DRAFT. NOT TO BE CITED OR DISTRIBUTED.

BREAST CANCER SURVIVAL, WORK, AND EARNINGS IN SWEDEN

FREDRIK ANDERSSON*, KRISTIAN BOLIN** AND BJÖRN LINDGREN**

* Lund University, Department of Economics.

** Lund University, LUCHE (Lund University Centre for Health Economics), Department of Health Sciences, Department of Economics, and the Vårdal Institute.

ABSTRACT

In two recent studies, Bradley et al. (2002, 2005) examined the consequences of breast cancer for women's labour market attachment. Using cross-section data from the first wave of the U.S. Health and Retirement Study, linked to longitudinal Social Security earnings data, Bradley et al. (2002) found that breast-cancer survivors (a) were less likely to be employed, but, given that they were employed, (b) worked more hours and (c) had higher earnings and wage rates. Bradley et al. (2005) used a longitudinal data set created from 445 telephone interviews with women diagnosed with breast cancer 6, 12, and 18 months after diagnosis. A matched control group was created by drawing a sample from the Current Population Survey. In this study, however, Bradley et al. (2005) certainly found that breast-cancer survivors were less likely to work 6 months after diagnosis as in their first study, but also that breast-cancer survivors worked fewer hours, i.e. contrary to their previous result. Thus, the evidence of the effect of breast cancer on labour-market behaviour is not quite clear.

In this paper, we (1) employed a stochastic demand-for-health model in order to theoretically analyse the individual's time-allocation response to severe illness and its dependence on the institutional structure and (2) replicated the estimates performed in the U.S. studies, using data from Sweden, a country in which healthcare is financed by general taxes and available to all residents, irrespective of labour market status. Our main findings were that breast-cancer survivors, compared to the general female population: (1) were less likely to be full-time employed, (2) did not differ significantly regarding wage rates, and (3) worked fewer hours.

BACKGROUND

Breast cancer screening is nowadays routinely applied to women aged 40 and over in the United States. Early detection has certainly increased the observed incidence rate, but - in combination with treatment of early-stage cancers – also resulted in a declining mortality rate. Labour-market behaviour of breast-cancer survivors is crucial, when evaluating the long-term consequences of screening programmes.

In two recent studies, Bradley et al. (2002, 2005) examined the consequences of breast cancer for women's labour market attachment. Using cross-section data from the first wave of the U.S. Health and Retirement Study, linked to longitudinal Social Security earnings data, Bradley et al. (2002) found that breast-cancer survivors (a) were less likely to be employed, but, given that they were employed, (b) worked more hours and (c) had higher earnings and wage rates. Bradley et al. (2005) used a longitudinal data set created from 445 telephone interviews with women diagnosed with breast cancer 6, 12, and 18 months after diagnosis. A matched control group was created by drawing a sample from the Current Population Survey. In this study, however, Bradley et al. (2005) certainly found that breast-cancer survivors were less likely to work 6 months after diagnosis as in their first study, but also that breast-cancer survivors worked fewer hours, i.e. contrary to their previous result.

Thus, the evidence of the effect of breast cancer on labour-market behaviour is not quite clear. Whereas the negative effects are consistent with what one would intuitively expect, the positive effects found in the first Bradley et al study are inconsistent with standard views of the disease. Several explanations for the unexpected findings were discussed and it was argued, even though there was no firm evidence to support the hypothesis, that the larger amounts of working time and earnings might be explained by health insurance being so tied to labour-market activity in the U.S.A. While an employed individual with a health problem who loses or changes jobs or who reduces hours of work does have some alternatives to her prior employment-based health-insurance coverage, she is likely to face substantially higher outof-pocket costs as well as exclusion from coverage. Empirical studies have reported that this fact creates a potential for job lock that decreases workers' mobility (for instance, Kapur, 1998, and Stroupe et al. 2001), while workers' willingness to exit the labour force or to reduce hours does not seem to have been addressed to the same degree. The issue needs further research.

A woman with breast cancer, who leaves the U.S. labour force (or reduces her hours worked), loses her employment-based health insurance and has to seek alternative health insurance. If she is married, one option would be to try and enrol in her husband's employment-based coverage; she could be excluded, however, or face lengthy waiting periods (6-12 months) due to her pre-existing condition. If her husband lacked coverage or if she were single, an alternative would be an individual and probably more expensive insurance with limited scope and depth of benefits, especially for a person with a pre-existing health problem. Since 1985, she might also be eligible for continuation coverage through her former workplace for up to 18 months; then she would typically have to pay 102 percent of the group premium all by herself instead of receiving some employer's contribution, while she was still employed. Since 1996, the use of pre-existing condition exclusions for a person with a health problem who leaves a job and obtains another is limited (provided that she obtains a new full-time job within a specified period of time). Finally, the public health-insurance programme Medicaid would be an alternative, if the woman were both very poor and disabled. Early stage breast cancer is not disabling, however. Furthermore, a woman with a working husband would generally not be eligible to the Medicaid programme, since their joint earnings would be too high.

In their papers, Bradley et al. (2002, 2005) referred briefly to the demand-for-health model (Grossman, 1972) and argued that incorporating a health production function into a labour supply model could capture the relationship between poor health and labour-market behaviour. The authors did not make any attempt in that direction themselves, however. Since the original formulation of the demand-for-health model assumes perfect certainty, it is not applicable to situations, which are characterised by risk or uncertainty. Certainly, the demand-for-health model has been extended in several directions, for instance, to include (1) the relationship between an employer and an employee, both with interests in the employee's health (Bolin et al. 2002a) and (2) various forms of uncertainty (Chang, 1996; Liljas, 1998). Also, similar models for analysing individual health behaviour when health status is uncertain and governed by a stochastic process have been developed (Dowie, 1975; Cropper, 1977, 1981; Dardanoni and Wagstaff, 1987, 1990; Selden, 1993; and Picone, Uribe and Wilson, 1998). However, none of them models unexpected changes in the health-capital stock as operating through the rate of depreciation of the health-capital stock, which appears to be a rather natural thing to do (Grossman, 1972). Thus, in order to analyse the effects of health-related risks and the structure of the institutional environment on individual health-related behaviour, the formal theoretical model has to be extended.

Early detection and treatment of breast cancer is a health priority also in Sweden. The Swedish National Board of Health and Welfare has recommended general screening since 1986, when it had already been going on for some time in six of the 24 counties; the final county to adapt screening did so in 1997 (National Board of Health and Welfare, 2005). In all counties, mammography is offered annually to all women aged 50-69; roughly 80 percent usually attend. Most counties offer mammography also to additional age groups in the interval 40-74 years of age. The number of women with diagnosed breast cancer has increased by 1.5 percent per year during the last decade; in 2003, 6,900 women were diagnosed (about half were younger than 65), which implies an (age-adjusted) incidence rate of 140 per 100,000 women. At the same time, breast cancer mortality is gradually going down, and in 2002, the (age-adjusted) mortality rate was 30 deaths per 100,000 women (National Board of Health and Welfare, 2005), to a large extent dependent on early detection as well as early and improved treatment (Baker et al, 2004). Incidence and mortality rates are, hence, roughly the same as for the United States (American Cancer Society, 2005).

Even though breast-cancer incidence and mortality rates are roughly the same, Sweden is different in many other respects. Government regulation of the Swedish labour market is stronger; securing that an employee cannot loose her job just because of illness, while the competitiveness of the Swedish labour market apparently is weaker. Healthcare is available to all residents, irrespective of labour market status, and financed by general taxes. So, women do not have to fear loosing their jobs because of their health problem; nor do they have to hesitate to leave the labour market or to reduce their hours of work for fear of having to pay substantially more for their healthcare. Swedish panel data from several waves of a population survey is available in order to analyse the issues that Bradley et al (2002, 2005) examine, but in a context, which is quite different from the U.S. one.

This paper adds the following features or results to the analyses by Bradley et al. (2002, 2005). *First*, it utilises an extension of the demand-for-health model, which incorporates health-risks by assuming that future rates of depreciation of the stock of health capital are risky, in order to analyse the time-allocation responses of women who have been struck by and survived breast cancer. From the model, predictions are derived for labour market behaviour in different institutional settings. *Second*, an empirical model is estimated and predictions are tested, using Swedish data. Since most variables used in the U.S. study are also available in Sweden, some direct comparisons of results are possible. *Third*, in accordance with the demand-for-health model, we treat health as an endogenous variable, whereas Bradley et al. (2002, 2005) take health as exogenously given. *Fourth*, since panel data from a representative sample of the population is available in Sweden, the potential impact of selection can be examined in a more convincing way by analysing whether breast-cancer survivors differ from the general female population *prior* to diagnosis.

The paper proceeds as follows: first, we will describe the theoretical framework; second, the empirical model will be developed and the data will be discussed. Third, we shall move on to a description of the specific empirical method used in the paper. Fourth, the empirical model will be specified in terms of the previously discussed method, and fifth, the model will be estimated. The paper is concluded with a discussion of the results.

THEORETICAL FRAMEWORK

In an on-going project the authors have developed a demand-for-health model, which incorporates risk. The model is based on the Grossman (1972a) model, and considers an individual deriving utility from consumption and from her *health*, which is a stock capital that is subject to depreciation; the stock can also be restored by health-related investments by the individual. In our formulation, the rate of depreciation is governed by a stochastic process switching it between a quick-depreciation and a slow-depreciation state.[1] This is, arguably, a germane modelling interpretation of some medical conditions. Depending on the application and the exact specification, the intensities with which the individual switches between the states can be endogenized. Other important assumptions are: (a) there is perfect complementarity between inputs to production of gross health investments (own time and market goods), (b) the utility function is additively separable in health and consumption, and (c) the amount of health which depreciates at each point in time is independent of the size of the stock of health.[2]

For the current application, it seems reasonable to consider the breast-cancer diagnosis as a one-time shock to the stock of health capital accompanied by a switch to a higher depreciation rate during recovery (conditional on surviving). For this purpose we consider a case where the depreciation rate may switch only once from the slow-depreciation to the quick-depreciation state; in this special case, the switch follows a standard Poisson process. The analysis can then be decomposed into a phase following the diagnosis where the standard – i.e. without risk – model can be employed unmodified, and an initial phase where the objective of the individual is amended by the indirect utility following a diagnosis; the “expected objective” of the

---

[1] Formally, we model it in the general case as a continuous-time two-state Markov process.

[2] On this point we distinguish ourselves from Grossman’s original formulation as well as from previous extensions of the demand-for-health model.

individual over the time of diagnosis (which may be "never") can then be maximized.[3] While the potential switch of "regimes" that occurs at the time of the diagnosis makes qualitative analysis of the full problem intractable, the cross-section implications of different institutions for our objects of interest affect only the post-diagnosis phase; that is, the cross-section implications can be derived by comparative statics on a standard problem. The key first-order condition for our standard problem is:

$$\dot{I} = \frac{U_H(H,Z)}{(\omega + c)^2 U_Z(H,Z)},$$

where I is the investment in health; H is the health stock; Z is consumption; ω is the wage rate; and c is the marginal cost of health investments. By integrating this expression over time from the occurrence to the end date and performing comparative statics, the following properties of interest can be established:

(i) a negative shock to H increases health investments and reduces labour supply subsequently;

(ii) a decrease in income – either through a negative monetary endowment or a reduction in the real net wage rate – decreases health investments and increases labour supply unless, essentially, risk aversion is increasing relatively rapidly with income.[4]

While the first property is natural but somewhat peripheral to our comparisons because of the absence of cross-section variation, the second one has a clear interpretation and it generates a clear hypothesis: Economic repercussions – whether in the form of a reduced wage, direct payment or indirect mechanisms to the same effect (such as a less generous insurance) – makes the individual invest less in health and work more. When this effect is added to the direct effect of the health-state shock – which is likely to be negative, but not identical to the effect under (i) above – the total effect is ambiguous, but a there is a clear prediction for variation across institutions.

[3] The technique follows largely Dasgupta and Heal (1974).

THE EMPIRICAL MODEL

We estimated reduced-form equations of (1) the probability of being full- and part-time employed (E), respectively, (2) the weekly average number of hours worked (T), and (3) the wage rate (W). In order to examine whether or not the estimated effects in these equations could be explained by selection bias – those surviving breast cancer possessing, for instance, more human capital or greater financial resources – we re-estimated the equations, using a panel-data set and substituting the indicator for whether or not the respondent have been diagnosed with breast cancer for the indicator for whether or not the respondent will be diagnosed with breast cancer in the future and survive at least one year. If there is a selection bias, those that survive breast cancer would differ from the general female population prior to the diagnosis and, hence, distinguish themselves from the general female population regarding (1) the probabilities of being full- and part-time employed, respectively, (2) the amount of time supplied to the labour market, and (3) the wage rates.

Formally, we estimated:

$$E_i = \alpha_T + \beta_T \cdot DIAGNOSIS + \gamma_T \cdot \mathbf{X}_i + \varepsilon_i \quad \text{(probability of employment),} \tag{1}$$

$$T_i = \alpha_T + \beta_T \cdot DIAGNOSIS + \gamma_T \cdot \mathbf{X}_i + \mu_i \quad \text{(hours worked),} \tag{2}$$

$$W_i = \alpha_T + \beta_T \cdot DIAGNOSIS + \gamma_T \cdot \mathbf{X}_i + \eta_i \quad \text{(wage).} \tag{3}$$

THE DATA

A set of individual data was created by using data from the Swedish biannual survey of living conditions, ULF (Undersökningar av levnadsförhållanden), and the Swedish Cancer Incidence Register (Cancerregistret). Each individual in the ULF data were linked to the Cancer Incidence Register. In each wave of the ULF, a sample of approximately 16,000 randomly selected people,

[4] Thus, it is true, for example, for constant-relative-risk-aversion preferences.

aged 16-84 years old, are interviewed about their living conditions; the response rate is normally 80-85 percent. Every wave of the survey covers a number of areas: housing, leisure, health, employment, education, private financial situation, and social relations. Responses are supplemented with individual data on income, taxes and various transfer payments from administrative registers. Furthermore, approximately 40 percent of the respondents are part of a rotating panel in which respondents are interviewed every eight year.

We restricted our attention to those above 20 years of age – those below 20 years of age rarely participate in the Swedish labour market – and below 65 years of age – the legal retirement age in Sweden. In order to be able to distinguish between age- and birth-cohort effects we pooled ULF data from the years 1988/89 and 1999/2000; and in order to be able to treat health as an endogenous variable, these data were supplemented by lagged ULF data from the years 1980/81 and 1991/92, respectively. Thus, we constructed a balanced panel, which in its final size consisted of 3,656 women, of which 29 had been diagnosed with breast cancer one year or more prior to the interview.

Further, in order to study the effects of selection we constructed another panel consisting of ULF data from the years 1980/81, and 1990/91, which were supplemented by information on breast cancer diagnosis collected from the years 1988/89 and 1999/2000, respectively. This (pooled) panel data set consisted of 9,691 women. Finally, in order to compare our results to those of Bradley et al. (2002) we utilised a cross section of the ULF data from the years 1999/2000 complemented with information on breast cancer diagnosis from the same years, which resulted in a data set of 8,505 women.

Chosen variables are described below; means and standard deviations, for the 3,656 individuals sample, are reported in Table 1.

Dependent variables

- WORKFT is a dummy variable, which takes the value 1 if the respondent was full-time employed in the year of interview, and 0 otherwise.
- WORKPT is a dummy variable, which takes the value 1 if the respondent was part-time employed in the year of interview, and 0 otherwise.
- HOURS is a continuous variable indicating the average number of work hours per week in the year in which the interview was conducted.
- WAGE is a continuous variable for the wage rate in the year of interview.

Explanatory variables

- DIAGNOSIS is a dummy variable, which takes the value 1 if the respondent was diagnosed with breast cancer 1 year, or more, prior to the interview, and 0 otherwise.
- HEALTH is the *predicted* level of self-assessed health in the year of interview. The variable is reported with three levels: 1 corresponds to good health; 2 to less good health; and 3 to bad health.
- AGE is the respondent's age in years in the year of interview.
- YEAR is the year of interview.
- WEALTH is a continuous variable indicating the income from capital in the year of interview (in the years 1999 and 2000 only tax paid on capital income is available. Thus, we have calculated income from capital as paid tax divided by the tax rate).
- WORKINCM is a continuous variable indicating the income from work earned by the respondent's spouse.
- HSCHOOL is a dummy variable, which takes the value 1, if the respondent's attained educational level is high school in the year of interview and 0 otherwise (corresponds to levels 0 – 20 in Statistics Sweden's educational measure, SUN86).

- COLLEGE is a dummy variable, which takes the value 1, if the respondent's attained educational level is college level in 1996/97 and 0 otherwise (corresponds to levels 31, 32 and 40 in Statistics Sweden's educational measure, SUN86).
- NEVMARR is a dummy variable, which takes the value 1, if the respondent has never been married and 0 otherwise.
- DIVORCED is a dummy variable which takes the value 1, if the respondent was divorced in the year of interview and 0 otherwise.
- CHILD is a dummy variable which takes the value 1, if the respondent has children below the age of 8 years of age in the year of interview.
- SCAND is a dummy variable which takes the value 1, if the respondent is born in a Scandinavian country and 0 otherwise.

THE ECONOMETRIC METHOD AND MODEL SPECIFICATION

The empirical model was estimated using a two-step estimation procedure. In the first step an ordered probit model (Greene, 1997; p 926) of health was estimated, employing lagged observations on wage, education, spousal income, and marital status; in the second step the probability of being full-time employed, the probability of being part-time employed, and the hours worked, respectively were estimated using the first-stage predictions of health as an explanatory variable. The correction of the covariance matrix in the second step, to take into account the errors in the predicted values of health, was achieved applying the Murphy and Topel (1985) method.[5]

We estimated probit models for the probability of being full- or part time employed, and tobit models were employed regarding hours worked and wage rates. The probability model is well established in economics and, hence, will not be reproduced here

[5] All calculations were performed using the LIMDEP computer programme.

(Green, 1997; p 871). However, the Tobit model is less well known. Formally, the Tobit model, which was applied, was based on the following specification (Green, 1997; p 962):

$$y_i^* = \beta'\mathbf{x}_i + \varepsilon_i, \tag{4}$$

where β is the vector of parameters to be estimated and $\varepsilon_i \sim N[0,\sigma^2]$. y_i^* is the observed dependent variable: if $y_i^* \leq 0$ then $y_i^* = 0$ and if $y_i^* = y_i > 0$ then $y_i = y_i^* = \beta'\mathbf{x}_i + \varepsilon_i$.

In a first best empirical specification we would employ the same explanatory variables as Bradley et al. (2002). However, available data did not allow strict adherence to this policy. We used the same explanatory variables as Bolin et al. (2002b) and, in addition, incorporated indicators for ethnicity and breast cancer diagnosis.

EMPIRICAL RESULTS AND DISCUSSION

We begin this section by presenting our results and move on to a discussion in which we relate our results to results obtained in previous studies.

The main results which can be inferred from the above tables are that breast cancer survivors (1) are less likely to be full-time employed and (2) work fewer hours, conditional on being employed, than the general female population. However, breast cancer survivors could not be distinguished from the general female population regarding the probability of being part-time employed and wage rates, respectively. The impact of selection on these results was examined by performing regressions similar to those above, but where the indicator for diagnosed breast cancer was changed to an indicator of a *future* breast cancer diagnosis. In neither case did the estimated coefficient on future breast cancer diagnosis show up as significant, which implies that women who are future breast cancer survivors cannot be distinguished from the general female population regarding their labour market behaviour.[6]

[6] Due to data-restrictions these estimates were calculated without taking into account that health is endogenous. The estimates can be obtained from the authors upon request.

DISCUSSION

In this paper we have made use of a theoretical model in which (1) health is treated as a part of the stock of human capital and (2) the rate of depreciation of the stock follows a two-state Markov chain. Theoretically, breast cancer was conceptualised as a prolonged time period in which the rate of depreciation of the stock of health capital is high. Thus, the theoretical model was applied to the analysis of the impact of breast cancer on the time-allocation. Moreover, the theoretical model was used for analysing the impact of the "generousness" of the insurance, which was formalised as a monetary endowment, on time allocation. The theoretical results were (1) that women who are struck by breast cancer allocate less time to market-work than women who are not struck by breast cancer, and (2) that a less generous insurance system induces the individual to allocate more time to the labour market.

In this paper labour supply was empirically represented (1) by a dichotomous variable indicating whether or not the individual was employed or not and (2) as a continuous variable indicating the number of hours supplied to the market. The theoretical predictions could not be rejected.

To be continued and concluded.

REFERENCES

Baker SG, Kramer BS, Prorok PC. Comparing breast cancer mortality rates before-and-after a change in availability of screening in different regions: Extension of the paired availability design. *BMC Medical Research Methodology* 2004;4:1-9.

Bolin K, Jacobson L, Lindgren B. Employer investments in employee health. Implications for the family as health producer. *Journal of Health Economics* 2002;21: 563-583. (a)

Bolin K, Jacobson L, Lindgren B. The demand for health and health investments in Sweden 1980/81, 1988/89, and 1996/97. In: Lindgren B (ed) *Individual Decisions for Health*. London: Routledge, 2002:93-112. (b)

Bradley CJ, Bednarek HL, Neumark D. Breast cancer survival, work, and earnings. *Journal of Health Economics* 2002;21:757-779.

Bradley CJ, Neumark D, Bednarek HL, Schenk M. Short-term effects of breast cancer on labor market attachment: results from a longitudinal study. *Journal of Health Economics* 2005;24:137-160.

Chang F. Uncertainty and investment in health. *Journal of Health Economics* 1996;15:369-376.

Cropper ML. Health, investment in health, and occupational choice. *Journal of Political Economy* 1977;85:1273-1294.

Cropper, ML., 1981. Measuring the benefits from reduced morbidity. *American Economic Review* 71:235-240.

Cutler, D.M., and Zeckhauser, R.J., 2000. The anatomy of health insurance. In: Culyer, A.J. and J.P. Newhouse, (Eds.). *Handbook of Health Economics*, Elsevier, Amsterdam, 564-629.

Dardanoni, V. and A. Wagstaff, 1987. Uncertainty, inequalities in health, and the demand for health. *Journal of Health Economics* 6:283-290.

Dardanoni, V. and A. Wagstaff, 1990. Uncertainty and the demand for medical care. *Journal of Health Economics* 9:23-38.

Dasgupta, P. and G. Heal (1974). The optimal depletion of exhaustible resources. *Review of Economic Studies* 41: 3-28.

De Meca, D. 1983. Health insurance and the demand for medical care. *Journal of Health Economics* 2:47-54.

Dowie, J., 1975. The portfolio approach to health behaviour. *Social Science & Medicine* 9:619-631.

Greene, W.H. *Econometric Analysis*. Third Edition. New York: Prentice Hall, 1997.

Grossman, M., 1972. On the concept of health capital and the demand for health. *Journal of Political Economy* 80:223-255.

Gruber, J., 2000. Health insurance and the labor market. In: Culyer, A.J. and J.P. Newhouse, (Eds.). *Handbook of Health Economics*, Elsevier, Amsterdam, 646-700.

Jacobson, L., 2000. The family as producer of health – An extension of the Grossman model. *Journal of Health Economics* 19:611-637.

Kapur, K., 1998. The impact of health on job mobility: A measure of job lock. *Industrial and Labor Relations Review* 51:282-298.

Liljas, B., 1998. The demand for health with uncertainty and insurance, *Journal of Health Economics* 17:153-170.

Murphy, K. Topel, R., 1985. Estimation and inference in two-step econometric models. *Journal of Business and Economic Statistics* 3:370-379.

Picone, G., Uribe, M., and R.M. Wilson, 1998. The effect of uncertainty on the demand for medical care, health capital, and wealth. *Journal of Health Economics* 17:171-185.

Selden, T., 1993. Uncertainty and health care spending by the poor: the health capital model revisited. *Journal of Health Economics* 12:109-115.

Stroupe, K.T., Kinney, E.D., and T.J.J. Kniesner. Chronic illness and health insurance-related job lock. *Journal of Policy Analysis and Management* 20:525-544.

Zweifel, P., and Manning, W.G., 2000. Moral hazard and consumer incentives in health care. In: Culyer, A.J. and J.P. Newhouse, (Eds.). *Handbook of Health Economics*, Elsevier, Amsterdam, 409-459.

Table 1. Descriptive statistics.[7]

Variable	Mean	St dev	Mean	St dev
No diagnosis			**Diagnosis**	
N = 3627			**N = 29**	
<u>**Dependent variables**</u>				
WORKFT	0.44	0.50	0.21	0.41
WORKPT	0.34	0.47	0.44	0.51
HOURS	27.24	15.83	19.17	15.88
WAGE	34.83	31.67	26.85	31.71
<u>**Explanatory variables**</u>				
DIAGNOSIS	0.008	0.089	-	-
HEALTH	1.53	0.59	1.27	0.70
AGE	43.62	11.68	53.38	7.37
YEAR	1993	5.51	1994	5.56
WEALTH	53.79	676.35	3.33	10.43
WORKINCM	1342.19	1392.38	1289.21	1269.78
HSCHOOL	0.22	0.41	0.38	0.49
COLLEGE	0.45	0.50	0.31	0.47
NEVMARR	0.27	0.44	0.07	0.26
DIVORCED	0.16	0.36	0.28	0.45
CHILD	0.38	0.48	0.34	0.48
SCAND	0.94	0.24	0.93	0.26

[7] The explanatory variables are later re-scaled in order to facilitate convergence in the numerical maximisation of the likelihood function.

Table 2. Estimated marginal effects in the Bradley et al. (2002) head-to-head specifications. (Bold indicates that the estimated marginal effect is significant at the 10 percent-level; bold and * indicate that the estimated marginal effect is significant at the 5 percent-level; and bold and ** indicates that the estimated marginal effect is significant at the 1 percent-level.)

Variable	Full-time employment	(p-value)	Part-time employment	(p-value)	Hours	(p-value)	Wage	(p-value)
CONSTANT	**-11.369****	0.004	**12.103****	0.001	19.042	0.887	**-2568.070****	0.000
DIAGNOSIS	**-0.283****	0.002	0.025	0.809	**-9.944***	0.018	-4.078	0.800
HEALTH	**0.044****	0.001	**0.048****	0.000	**8.831****	0.000	**4.526***	0.014
AGE	**-0.007****	0.000	**0.003****	0.000	**-0.173****	0.000	**-0.327****	0.001
YEAR	**0.006****	0.003	**-0.006****	0.001	-0.003	0.959	**1.294****	0.000
WEALTH	**-0.526e-4**	0.063	-0.884e-5	0.519	**-0.001***	0.018	**-0.009****	0.008
WORKINCM	**0.175e-4***	0.013	**0.411e-4****	0.000	**0.002****	0.000	**0.005****	0.000
HSCHOOL	**-0.234****	0.000	**0.105****	0.000	**-6.684****	0.000	**-17.426****	0.000
COLLEGE	**-0.153****	0.000	**0.115****	0.000	**-2.903****	0.000	**-10.893****	0.000
NEVMARR	0.016	0.553	**-0.062****	0.007	**2.790****	0.003	**-7.879***	0.031
DIVORCED	**0.145****	0.000	**-0.062****	0.003	**4.890****	0.000	**6.380***	0.041
CHILD	**-0.176****	0.000	**0.143****	0.000	**-7.234****	0.000	**-4.624**	0.077
SCAND	**0.055**	0.079	0.017	0.563	**2.917****	0.010	**9.177***	0.036

Table 3. Estimated marginal effects treating health as endogenous. (Bold indicates that the estimated marginal effect is significant at the 10 percent-level; bold and * indicate that the estimated marginal effect is significant at the 5 percent-level; and bold and ** indicates that the estimated marginal effect is significant at the 1 percent-level.)

Variable	Full-time employment	(p-value)	Part-time employment	(p-value)	Hours	(p-value)	Wage	(p-value)
CONSTANT	**-7.568***	0.037	**13.271****	0.001	**262.828***	0.031	**-2303.290***	0.000
DIAGNOSIS	**-0.196***	0.024	0.109	0.246	**-6.023**	0.067	**-9.443**	0.094
HEALTH (predicted)	**0.168****	0.002	**0.120***	0.021	**9.918****	0.000	**10.518****	0.001
AGE	**-0.008****	0.000	0.001	0.256	**-0.232****	0.000	0.103	0.858
YEAR	**0.004***	0.032	**-0.007****	0.000	**0.146***	0.016	**1.167****	0.000
WEALTH	-0.296e-4	0.164	-0.756e-5	0.587	**-0.001**	0.090	-0.001	0.194
WORKINCM	**0.165e-4***	0.021	**0.450e-4****	0.000	**0.002***	0.000	**0.004****	0.000
HSCHOOL	**-0.254****	0.000	**0.102****	0.000	**-9.514***	0.000	**-14.764****	0.000
COLLEGE	**-0.161****	0.000	**0.098****	0.000	**-4.303***	0.000	**-8.977****	0.000
NEVMARR	0.034	0.166	**-0.086****	0.000	**-1.470**	0.074	-1.502	0.208
DIVORCED	**0.131****	0.000	**-0.007****	0.002	**2.842****	0.001	**5.565****	0.000
CHILD	**-0.143****	0.000	**0.113****	0.000	**-2.942****	0.000	-0.813	0.489
SCAND	0.052	0.140	0.021	0.538	1.754	0.150	-2.495	0.224