chances of both survival and employment. The effect of the different cancer types are not reported in tables, but are available from authors upon request. However, their effects are similar to unadjusted mean rates reported in Figure 2. The models explanatory power increase to 40 percent and 19 percent for survival and work resumption, respectively, when disease characteristics are included.

**Table 5: The relation between observables and survival five years after diagnosis**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Metastasis (localized=ref) | | | | | |
| - *Regional* | | -0.1826 | -0.1815 | -0.1792 | -0.1787 |
| | | (0.0054)*** | (0.0054)*** | (0.0054)*** | (0.0054)*** |
| - *Distant* | | -0.5363 | -0.5335 | -0.5292 | -0.5269 |
| | | (0.0060)*** | (0.0060)*** | (0.0059)*** | (0.0059)*** |
| - *Unknown* | | -0.1151 | -0.1144 | -0.1120 | -0.1098 |
| | | (0.0056)*** | (0.0056)*** | (0.0056)*** | (0.0056)*** |
| Gender | | | 0.0439 | 0.0480 | 0.0547 |
| | | | (0.0046)*** | (0.0047)*** | (0.0051)*** |
| Education (<=low.sec=ref) | | | | | |
| - *Upper sec. (11-12)* | | | | 0.0224 | 0.0155 |
| | | | | (0.0045)*** | (0.0045)*** |
| - *Upper sec. final (13)* | | | | 0.0407 | 0.0310 |
| | | | | (0.0056)*** | (0.0057)*** |
| - *Upper sec. extension (14)* | | | | 0.0437 | 0.0324 |
| | | | | (0.0110)*** | (0.0111)*** |
| - *Higher ed.- lower level (14-17)* | | | | 0.0507 | 0.0402 |
| | | | | (0.0053)*** | (0.0058)*** |
| - *Higher ed.- upper level (18+)* | | | | 0.0744 | 0.0660 |
| | | | | (0.0087)*** | (0.0091)*** |
| Marital status (married=ref) | | | | | |
| - *Never married* | | | | -0.0446 | -0.0401 |
| | | | | (0.0054)*** | (0.0054)*** |
| - *Widow/widower* | | | | -0.0318 | -0.0274 |
| | | | | (0.0103)*** | (0.0103)*** |
| - *Divorced* | | | | -0.0257 | -0.0225 |
| | | | | (0.0053)*** | (0.0054)*** |
| - *Separated* | | | | -0.0294 | -0.0267 |
| | | | | (0.0110)*** | (0.0110)** |
| - *Other* | | | | -0.0822 | -0.0881 |
| | | | | (0.1111) | (0.1110) |
| Labor market status the year prior to diagnosis (not in labor market=ref) | | | | | |
| - *Employee (part time, 4-19h)* | | | | | 0.0611 |
| | | | | | (0.0211)*** |
| - *Employee (part time, 20-29h)* | | | | | 0.0554 |
| | | | | | (0.0209)*** |
| - *Employee (full time, 30h+)* | | | | | 0.0569 |
| | | | | | (0.0204)*** |
| $R^2$ | 0.0044 | 0.4031 | 0.4078 | 0.4126 | 0.4154 |
| F-stat for joint sign of $\eta_j$ | 1.81 | 1.64 | 1.65 | 1.36 | 1.39 |
| Prob > F | 0.0003 | 0.0022 | 0.0018 | 0.0419 | 0.0315 |

Note: N = 46,720. N catchment areas = 55. Reported are OLS estimates. Standard errors within brackets. Year dummies and a constant term are included in all specifications. Included in specification (2)-(5) are dummy variables for cancer type. Included in specifications (3)-(5) are dummy variables for age. Included in specifications (4) and (5) are dummy variables for missing information on marital status and education. Included in specification (5) are dummy variables for industry. */**/*** statistically significance at the 10/5/1 percent level respectively.

**Table 6: The relation between observables and employment five years after diagnosis**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Metastasis (localized=ref) | | | | | |
| - *Regional* | | -0.1366 | -0.1368 | -0.1317 | -0.1294 |
| | | (0.0064)*** | (0.0063)*** | (0.0062)*** | (0.0059)*** |
| - *Distant* | | -0.3302 | -0.3258 | -0.3155 | -0.3044 |
| | | (0.0071)*** | (0.0069)*** | (0.0068)*** | (0.0066)*** |
| - *Unknown* | | -0.0756 | -0.0741 | -0.0686 | -0.0578 |
| | | (0.0067)*** | (0.0066)*** | (0.0064)*** | (0.0062)*** |
| Gender | | | -0.0219 | -0.0050 | 0.0214 |
| | | | (0.0054)*** | (0.0054) | (0.0056)*** |
| Education (<=low.sec=ref) | | | | | |
| - *Upper sec. (11-12)* | | | | 0.0856 | 0.0469 |
| | | | | (0.0051)*** | (0.0050)*** |
| - *Upper sec. final (13)* | | | | 0.1479 | 0.0907 |
| | | | | (0.0065)*** | (0.0063)*** |
| - *Upper sec. extension (14)* | | | | 0.1534 | 0.0879 |
| | | | | (0.0126)*** | (0.0122)*** |
| - *Higher ed.- lower level (14-17)* | | | | 0.2102 | 0.1251 |
| | | | | (0.0061)*** | (0.0064)*** |
| - *Higher ed.- upper level (18+)* | | | | 0.2399 | 0.1574 |
| | | | | (0.0099)*** | (0.0100)*** |
| Marital status (married=ref) | | | | | |
| - *Never married* | | | | -0.0437 | -0.0262 |
| | | | | (0.0062)*** | (0.0060)*** |
| - *Widow/widower* | | | | -0.0334 | -0.0117 |
| | | | | (0.0118)*** | (0.0114) |
| - *Divorced* | | | | -0.0451 | -0.0339 |
| | | | | (0.0061)*** | (0.0059)*** |
| - *Separated* | | | | -0.0539 | -0.0441 |
| | | | | (0.0126)*** | (0.0122)*** |
| - *Other* | | | | -0.2165 | -0.2405 |
| | | | | (0.1275)* | (0.1227)* |
| Labor market status the year prior to diagnosis (not in labor market=ref) | | | | | |
| - *Employee (part time, 4-19h)* | | | | | 0.2360 |
| | | | | | (0.0233)*** |
| - *Employee (part time, 20-29h)* | | | | | 0.2837 |
| | | | | | (0.0231)*** |
| - *Employee (full time, 30h+)* | | | | | 0.3087 |
| | | | | | (0.0225)*** |
| $R^2$ | 0.0038 | 0.1885 | 0.2280 | 0.2566 | 0.3127 |
| F-stat for joint sign of $\eta_j$ | 5.35 | 4.89 | 5.05 | 3.40 | 2.36 |
| Prob > F | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Note: See Table 5

Demographic and socio-economic variables are also strongly associated with successful treatment. Women have higher chances of both survival and post-cancer employment than men. The probability of successful treatment decreases with age (not reported). Patients with higher education tend to survive cancer and return to work to a larger extent than patient with lower education. These findings are in line with several previous studies that document considerable variation in health outcomes across socio-economic groups. Cutler et al. (2006) offers a discussion based on the international evidence, and Kravdal (2006) documents considerable health inequalities also in Norway. Patients who are married at the date of diagnosis tend to have more positive outcomes. This is in line with the finding of Kravdal (2001). Finally, both survival and post-cancer employment is positively associated with being in the labor market one year prior to diagnosis. For survival, the $R^2$ measure is basically unaltered when demographic and socio-economic characteristics of the patient are included in addition to disease characteristics. But, as is reasonable to expect, patient characteristics have larger explanatory power for employment. The $R^2$ increases from 0.19 to about 0.31 when patient characteristics are included. The relationship between different industry dummy variables and health status after cancer are omitted for brevity.[9]

In Figures 6 and 7 we show scatterplots of unadjusted and adjusted success rates for the two outcomes. The correlation between unadjusted and adjusted indicators is 0.62 for survival and 0.84 for employment. These correlations indicate that unadjusted and adjusted estimates of quality of care reveal broadly the same picture. Hospital areas that do well according to unadjusted indicators tend to do well also according to the adjusted ones. However, for a number of areas adjusting for patient characteristics gives substantial new information. In the figures, this is seen as a large distance from the 45-degree line. From the correlation coefficients, one might conclude that adding observed characteristics matters more for indicators based on survival than for those based on employment. However, a problematic aspect with interpreting the correlation coefficients and scatterplots is that they do not take into account the uncertainty related to each point estimate. As reported above, there is less variation in adjusted survival rates (coefficient of variation of 0.038) than employment rates (coefficient of variation of 0.065), and the hospital fixed effects for survival are jointly significant at the five percent level, while for employment they are significant well above the 0.1 percent level.

[9] The industry dummy variables are jointly statistically significant at the one percent level for employment and statistically insignificant for survival.

**Figure 6: Relation between unadjusted and adjusted survival rate – catchment areas**

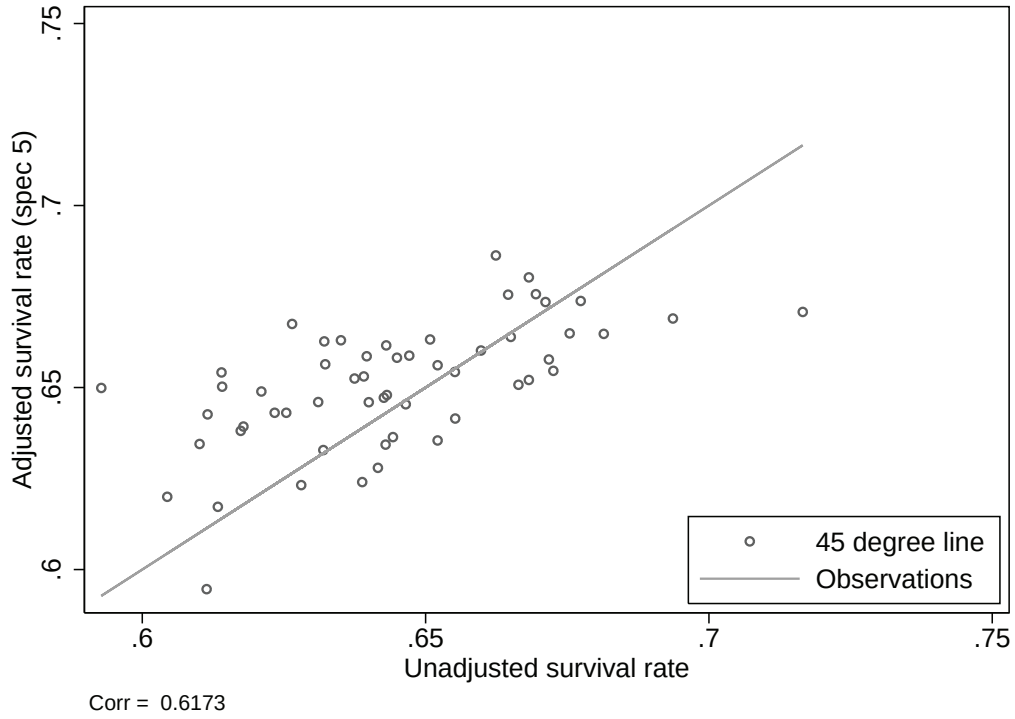
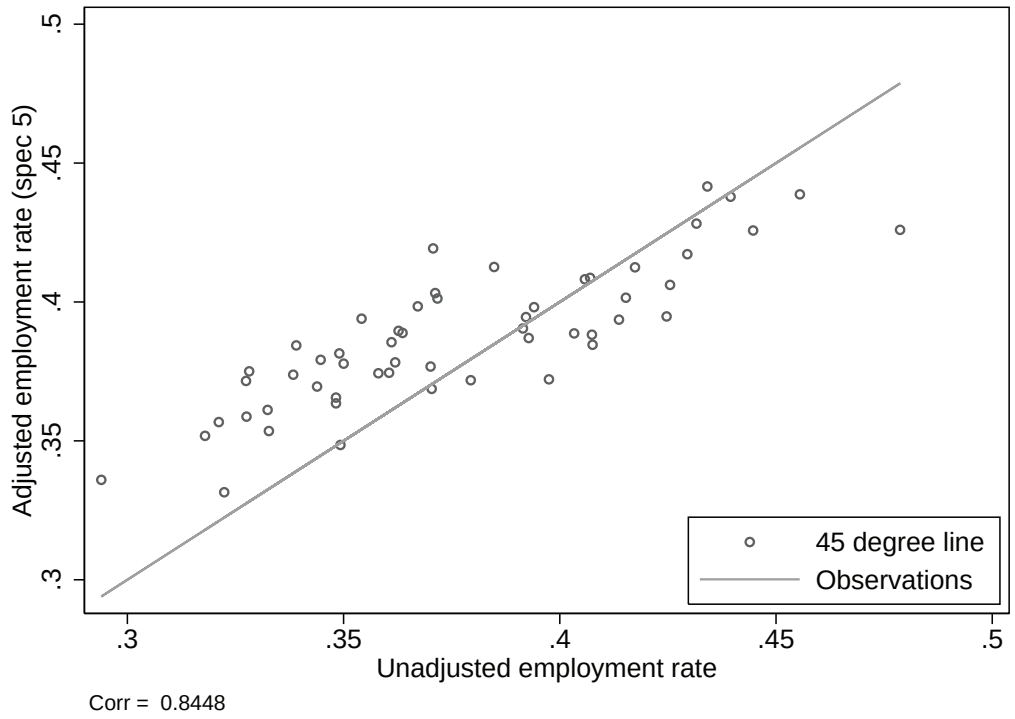



**Figure 7: Relation between unadjusted and adjusted employment rate – catchment areas**



After controlling for characteristics of the disease (specification 2) the estimated catchment area fixed effects ($\hat{\eta}$) are very insensitive to the inclusion of additional control variables. The correlation between the $\hat{\eta}$ derived from specification 2 and the $\hat{\eta}$'s derived from specification 3 to 5 in Table 5 and 6 range from 0.99 to 0.97 for survival and from 0.99 to 0.91 for employment. Since the estimates change very little when we include a rich set of observable patient characteristics on top of disease characteristics, they are arguably unlikely to change much if we could include potentially relevant unobserved patient characteristics. Hence, selection on unobservables does not seem to be a major problem and observed differences across hospital catchment areas are arguably very likely to stem from actual differences in quality of care.

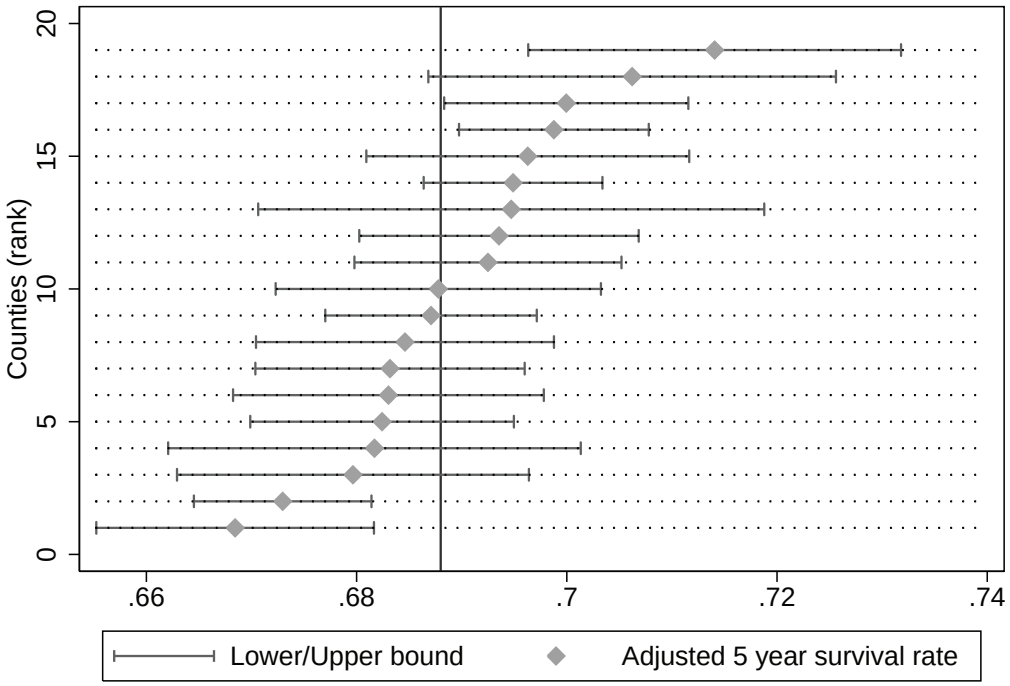
# 6 Sensitivity analysis

## 6.1 Analysis at the county level

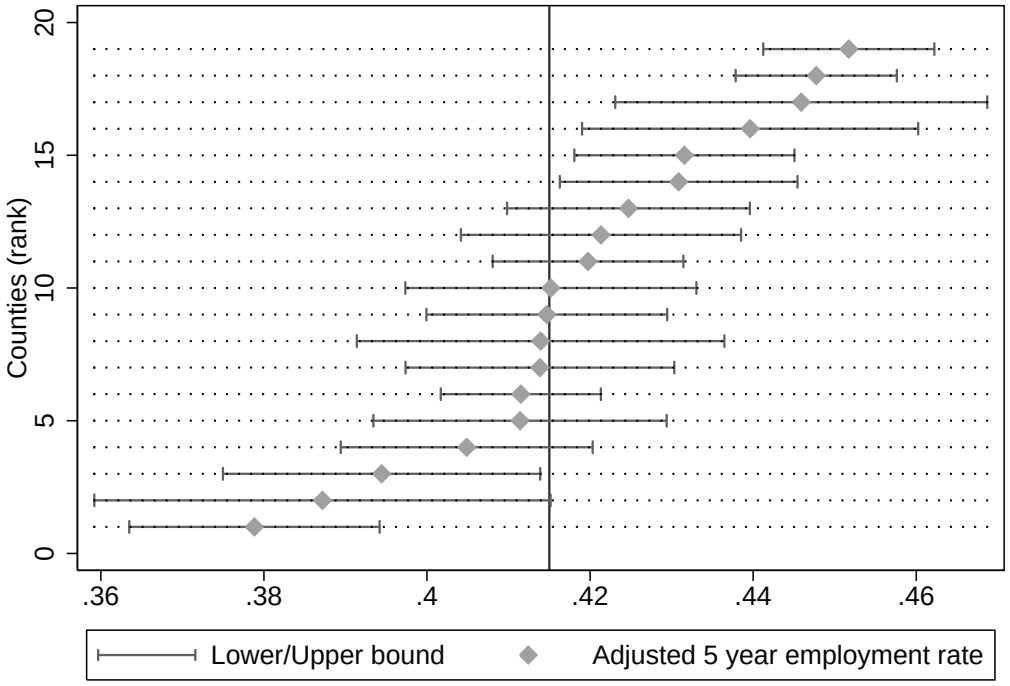
As documented in Figures 3 and 4, the confidence intervals related to each estimate of quality of care are for several catchment areas quite wide. The low correlation between the adjusted survival and employment rates may also partly be driven by imprecisely estimated coefficients. Aggregating the hospital catchment area to the county level and re-running the analysis will offer smaller confidence intervals, because more observations are behind each area. The results from the county level analysis are qualitatively similar to our main analysis at the catchment area level. For both survival and employment, the county fixed effects are jointly statistically significant above the 1 percent level (p-value for survival is 0.008, whereas p-value for employment is 0.000).

In Figure 8 we report the adjusted success rates and corresponding 90 percent confidence intervals at the county level. The adjusted survival rates are given in the upper panel, whereas the adjusted employment rates are given in the lower panel. For counties we find that confidence intervals are to a slightly larger extent overlapping for survival rates relative to employment rates. Five counties (26 percent) have confidence intervals that do not include the point estimate of the median performing county (three above and two below). While eight counties (42 percent) have confidence interval based on adjusted employment rates that do not include the point estimate of the median performing county (six above and two below). Again we find that the correlation across indicators based on the two adjusted indicators is low (0.41), as documented in Figure 9. Also as above, we find that the correlations between unadjusted and adjusted indicators are relatively high, 0.68 for survival rates and 0.89 for employment.

**Figure 8: Adjusted success rates and corresponding percent confidence intervals – counties**

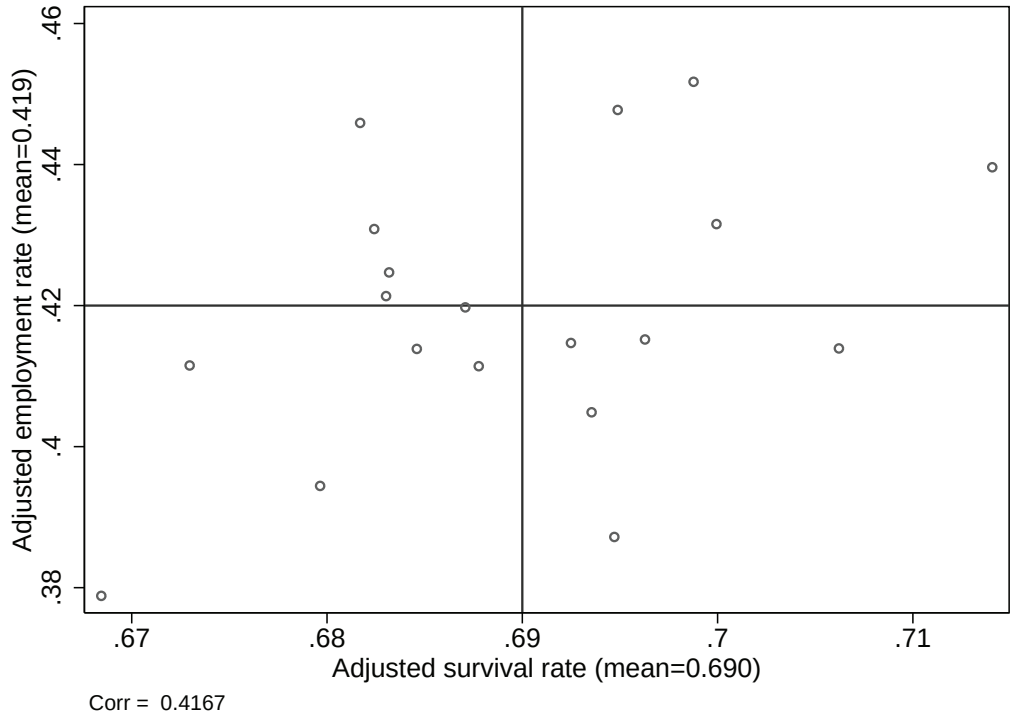



(median=0.688)




median=0.415

**Figure 9: Relation between adjusted survival and employment rates – counties**




## 6.2 Changes in local labor market conditions

The results presented above strongly suggest that which hospital catchment area you belong to matter for employment after cancer. Our interpretation is that this result is driven by regional variation in quality of care. A competing explanation is that there are differential trends in local labor market conditions that drive our key result.[10] To investigate the relevance of this explanation, we include a control variable which captures changes in the local unemployment rate (measured at the local government level) from year *t* (diagnosis year) to year *t+5* (five years after diagnosis). The point estimate indicates that the probability of employment decreases if local economic conditions are worsening, but the effect is not statistically significant at conventional levels (p-value of 0.13). The inclusion of this variable leaves the hospital catchment area fixed effects, as well as the confidence intervals, basically unaltered.[11]

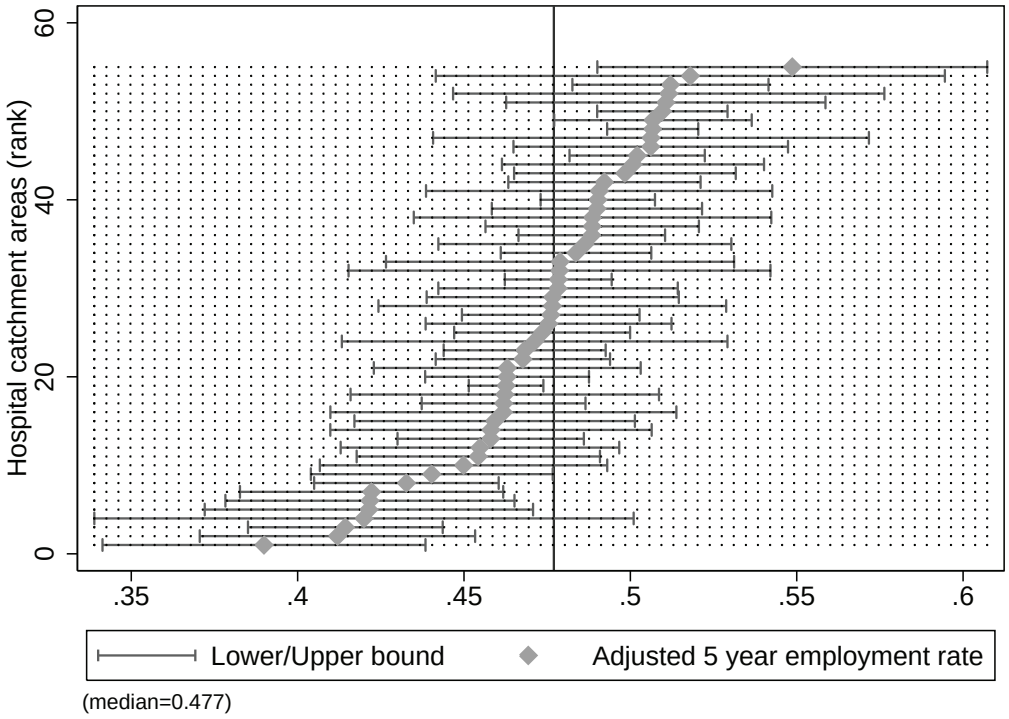
[10] General time trends, common across all catchment areas, are taken out by the year fixed effects. Also, each patient's pre-diagnosis attachment to the labor market is controlled for by the inclusion of labor market status before diagnosis.

[11] Results are omitted for brevity, but are available upon request.

### 6.3 Restricting the sample to those employed when diagnosed with cancer

As a final sensitivity check, we restrict our sample to those who were strongly attached to the labor market (full-time or long part-time) prior to diagnosis. This reduces the sample with around one third. The catchment area fixed effects are still strongly jointly significant, and the estimated adjusted employment rates are shown in Figure 10. The rank correlation coefficient between these indicators and the corresponding from the full sample is 0.92.

**Figure 10: Adjusted employment rates and corresponding 90 percent confidence intervals for those who were participating in the labor market (full time + part time) the year prior to diagnosis – catchment areas**




# 7 Conclusion

We have shown that indicators for quality of health care are sensitive to which outcome measure that forms the basis for the indicator. Hence, conventional quality indicators based on differences in survival rates may not reveal the full picture of differences in care across units. This is not to say that any of the indicators are "wrong", but rather that they focus on different discrete, observable points of a continuous latent health status distribution, and that units score differently with respect to different outcomes. Hence, focusing on only a single set of indicators may give a distorted picture of quality differences. This should be taken into account when designing accountability systems for health care.

For diagnoses where expected survival is high, indicators based on survival rates may be less adequate; they will show little variation and in principle capture quality differences at the lower end of the scale. Vice verse, when survival rates are low, indicators based on employment may contain little information on quality differences, since few patients are at this margin.

Our approach is based on data from comprehensive registers covering the whole population of cancer patients in Norway. We include detailed information on patient characteristics both prior to and after diagnosis and treatment, allowing us to control for patient characteristics that may affect or be correlated with outcomes. Clearly, register data may not contain all relevant information on diagnoses and patient characteristics that may matter for outcomes. Our analysis suggests, however, that there is only moderate systematic variation across hospital catchment areas with respect to observable characteristics. When the estimated quality indicators change little as we control for a rich set of relevant observable characteristics, they are unlikely to change much if we could control for potentially relevant unobservable characteristics. The quality differences that we establish in this analysis are therefore unlikely to be spurious.

Our results show considerable differences between catchment areas, with respect both to the probability of surviving cancer and of being employed after cancer. Though there is uncertainty associated with the estimates, a substantial fraction of the differences are statistically significant. It may actually matter which hospital you belong to. Large differences in outcomes indicate that there may be substantial welfare gains if all institutions adopted best practice. However, our study is silent about what the sources of differences are, a topic for future research.

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# A Appendix

**Figure A1: Hospital catchment areas and counties**

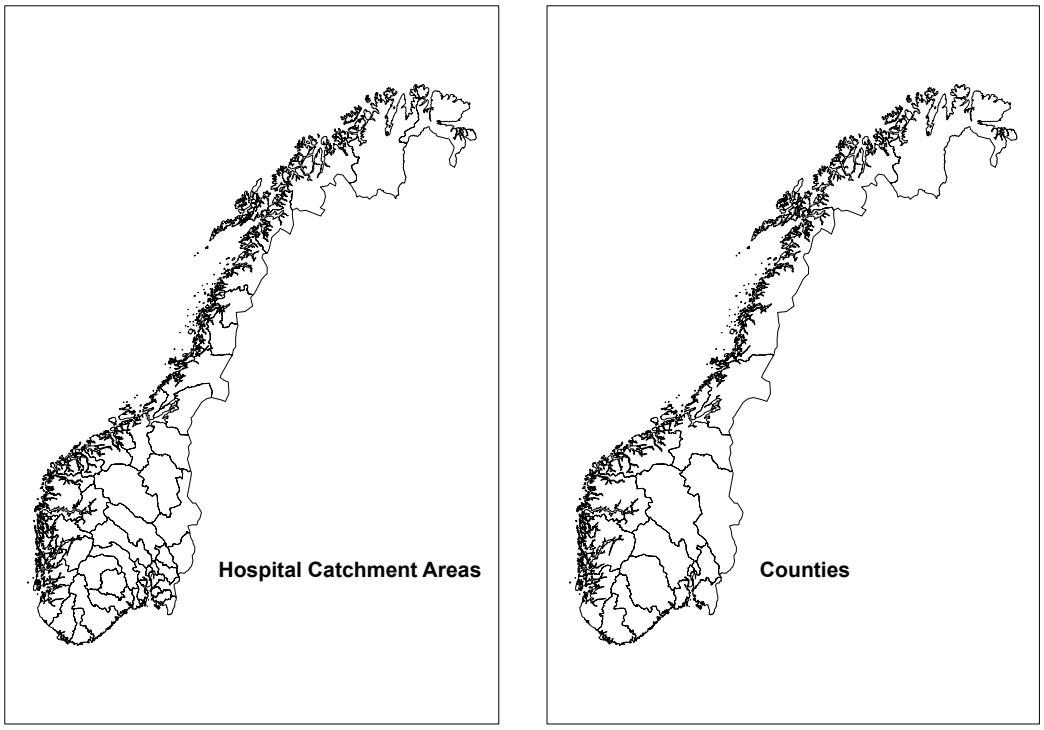
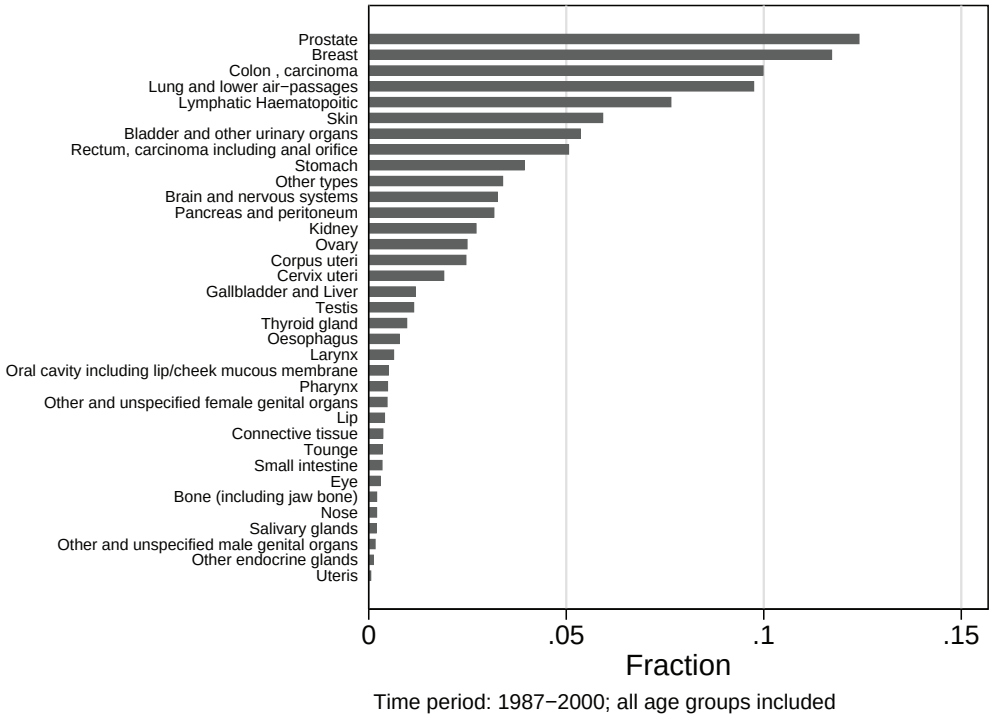



**Figure A2: The distribution of the different cancer types**




Time period: 1987−2000; all age groups included

**Table A1: Control variables, summary statistics**

| | Mean | St.dev |
|---|---|---|
| DEMOGRAPHIC CHARACTERISTICS | | |
| Age at the date if diagnosis | 47.86 | 8.94 |
| Female | 0.59 | 0.49 |
| | | |
| SOCIOECONOMIC CHARACTERISTICS | | |
| Education | | |
| - <=Low. sec | 0.29 | 0.46 |
| *- Upper sec. (11-12)* | 0.30 | 0.46 |
| *- Upper sec. final (13)* | 0.15 | 0.36 |
| *- Upper sec. extension (14)* | 0.03 | 0.16 |
| *- Higher ed.- lower level (14-17)* | 0.18 | 0.38 |
| *- Higher ed.- upper level (18+)* | 0.05 | 0.21 |
| Marital status | | |
| *- Married* | 0.67 | 0.47 |
| *- Never married* | 0.16 | 0.36 |
| *- Widow/widower* | 0.03 | 0.17 |
| *- Divorced* | 0.12 | 0.33 |
| *- Separated* | 0.03 | 0.16 |
| Labor market status the year prior to diagnosis | | |
| *- Not in labor market* | 0.23 | 0.42 |
| *- Employee (part time, 4-19h)* | 0.09 | 0.28 |
| *- Employee (part time, 20-29h)* | 0.10 | 0.31 |
| *- Employee (full time, 30h+)* | 0.58 | 0.49 |
| Dummy variables for industry | | |
| *- Agriculture including hunting* | 0.0034 | 0.0582 |
| *- Forestry* | 0.0010 | 0.0317 |
| *- Fishing* | 0.0017 | 0.0408 |
| *- Mining of coal and lignite* | 0.00002 | 0.0046 |
| *- Extraction of crude petroleum and natural gas* | 0.0082 | 0.0902 |
| *- Mining of metal ores* | 0.0007 | 0.0266 |
| *- Other mining and quarrying* | 0.0013 | 0.0358 |
| *- Manufacture of food products, beverages and tobacco* | 0.0214 | 0.1448 |
| *- Manufacture of textiles (including footwear) and textile products including leather* | 0.0047 | 0.0680 |
| *- Manufacture of wood and wood products* | 0.0087 | 0.0927 |
| *- Wood processing, graphic production and publishers* | 0.0173 | 0.1304 |
| *- Manufacture of chemical, oil, coal, plastic and rubber products* | 0.0110 | 0.1044 |
| *- Manufacture of mineral products* | 0.0045 | 0.0666 |
| *- Manufacture of metal* | 0.0084 | 0.0912 |
| *- Manufacture of tools* | 0.0422 | 0.2011 |
| *- Other manufacturing products* | 0.0033 | 0.0573 |

**Table A2: Table A1 cont'd**

| | Mean | St.dev |
|---|---|---|
| *- Electricity and gas supply* | 0.0080 | 0.0890 |
| *- Water supply* | 0.0002 | 0.0146 |
| *- Construction* | 0.0386 | 0.1926 |
| *- Wholesale and agency business* | 0.0466 | 0.2108 |
| *- Retail trade* | 0.0582 | 0.2342 |
| *- Hotels and restaurants* | 0.0156 | 0.1240 |
| *- Transport, storage and communication* | 0.0421 | 0.2009 |
| *- Post and telecommunications* | 0.0195 | 0.1384 |
| *- Financial intermediation* | 0.0210 | 0.1433 |
| *- Insurance and pension funding (except compulsory social security)* | 0.0059 | 0.0768 |
| *- Real estate, renting and business activities* | 0.0396 | 0.1950 |
| *- Public administration and defence* | 0.0722 | 0.2589 |
| *- Waste management and cleaning* | 0.0045 | 0.0669 |
| *- Personal service activities* | 0.0072 | 0.0848 |
| *- Embassy activities (both international and national)* | 0.00002 | 0.0046 |
| *- Education and training activities* | 0.0814 | 0.2735 |
| *- Research activities* | 0.0047 | 0.0680 |
| *- Health and veterinary activities* | 0.0920 | 0.2891 |
| *- Social work activities* | 0.0508 | 0.2197 |
| *- Activities of professional organizations* | 0.0044 | 0.0663 |
| *- Activities of other membership organizations* | 0.0039 | 0.0625 |
| *- Motion picture, video, radio and television activities* | 0.0036 | 0.0600 |
| *- Library, archives and museum activities* | 0.0034 | 0.0579 |
| *- Sporting activities and other recreational and cultural activities* | 0.0022 | 0.0465 |

N=46,720