Assessing the Effect of Economic Incentives on Incidence and Duration of Work Absence*

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Abstract

The incidence and duration of work absence spells for a sample of Swedish blue collar workers in 1991 are analyzed using the Kaplan-Meier estimator, discrete time hazard regression as well as stratified Cox regression. The main interest is directed towards the effect of economic incentives. The effect of a decrease in the replacement level of the compulsory Swedish sickness insurance that took place in March 1991 is analyzed. The incidence of work absence spells decreases markedly after the reform, although no effects on the duration of the spell is found. Significant male-female differences are also found. The main results are robust to the different methods used.

Key word and phrases: discrete time Cox regression; sickness insurance; stratified Cox regression.
JEL Classification: J22, C41.

1. Introduction

Most workers, in most countries, are covered by some form of sickness insurance. The objective of these insurance schemes is to provide income security

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if the worker's health does not permit regular work. However, as it is not possible, or at least very costly, to perfectly observe the insured worker's health, the insurance schemes have to rely on some form of excess in order to provide incentives for the worker not to be absent from work.[1] Several recent empirical studies have concluded that economic incentives affect work absence behavior.[2] This is an important finding, since provided that economic incentives matters, the construction of these insurance schemes, which often are at least regulated by the government or influenced by trade unions, will affect the actual behavior of the workers. However, as the worker's decision on being absent from work is likely to be affected by several components and also to be dynamic in nature, it is not obvious how an econometric model for work absence behavior should be specified and how the results should be interpreted.

From an economic point of view, three factors may determine individual work absence behavior. First, the short term cost of being absent from work, i.e. the difference between what the worker would have earned if she would not have been absent compared to what she actually get when she is absent. If the worker is covered by some form of sickness insurance, this cost correspond to the excess in the sickness insurance. Second, future income. It is well known that work absence may influence the worker's chance of being promoted, and, thus, future wage growth. Repeated work absence may also lead to that the worker may lose her job. When a firm scale down, one important factor in determining which workers who stay employed is likely to be the frequency of work absence. That is, the worker's decision on work absence is likely to be influenced by more long term consideration than the just the short term cost. Third, investment in health. Work absence, like utilization of other forms of medical care, can be seen as an investment in the individual's health. By being absent from work due to minor health problems, the individual may increase the chance of a relatively fast recovery and therefore may obtain a higher productivity in the next time period.

In previous studies on work absence behavior, the analysis is most often performed on time-aggregated data, i.e. number of days absent during a time period (one year, a week etc.).[3] In this study, we use a data-set that contains work absence records for each day in 1991 for a random sample of Swedish blue collar workers. We have chosen an event history analysis approach. We will study both the incidence of work absence spells, i.e. the transition from

[1] See Lantto (1991) for a theoretical analysis of design of optimal excess in sickness insurance schemes.

[2] See e.g. Johansson and Palme (1996) or Barmby, Orme and Treble (1995).

[3] See for instance Allen (1981a,b), Dunn and Youngblood (1986), or Johansson and Palme (1996).

work to work absence (W $\rightarrow$ WA), as well as the duration of the work absence spells, i.e. transition from work absence to work (WA $\rightarrow$ W).

As in most micro-econometric analysis, it is of essential importance in empirical studies of work absence behavior to separate out the effects of economic incentives from the effects of individual heterogeneity. In the study we use two different methods in order to control for individual heterogeneity. First, our data-set contains extensive information on individual health status as well as work-place characteristics. All these variables will be included in a discrete time Cox regression model. Second, we make a stratified analysis. In the stratified analysis only time varying covariates, with interactions, can be analyzed. We have three variables that fulfills this requirement: the monthly local unemployment rates, whether or not the individual are on holiday (July), and a reform of the sickness insurance that was implemented in March 1 1991. In this reform the replacement level in the Swedish compulsory sickness insurance, the share of the insured worker's income from labor that is payed out from the insurance, was substantially decreased, i.e. the excess in the insurance scheme was increased. This over-night change creates an exogenous change in one of the most important variables in our model. This enables us to use the pre-reform behavior as an implicit control group.

The data set is obtained from the 1991 *Swedish Level of Living Survey* (SLLS). This data set contains, in addition to the day-to-day information on work absence, extensive individual information on economic resources, health, work environment and other work place characteristics. The analyzed data is restricted to a sample of 1,609 Swedish blue collar workers (814 men and 795 women). Descriptive statistics (with explanations) for the variables used in the estimation are given in Tables 1 and 2.

The analysis is performed with a discrete time hazards model.[4] The exception is the stratified approach, in which ties are almost fully removed by design, where we use continuous time Cox regression. Our data contains left truncations (i.e. late start points). To deal with this problem we graphically examine whether the interval in which a spell is started can be counted fully or not.

A comparatively rich set of results were obtained in this study. Although most of these results have been obtained in previous studies on work absence behavior, we believe that additional insight were gained from the event history analysis. Several of the variables were affected by state dependence in the sense that they did not have the same effect on the incidence of work absence spells as they had on the duration of these spells. This form of state dependence can be handeled, and analysed, in the hazard function

[4]For a full description of the method and software used, see Broström (1998).

framework. For example, our results shows that the reform in the sickness insurance did have a large effect on the incidence of work absence spells, but did not affect the duration of these spells. Several male-female differences were also found. In general, women have more frequent, but shorter, work absence spells.

The paper is organized as follows. Section 2 describes the institutional settings and data. In Section 3 the absence and work behavior are analyzed non-parametrically. In Section 4 we obtain the econometric model departing from a comparative static analysis of work absence behavior. Section 5 presents the estimation procedures. Section 6 discusses the results and the study is concluded in Section 7.

2. Institutions and Data

The data are collected from the 1991 Swedish Level of Living Survey (SLLS). The SLLS is a micro data set that contains information obtained from interviews as well as public registers for a random sample of about 6,000 individuals. This survey is described in detail in Fritzell and Lundberg (1994). For this study, we have restricted the sample to blue collar workers aged between 20 and 64 who were employed during the year 1991, the year of the survey. The motive for limiting to blue collar workers is to limit heterogeneity arising from differences sickness insurances. Swedish white collar workers often have negotiated sickness insurances, the rules for these insurances cannot be obtained from the available data. The final sample consists of 1,609 individuals.

The definition of work absence, is that the individual is compensated from the compulsory sickness insurance. Data on work absence is obtained from the National Social Insurance Board by matching with the SLLS sample. For days in a sequence of more than seven days, the individual has a certificate from a physician. As the data was collected from registers of actual payments to the insured individual, the quality is likely to be good. However, if we define work absence as time when the employee is absent from work which is not agreed in advance with the employer and statutory leisure time (such as statutory holiday), a small fraction of work absence is likely not to be included in the sickness insurance data.[5]

The insured individual is entitled to compensation also at weekends and holidays. We will add one dummy variable for the month of the holiday (HOLI) for industrial workers (July), to find out if the utilization of the sickness insurance differ for these days compared to regular work days.

[5]According to one survey the amount was 2.9 per cent in 1986 (SAF, 1986).

Two economic variables are included in the econometric model: the hourly wage rate (w) and daily non-labor income (R). Both these variable are likely to be very much influenced by income taxes, as they are defined as net of taxes.[6] The Swedish income tax system consists of two separate parts: taxes on labor income and taxes on income from capital. The taxes on labor income consist of a proportional tax imposed by the local authorities and a progressive tax imposed by central government. The local tax rate varies somewhat between Sweden's 286 municipalities and has a mean of 30.3 per cent. In 1991, the state tax on labor income was zero below taxable income[7] of 170,000 SEK and was proportional at a rate of 20 per cent on labor income beyond this level. Income from capital is taxed at a flat rate state tax on 30 per cent. There is no local government tax on income from capital.

The hourly wage rate is calculated in several steps. First, we calculate the income from labor the worker would have received if she would have had no work absence during the year 1991, i.e. potential income from labor. That is, we add the share of the income not covered by the sickness insurance for the days each worker was absent. We then calculate and deduct income taxes from potential income. Finally, we divide the number of hours of work stated by the worker in the survey to get the hourly wage rate. Data on income from labor is obtained from tax registers match on to the SLLS survey.

Non-labor income consists of three parts: income from capital, child and housing allowances. Data on all these components are obtained from tax registers match on to the SLLS survey.

The share of the worker's daily earnings covered by the sickness insurance below the social security ceiling,[8] δ, was 90 per cent, independently on the length of the sickness spell, before the reform of March 1, i.e. for the period January 1 to February 28 in our sample. After the reform, between March 1 and December 31, δ was decreased to 65 per cent for the first 3 days in a sickness spell and to 80 per cent for the following 87 days in a spell. For the days after day 90, δ remained at 90 percent. That is, the cost of being absent from work increased substantially independently of the length of the spell after the reform. The cost of short spells increased relatively more than others. This information can, however, not be used in our model since the dependent variable is the length of the spell. We have chosen to model the increased cost of work absence simply as a dummy variable taking the value

[6] For a detailed description of the Swedish tax and benefit system, see Aronsson and Walker (1997).

[7] Taxable income from work, is defined as income from work minus a deduction that depends on the income. The deduction is in the range 10,304 - 18,384 SEK.

[8] The social insurance ceiling corresponded to an annual income of 241,500 SEK. All blue collar workers in our sample have income belows this ceiling.

0 before the reform and 1 after.

In 1991 the Swedish economy entered a recession. The open unemployment rate increased from 3.5 per cent in January to 5.2 per cent in December. The reform of the sickness insurance was a part of the government's policy to handle the economic recession. As is extensively discussed in Section 4, the increase in the rate of unemployment is likely to affect the work absence behavior. Therefore, we include monthly data on the unemployment rate on the local labor market of each worker in the sample. Sweden is administratively divided into 24 counties and 283 municipalities. We define each county as one local labor market. That is, we use the monthly unemployment rate of each county and match it with the county of residence for each worker obtained in the survey. Data for the unemployment rates are obtained from the Swedish Labor Market Board.

3. Non-parametric Analysis of Work and Work Absence Spells

Figures 1 through 4 show Kaplan-Meier estimates of the survival function for the work absence spells as well as work spells by different subdivision.

Figure 1 shows the over all male-female difference in exit rates from work and work absence spells. The first panel in Figure 1 displays the work absence survival function for males and females. Both survival functions in this panel show a similar pattern: A steep decrease until day seven and then a relatively flat segment. This marked pattern is determined by the fact that a certificate from a physician is needed for continuing a work absence spell after day seven. It can also be seen that women have a somewhat higher exit rate from short work absence in spells up to five days. For longer spells, the survival functions are very similar. The second panel reveals male-female differences in work spells. Although the difference is very small, this panel shows that the graph for the male sub-sample exceeds the graph for the female sample. This difference reflects the fact that women have a higher incidence of work absence spells, i.e. men tend to stay longer in their work spells.

Figure 2 shows the effect of the reform of the sickness insurance on the work absence behavior. The first two panels in Figure 2 show the effect on the survival functions on the work spells for men and women respectively. These two panels show that both the men and the women in the sample change their work absence behavior after the decrease in the contribution level of the sickness insurance; the incidence of work absence decrease markedly after the reform. It can also be seen that women change their behavior somewhat more than men. The third and fourth panel of Figure 2 also show an interesting

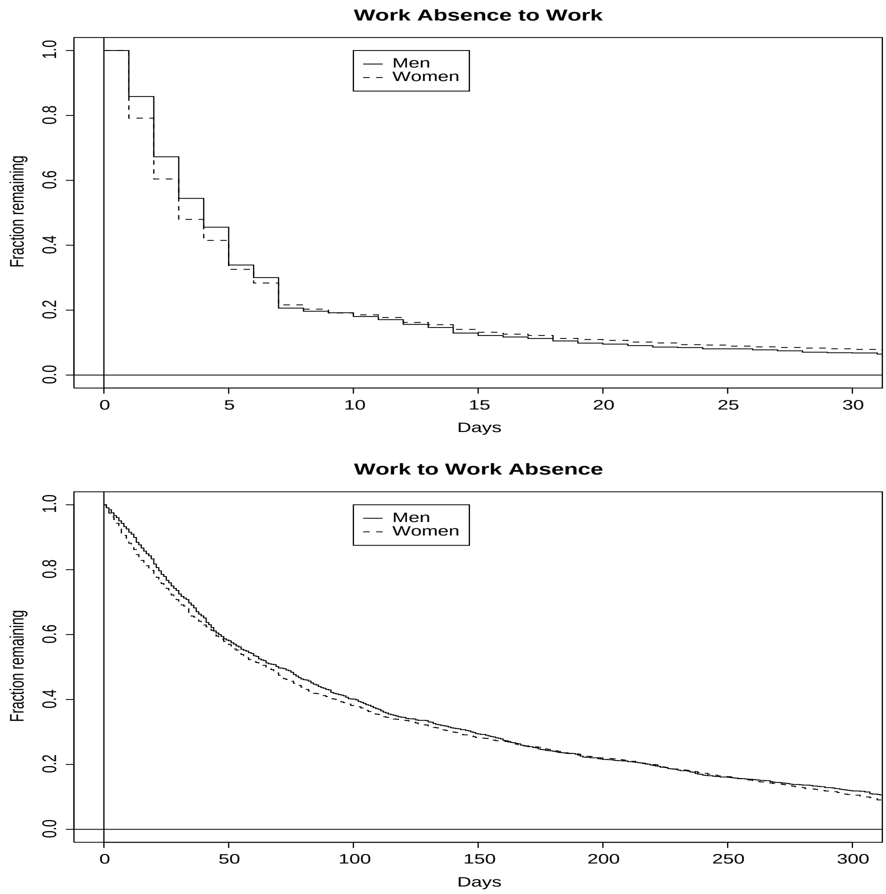

Figure 1: Overall male-female differences in fraction remaining.

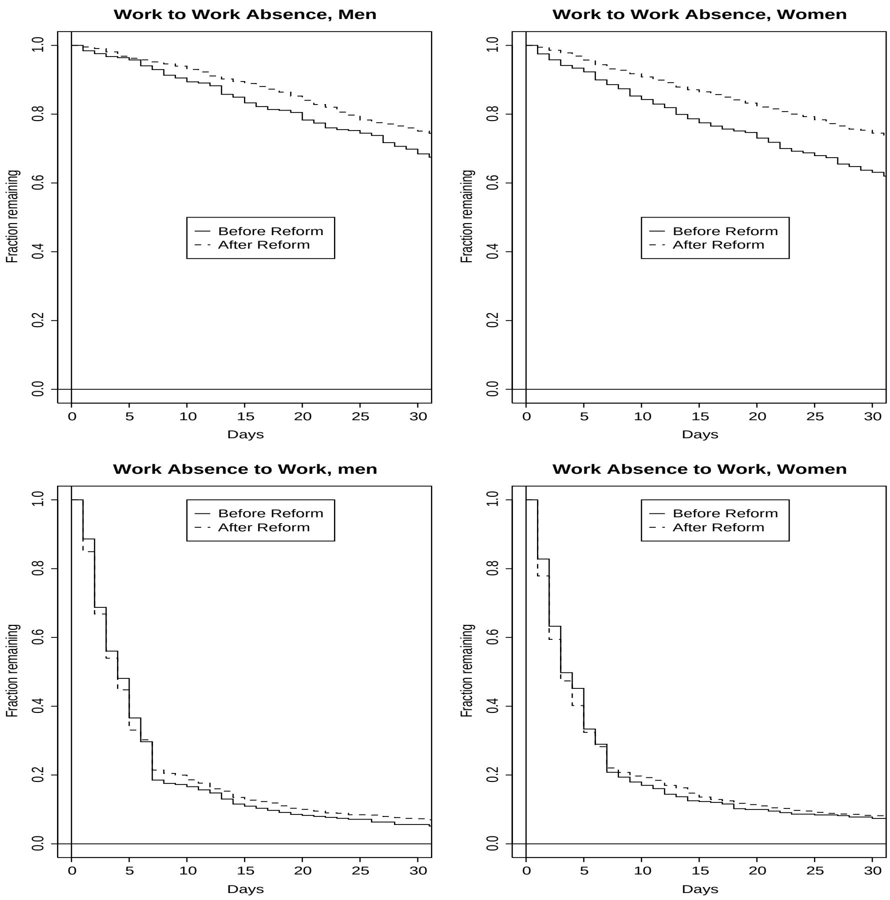

Figure 2: Overall before-after reform differences in fraction remaining.

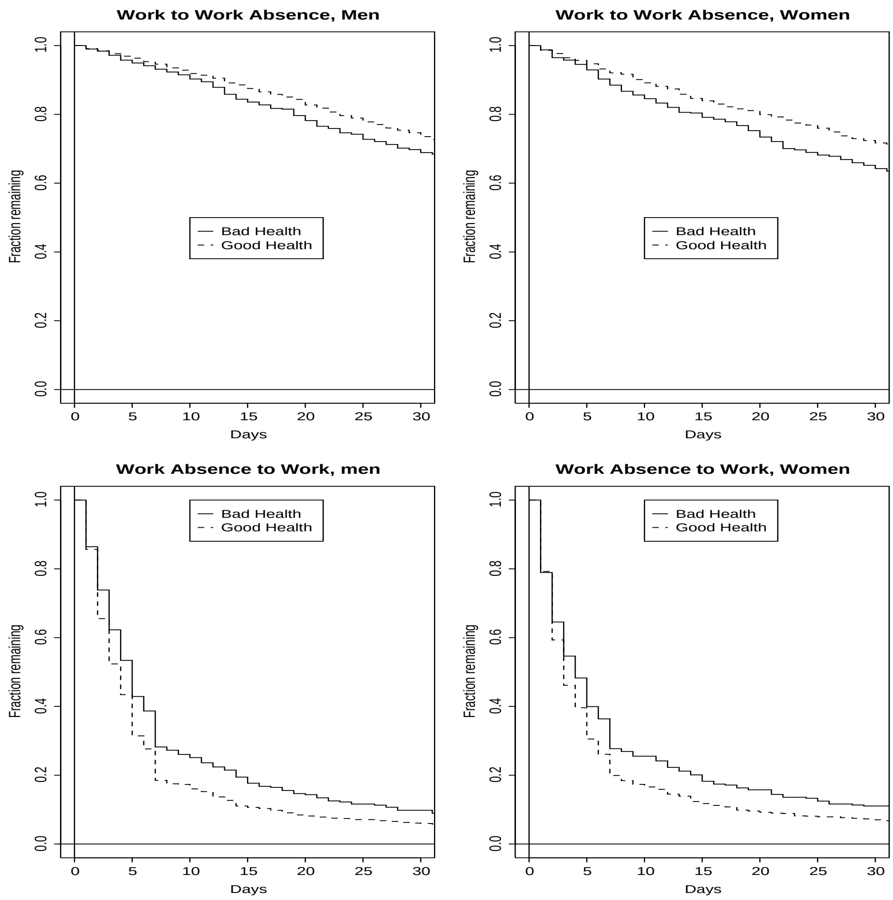

Figure 3: Overall differences in fraction remaining between workers with different health statuses.

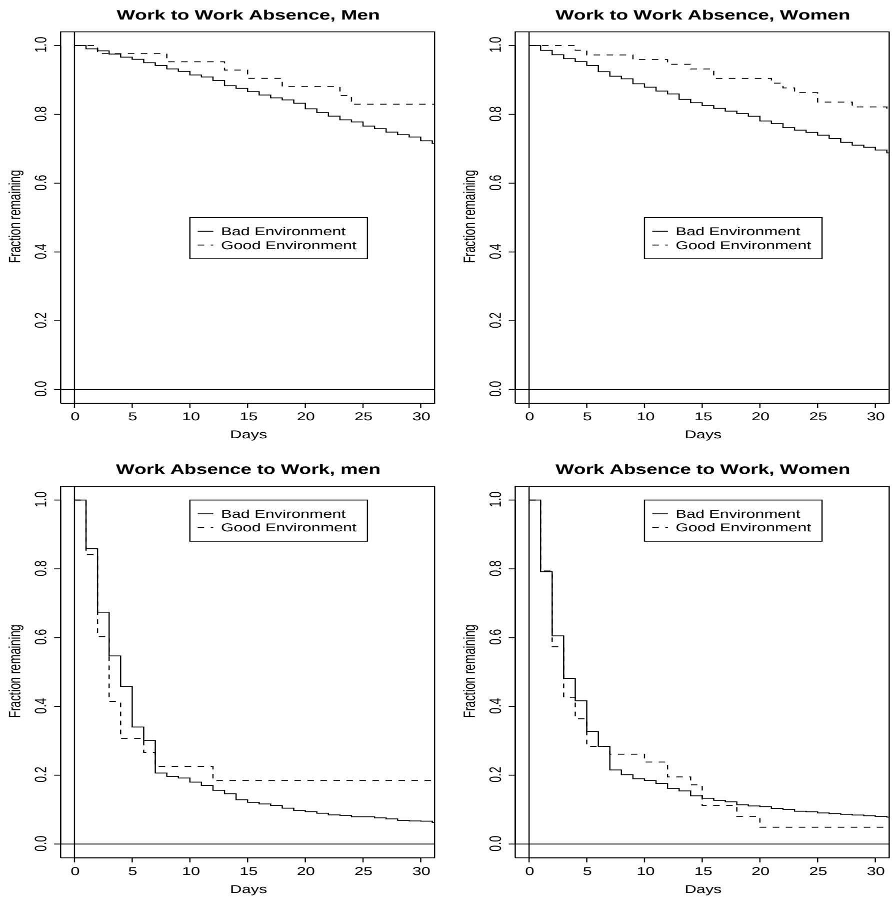

Figure 4: Overall differences in fraction remaining between workers with different work environments.

pattern: The probability of leaving a work absence spell increases somewhat the first five or six days for both men and women. After that, the relation is reversed: the individuals tend to stay longer in their work absence spells. To some extent these changes in the shape of the survival function correspond to the changes in the economic incentives implied by the reform: The largest decrease in the contribution level in the sickness insurance, i.e., the largest increase in the cost of being absent, were on the first three days of a absence spell. We can see that the two genders seem to react very similar to the reform.

Figure 3 compares the survival functions of individuals with different health status. Individuals with bad health are defined as those who have at least one indication of health problem among the 13 indicator variables used in order to characterize health differences among the individuals in the sample (see Tables 1 and 2 for descriptions as well as descriptive statistics of these variables). About 23 per cent if the individuals in the sample meet the definition of having bad health (25.5 per cent among the women and 20.5 per cent among the men).

The first and second panel of Figure 3 shows that workers with bad health status have somewhat higher exit rate from work spells. The difference is very similar among both men and women. The third and fourth panel shows that the exit rates for individuals with good health are always larger than the exit rates from work absence for the individuals with bad health. Men with bad health has a much lower exit rates than men with god health. For women the difference in exit rates are smaller. For long absence spells, however, the difference between men and women in this respect is very small.

The effect of bad working conditions are explored in Figure 4. We use the same strategy to define bad working conditions as we used for bad health: The 97.2 per cent of the sample (96.3 per cent among the women and 98 per cent among the men) who are defined as having bad working conditions have at least one indication of bad working conditions among the 13 indicator variables used in order to define individual differences in working conditions.[9]

The survival functions for the females and males of the work spells are given in panel one and two. As expected is the exit rates for those with bad environment larger than those with good environment. The effect is larger for the female sub-sample. The third and fourth panel of Figure 4 shows that workers exposed to bad working conditions on average have somewhat lower exit rate from short absence spells, while they have higher exit rates from longer spells. This pattern is driven by the male sub-sample. These result

[9]We need to be cautious interpreting Figure 4, since only 34 (22 females and 12 males) individuals has indication of no bad working conditions.

Table 1: Descriptive statistics: All individuals in the data set.

Variable	Mean	St. Dev	Mean	St. Dev.	Mean	St. Dev.
	All (n = 1609)		Males (n = 814)		Females (n = 795)	
Number of days absent	29.65	66.34	25.62	61.80	33.76	70.49
Personal Characteristics						
FEMALE	0.49	0.50				
MARR (married)	0.71	0.45	0.67	0.47	0.75	0.43
DIV (divorced)	0.07	0.25	0.05	0.22	0.09	0.28
AGE	39.13	12.11	38.39	12.01	39.88	12.18
DISAB (disabled)	0.03	0.16	0.02	0.15	0.03	0.16
NRCH (number of children below 16 years)	0.71	1.03	0.64	1.03	0.78	1.03
Economic Incentives						
w (net hourly wage rate)	34.74	10.97	37.83	10.93	31.58	10.09
R (daily non-labor income)	25.66	37.32	22.25	37.76	29.16	36.56
t^c (contracted daily working hours)	7.24	1.34	7.78	0.84	6.70	1.53
FEW (fewer working hours preferable)	0.10	0.31	0.08	0.28	0.13	0.33
MORE (more working hours preferable)	0.08	0.27	0.05	0.21	0.12	0.32
Work Invironment						
NOISE1 (noisy environment)	0.11	0.31	0.17	0.38	0.05	0.21
NOISE2 (noisy environment)	0.34	0.47	0.44	0.50	0.23	0.42
SMOKE (exposed to gas, dust or smoke)	0.26	0.44	0.34	0.47	0.18	0.39
SHAKE (exposed to strong shakes or vibrations)	0.08	0.28	0.15	0.35	0.02	0.13
POISON (exposed to gas, dust or smoke)	0.11	0.31	0.16	0.37	0.05	0.21
LIFT (heavy lifting)	0.25	0.43	0.35	0.48	0.16	0.36
HARD (work is physically exhausting)	0.61	0.49	0.60	0.49	0.62	0.49
SWEAT (work causing daily sweating)	0.35	0.48	0.40	0.49	0.30	0.46
EXHM (work is metally exhausting)	0.40	0.49	0.32	0.47	0.47	0.50
STRESS (work is stressfull)	0.64	0.48	0.60	0.49	0.68	0.47
REP (work is repititive)	0.27	0.45	0.27	0.44	0.28	0.45
MBM (monotonous movements)	0.53	0.50	0.50	0.50	0.57	0.50
UBP (unpleasent body positions)	0.58	0.49	0.62	0.49	0.55	0.50
RISK1 (SIR, work accidents)	1.28	1.01	1.62	1.03	0.93	0.86
RISK2 (SIR, work-related diseases)	1.25	1.00	1.87	1.01	0.62	0.45
Health Status						
STRUM (struma)	0.01	0.10	0.00	0.05	0.02	0.13
TBC (tuberculosis)	0.00	0.04	0.00	0.05	0.00	0.04
HARTP (problem with hart)	0.01	0.12	0.02	0.14	0.01	0.08
HBLOD (high blood presure)	0.07	0.26	0.08	0.27	0.07	0.25
STOMA (gastric ulcer)	0.02	0.15	0.03	0.16	0.02	0.14
HEMOR (haemorrhoids)	0.05	0.21	0.04	0.20	0.05	0.22
LBROCK (groin rapture)	0.01	0.09	0.01	0.12	0.00	0.05
ABROCK (varicose vains)	0.05	0.21	0.03	0.17	0.07	0.25
MENTAL (mentally sick)	0.00	0.07	0.00	0.06	0.01	0.08
CANCER (cancer)	0.01	0.10	0.01	0.10	0.01	0.10
DIABETIC (diabetic)	0.01	0.12	0.02	0.13	0.01	0.11
NEURO (neurological illnes, e.g. polio)	0.00	0.07	0.00	0.07	0.00	0.06
PREGNANT (pregnacy difficulty)	0.02	0.15			0.04	0.21
D(t^a)						
UNEM (local unemployment rate)	3.62	1.05	3.64	1.05	3.59	1.03
FLEX (flexibel working schedule)	0.67	0.47	0.65	0.48	0.70	0.46
CLOCK (use of punch clock)	0.35	0.48	0.41	0.49	0.28	0.45

Table 2: Descriptive statistics: Sub-sample of individuals with at least one day of work absence and at least one day of work during 1991.

Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev
	All (n = 1164)		Males (n = 556)		Females (n = 608)	
Number of days absent	32.51	56.13	29.64	52.89	35.14	58.85
Personal Characteristcs						
FEMALE	0.52	0.50				
MARR (married)	0.71	0.46	0.66	0.47	0.75	0.43
DIV (divorced)	0.07	0.25	0.05	0.22	0.09	0.28
AGE	38.04	11.97	37.09	11.96	38.90	11.92
DISAB (disabled)	0.02	0.14	0.02	0.14	0.02	0.14
NRCH (number of children below 16 years)	0.72	1.01	0.63	1.00	0.80	1.02
Economic Incentives						
w (net hourly wage rate)	34.23	10.39	37.14	10.37	31.57	9.67
R (daily non-labor income)	25.83	36.61	21.91	36.01	29.41	36.81
FEW (fewer working hours preferable)	0.11	0.31	0.09	0.29	0.13	0.33
MORE (more working hours preferable)	0.08	0.28	0.05	0.21	0.12	0.32
t^c (contracted daily working hours)	7.21	1.35	7.80	0.79	6.67	1.32
Work Environment						
NOISE1 (noisy environment)	0.11	0.31	0.17	0.37	0.05	0.22
NOISE2 (noisy environment)	0.34	0.47	0.46	0.50	0.24	0.43
SMOKE (exposed to gas, dust or smoke)	0.27	0.45	0.36	0.48	0.20	0.40
SHAKE (exposed to strong shakes or vibrations)	0.08	0.28	0.15	0.36	0.02	0.14
POISON (exposed to gas, dust or smoke)	0.11	0.31	0.17	0.37	0.06	0.23
LIFT (heavy lifting)	0.24	0.43	0.34	0.47	0.16	0.37
HARD (work is physically exhausting)	0.63	0.48	0.64	0.48	0.62	0.49
SWEAT (work causing daily sweating)	0.37	0.48	0.43	0.50	0.31	0.46
EXHM (work is metally exhausting)	0.40	0.49	0.31	0.46	0.49	0.50
STRESS (work is stressfull)	0.65	0.48	0.61	0.49	0.69	0.46
REP (work is repititive)	0.30	0.46	0.31	0.46	0.29	0.46
MBM (monotonous movements)	0.55	0.50	0.53	0.50	0.57	0.50
UBP (unpleasent body positions)	0.61	0.49	0.65	0.48	0.57	0.50
RISK1 (SIR, work accidents)	1.28	1.04	1.66	1.05	0.94	0.89
RISK2 (SIR, work-related diseases)	1.23	1.02	1.90	1.03	0.62	0.46
Health Conditions						
STRUMA (struma)	0.01	0.10	0.00	0.04	0.02	0.13
TBC (tuberculosis)	0.00	0.04	0.00	0.04	0.00	0.04
HARTP (problem with hart)	0.01	0.11	0.02	0.13	0.01	0.08
HBLOD (high blood presure)	0.07	0.26	0.07	0.26	0.07	0.26
STOMACH (gastric ulcer)	0.02	0.16	0.03	0.17	0.02	0.14
HEMORR (haemorrhoids)	0.04	0.20	0.04	0.21	0.04	0.20
LBROCK (groin rapture)	0.01	0.09	0.01	0.12	0.00	0.04
ABROCK (varicose vains)	0.05	0.22	0.03	0.18	0.07	0.25
MENTAL (mentally sick)	0.01	0.07	0.01	0.07	0.00	0.07
CANCER (cancer)	0.01	0.10	0.01	0.11	0.01	0.09
DIABETI (diabetic)	0.01	0.12	0.02	0.13	0.01	0.11
NEURO (neurological illnes, e.g. polio)	0.01	0.08	0.01	0.08	0.00	0.07
PREGNANT (pregnacy difficulty)	0.03	0.16			0.05	0.22
D(t^a)						
UNEM (local unemployment rate)	3.64	1.06	3.64	1.05	3.64	1..07
FLEX (flexibel working schedule)	0.68	0.47	0.67	0.47	0.69	0.46
CLOCK (use of punch clock)	0.35	0.48	0.40	0.49	0.29	0.45

shows that workers exposed to bad working conditions on average is absent somewhat longer before they are able to go back and do their job. The result that these workers have a higher exit rate from long absence spells may be explained by a selection of workers with good health into more demanding jobs. This effect is often referred to as the "healthy worker effect". An interesting gender difference is that the above described pattern can not be seen at all among women. In the female sub-sample, workers holding jobs with good work conditions have on average lower survival rates in long work absence spells.

To sum up, the non-parametric analysis showed that the reform of the sickness insurance, gender, differences in health status as well as differences in exposure to bad working conditions all influence individual work absence behavior. The influence of these factors are, however, very different and they also affect distinct segments of the survival function differently.

4. Absence and Work Spells Modelling

To model work absence behavior, we depart from individual utility maximization, i.e. the same framework as has been used in numerous labor supply studies. We follow Allan (1981a) and use a comparative static model to analyze the length of the time an individual stay in a work and a work absence spell respectively.

Assume that an individual have the following utility function

$$u = U(x, L; \mathbf{s}), \tag{1}$$

where x is a composite good, with the price normalized to one, L is leisure and $\mathbf{s}$ is a vector of socioeconomic variables. L can be broken down in to contracted leisure time, t^l, time absent, t^a. We assume that contracted leisure time is fixed over the time period studied (one year).

We further assume that demand for time absent is obtained when the individual maximizing the utility function (1) subject to the budget constraint

$$w\left(t^c - \delta t^a\right) + R - x - D(t^a) = 0, \tag{2}$$

where t^c is the contracted number of daily working hours, δ is the share of the income the worker receives when absent and $D(t^a)$ is the loss of being absent from work in addition to the direct cost represented by the excess in the sickness insurance. If the worker is absent frequently she will experience less on-the-job training and, therefore, her future earnings growth rate are likely to be less than it otherwise would have been. Furthermore, in most cases, work absence involves costs for the firm as there are cost involved with changing production plans, or to temporarily hire workers to do the absent worker's job. Therefore, a frequently absent worker may experience a higher risk of losing her job, which of course also can be seen as a secondary cost of work absence.

Substitution of (2) in to (1) and differentiation with respect to t^a gives the following first order condition

$$\frac{du}{dL} - (w\delta + \frac{dD(t^a)}{dt^a})\frac{du}{dx} = 0.$$

By differentiating the first order conditions it is possible to show that

$$\frac{\partial t^a}{\partial w} \gtreqless 0, \frac{\partial t^a}{\partial \delta} > 0, \frac{\partial t^a}{\partial R} > 0, \frac{\partial t^a}{\partial t^c} > 0 \text{ and } \frac{\partial t^a}{\partial D(t^a)} < 0.$$

The effect of a change in the wage rate follows the well known result from the labor supply literature. An increase in the wage rate makes the relative price of being absent from work higher and the worker willing to substitute work absence time for work. However, in this process, the income of the worker will also increase and, assuming work absence to be a normal good, this will increase the worker's demand for work absence. It is not possible solely from theory to determine which of these effects that will dominate. The effect of a decrease in the replacement level in the sickness insurance is, again assuming that work absence is a normal good, on the other hand unambiguous: the income and substitution effect will in this case work in the same direction.

The effect of an increase in unearned income isolates the income effect. The increased demand for work absence when contracted number of hours of work is increased is explained by the fact that the utility function is concave in leisure. The effect of increased penalties for work absence is, by the same argument as for an increase in the excess, decreased demand for work absence.

This discussion above leads to the following general formulation for the hazard functions for work absence (WA) and work (W) for individual i

$$\lambda_i^{(k)} = g(t^c, w, \delta, R, D(t^a); \mathbf{s}_{it}, \theta_i, g(\gamma)^{(k)}), \ k = \text{W and WA}. \tag{3}$$

Here $\mathbf{s}_{it}$ is a vector of exogenous socioeconomic variables, θ_i is unobserved heterogeneity and $g(\gamma)^{(k)}$ is a function of the periods spent in the current state k. In the discrete time hazard model we assume that no individual unobserved heterogeneity is present, i.e. $\theta_i = \theta$ for all i. In the stratified analysis however, this restriction is relaxed.

It is not obvious from a theoretical point of view how the duration dependence, $g(\gamma)^{(k)}$ for $k = W$ and WA, should be specified. Institutional characteristics may generate non-monotonous duration dependence, at least for the transition from work absence to work, as a certificate from a physician is needed after seven days of work absence to be eligible for continued compensation from the sickness insurance. To preserve maximum flexibility the duration dependence is specified with a dummy variable for each day. Allowing for state dependence, we do not restrict parameters in $\lambda_i^{(k)}$ to be the same for $k = \mathrm{W}$ and $k = \mathrm{WA}$.

Most of these variables are directly observable from our data-set. However, the penalty for being absent can not be measured directly. On the other hand, it can be hypothesized that several observable characteristics of each workers workplace and local labor market can be related to the penalty of being absent from work.

As noted above, the frequently absent worker has a higher risk of losing her job. If the unemployment rate is relatively high on the local labor market where the worker is active, the worker's cost of losing her job is likely to be relatively high as the search cost of finding a new job is on average higher in labor markets with high unemployment rate. Therefore, the penalty function for work absence should be related to the unemployment rate on the local labor market.

A well known result from the human capital theory (see Willis, 1986), is that the benefits of on-the-job training is higher if this training take place relatively early in the worker's career as the wage increase of the improved skills is received for a longer period of time. As work absence is related to forgone on-the-job training the cost of work absence are likely to be inversely related to the worker's age, i.e. the worker's age should also be included in the penalty function. However, since the health of an worker is also likely to depend on the age, we are not able to identify the penalty effect from the effect of general health depreciation by age.

There are other means than the excess in the sickness insurance that can be used by the employer in order to decrease work absence. These include direct control as well as pay schemes that provide incentives for the worker to be present.

Following the discussion above, we simply define the penalty of being absent from work as a linear function of the local unemployment rate (UNEM) and two variables, whether or not there is a punch-clock at the worker's work place (CLOCK) and if the worker has flexible working hours (FLEX), defining the control by the worker's employer.

5. Estimation

5.1 Proportional hazards for discrete time data

The time scale is discrete in the analysis of work absence. An individual, i, is daily recorded as either being absent from work or working. For both models, we assume proportional hazards, which for a discrete time scale amounts to the following model for the hazards: The contribution at duration j days, for individual i with covariate vector $\mathbf{z}_i$, is given by

$$\lambda_j^{(k)}(\mathbf{z}_i) = 1 - \exp\left(-e^{\gamma_j + \mathbf{z}_i\beta}\right),\ j = 1, \ldots, T-1,\ i = 1, ..., n;\ k = \mathrm{WA}, \mathrm{W}, \quad (4)$$

where β is the parameter vector, to be estimated, and T is the maximum number of days a spell can contain, that is, $T = 365$ (cf. Kalbfleisch and Prentice, 1980, Ch. 4).

To compare the expression in (4) with the more well known continuous time models, assume that continuous time data are at hand, and that a proportional hazards model describes it well.

The proportional hazards model states that

$$h(t; \mathbf{z}_i) = h_0(t) e^{\mathbf{z}_i\beta}, \quad (5)$$

where t is the survival time. The hazard function is proportional to the hazard function with the value zero on all the components of the covariate vector. This *base-line* hazard function is $h_0(\cdot)$.

If survival time is grouped into intervals $A_j = [a_{j-1}, a_j), j = 1, \ldots, k + 1$ $(a_0 = 0, a_{k+1} = \infty)$, then a discrete time model is at hand. It must be assumed that censoring in an interval occurs at the interval end point, thus succeeding all deaths in the interval.

Now, let $\lambda_j(\mathbf{0}) = P_0$(dying in A_j, *given* survival up to a_{j-1}), where P_0 denotes "base line probability", then $\lambda_j(\mathbf{z})$, the hazard contribution at A_j, the jth interval, is given by

$$1 - \lambda_j(\mathbf{z}) = (1 - \lambda_j(\mathbf{0}))^{\mathbf{z}\beta},\ j = 1, \ldots, k,$$

which is the same as

$$\lambda_j(\mathbf{z}) = 1 - \exp\left(-e^{\gamma_j + \mathbf{z}\beta}\right),\ j = 1, \ldots, k,$$

with $\gamma_j = \log\left(-\log(1 - \lambda_j(\mathbf{0}))\right)$.

We can see that the hazards model for survival analysis in discrete time is equivalent to a regression model for binary data, the complementary log-log

(CLL) model in the generalized linear models (GLM) language (cf. McCullagh and Nelder, 1983). The CLL model preserves its properties, when adjacent time intervals are amalgamated.

The log likelihood function to be maximized with respect to $(\gamma, \beta$, where $\gamma = (\gamma_1, \ldots, \gamma_{T-1})'$, is given by

$$\ell(\beta, \gamma) = \sum_{j=1}^{T-1} \left\{ \sum_{l \in D_j} \ln(1 - \exp(-\exp(\gamma_j + \mathbf{Z}_l \beta) - \sum_{l \in R_j \setminus D_j} \exp(\gamma_j + \mathbf{Z}_l \beta) \right\}, \tag{6}$$

where R_j is the set of observations with spell lengths larger than or equal to j, D_j is the set of observations with spell length j, $j = 1, \ldots, (T-1)$ and $\mathbf{Z}_l$ is a vector of explanatory varaibles for each observation contained in D_j and R_j.

The variance-covariance matrix of the parameter estimates is as usual estimated by the negative of the inverse of the Hessian matrix, inserting the estimates $\hat{\gamma}$ and $\hat{\beta}$.

5.2 Left truncation

The problem to discuss here is how to treat those spells, that begin somewhere before the start of the study period and expands into it. A statistically correct method is to condition on the spell length obtained at January 1, but that is impossible because of data limitation. It is only known in which state, W or WA, a person is at the beginning of the year, not for how long she has been in that state. We have left truncation at an unknown duration.

We may think of two methods for handling this problem. First, a "generous" method; the interval, in which a spell is started, is counted fully. Second, the "restrictive" approach; a spell is accounted for only in intervals, where it contains the start of the interval.

The left truncation problem is not likely to be a big problem for the WA $\to$ W hazard, because only 486 out of 4033 spells entered as absent from work and these spells can safely be neglected since, 3547 sick spells still remain. That is, of the total of 4033 work absence spells, only 12.1 per cent are without known start date.

The situation is more complicated as regards the transition from W $\to$ WA, because as many as 1123 spells out of a total of 5139 work spells, or 21.9 per cent, are affected. Note that by throwing these 1123 spells away, we also throw away all individuals who never (at least during that year) are absent from work.

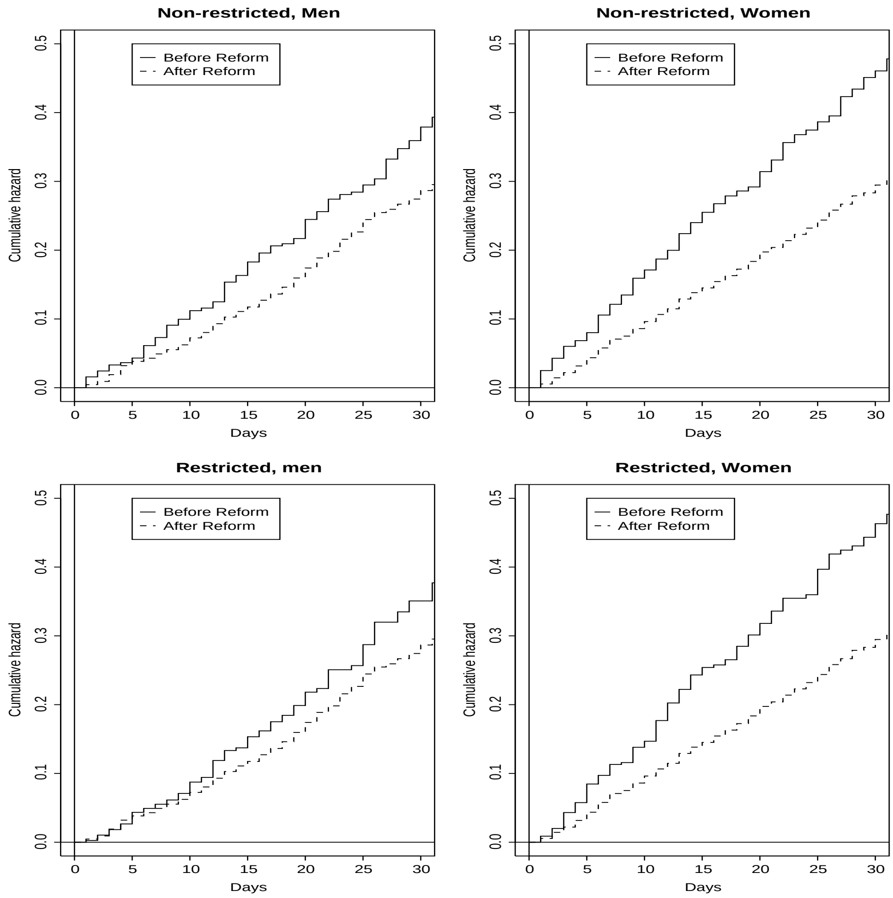

Figure 5: Overall cumulative hazard rates

In order to include the work spells starting before January 1 and pretending they started on that day, it is necessary to assume that the intensity of being absent from work a particular day is independent of how long the person has been in work. In other words, the individual duration has a geometric (or exponential, if time is regarded as continuous) distribution. For the work absence spells it is quite clear from Figure 1 that the inclusion of the left censored observations is not appropriate. For the work spells the Nelson-Aalen estimator[10] of the cumulative hazards functions are shown in Figure 5. It seems reasonable to assume that the duration of a work spell has a geometric distribution and we can use the non-restricted sample in the analysis of the work spells.

[10]The cumulative hazard is estimated under the restriction $\beta = 0$. Hence $\hat{\gamma}_j(\mathbf{0}) = \ln(-\ln(1 - D_j/n_j))$, where n_j is the number of observations at risk in R_j.

We have three explanatory variables that varies in the time period studied, the reform dummy (REFORM), the holiday in July (HOLI) and the monthly local unemployment rate (UNEM). The effect of these variables on the hazard rates can be separately analyzed using a stratified analysis (cf. Lancaster, 1990, p. 268 for a introductory description of this method).

The idea is to let each individual be her own control. A consequence is that an individual, in order to be included in the analysis, must have W or WA spells in both[11] of the studied time periods. The potential price of the stratification is lower power for detecting an effect of the reform, holiday, and unemployment level.

Technically, a separate proportional hazards model is fitted to the spells coming from each individual. Let us assume that there are n individuals qualifying for being included in the analysis, and that for individual i the hazard model is

$$\lambda^{(k)}(j; z_{it}) = \lambda_i(j) \exp\left(\beta^* \mathbf{z}_{it} + \sum_l \gamma_{il} u_{il}\right), \; j = 1, \ldots, n_i, \; i = 1, \ldots, n, \quad (7)$$

and $k = \mathrm{W}, \mathrm{WA}$. Here $\mathbf{z}_{it} = (\mathrm{REFORM}_{it}, \mathrm{HOLI}_{it}, \mathrm{UNEM}_{it})'$ are the variables that varies over the year and β^* is the corresponding sub-vector of parameters. REFORM_{it} and HOLI_{it} are indicator variables that takes value one if spell j for individual i starts after the date of the reform and holiday, respectively. UNEM_{it} is the local unemployment rate for the date t, of spell j. The $u_{il}, l = 1, \ldots, s$ variables are covariates that do not change during the year, eventually non-measurable. Spells starting before the date of the reform/holiday and the monthly change in unemployment rate and ending after are cut into two pieces, the first piece is right censored on the reform/holiday day and the monthly change in unemployment rate and the second piece is left truncated on the same day. This implies that we assume that the individual changes her behavior on the reform/holiday day and under the new unemployment rate.

Since the individuals are only compared with themselves, time constant covariates automatically cancel. This is of course also true for unobserved individual characteristics; thus, the stratified analysis is a simple way of eliminating unobserved heterogeneity. However, it is possible to measure *interactions* between the reform and holiday and individual characteristics. This is an interesting exception to the common rule "do not include interaction effects without the corresponding main effects". Consider the following

[11] When we study the effect of the unemployment rate we have twelve time periods. To be included in the analysis an individual must have at least two spells under different levels of the unemployment rate.

example where the time varying variable is interacted with gender:

$$\lambda(j; z_{it}, w_i) = \lambda_i(j) e^{(\beta^* + \omega w_i)\mathbf{z}_{it}}, \; j = 1, \ldots n_i; \; i = 1, \ldots, n, \tag{8}$$

where $w_i = 1$ for females and $w_i = 0$ for males. In this way, ω measures the extra effect on the time varying covariates in the female sub-sample. This is essentially the same as running two separate analyses for the genders and taking the difference between the two parameter estimates of the reform effect.

The contribution, L_i, to the partial likelihood from individual i is

$$L_i(\beta^*, \omega) = \prod_{j=1}^{n_i} \frac{\lambda(j; z_{it}, w_i)}{\sum_{l \in R_{ij}} \lambda(j; z_{il}, w_i)}, \tag{9}$$

where R_{ij} is the risk set for individual i at spell length j. Equation (9) reveals that all factors involving fixed covariates cancels.

A simple way of describing the analysis goes as follows: For one individual, there are n_i spells recorded for the reform, of which k_i are after the reform and $(n_i - k_i)$ are before the reform. All the n_i spells are ordered after increasing length, and the interesting quantity is the ranks of the k_i spells after the reform. If the reform has no effect on spell lengths, we would expect the ranks to be evenly spread between 1 and n_i and the parameters vector β^* measures the deviation from this balanced situation across individuals. The only crucial assumption is thus that the relative effect from the reform and holiday is the same for all individuals. We can see from Figure 2 that the incidence of work absence seem to be reduced more for the females than the for the males. To take account for this effect we include an interaction with females in the analysis.

The total partial likelihood is simply

$$L(\beta^*, \omega) = \prod_{i=1}^{n} L_i(\beta^*, \omega). \tag{10}$$

Estimation of standard errors is done as if we had an ordinary likelihood function, via asymptotic maximum likelihood theory.

6. Results

The main results from this study are reported in Tables 3 and 4. Table 3 shows the results from the discrete time hazard model for both the transition from work to work absence (W $\rightarrow$ WA), i.e. the incidence of work absence spells, as well as transition from work absence back to work (WA $\rightarrow$ W), the duration of the work absence spells. The results from the stratified analysis are shown in Table 4. As can be seen in Table 3, the independent variables have been grouped into five categories: Personal characteristics, economic incentives, work environment, health conditions and variables measuring secondary costs of being absent ($D(t^a)$). In order to save space, and to facilitate reading of the table, we only include parameters that are significant at the 10 per cent level, in at least one of the models. Significant estimates are shown with bold letters.[12] This section is organized as follows. We begin by discussing the effect of the explicit economic incentives on work absence behavior. We continue by discussing the influence of personal characteristics, health status, work environment, indicators of control at the work place and the unemployment rate. We conclude this section by discussing the over all male-female difference in work absence behavior.

6.1 Economic incentives

In the comparative static analysis of Section 4 we found that the effect of an increase in hourly wage rate on work absence can be either positive or negative. Assuming time spent on work absence, i.e. leisure time, to be a normal good, higher income, ceteris paribus, will increase the demand for being absent. On the other hand, higher hourly wage rate will increase the cost of being absent, as the cost of being absent is proportional to the wage rate. This increased cost, holding income constant, will unambiguously decrease the demand for being absent, i.e. the substitution effect. If the substitution effect is larger than the income effect we will observe a negative parameter for the hourly wage rate variable in the model for the incidence of work absence spells (W $\rightarrow$ WA) and a positive sign on the coefficient for the duration of the work absence spell (WA $\rightarrow$ W). If, on the other hand, the income effect is larger the opposite sign will apply in both models. That is, the parameter of the hourly wage rate variable measures the *net* effect from the income and substititution effects.

There are, however, several reasons why the estimat for the hourly wage rate variable may be biased. If jobs are heterogenous with respect to the tolerance of admitting work absence and if workers differ in their preferences to be absent from work, workers with preferences to be frequently absent from work may sort themselves into jobs with high tolerance for work absence but lower wage rate as a compensating wage differential. Moreover, if there is a component of on-the-job training in a particular job, a worker with

[12] The complete set of parameter estimates are given in Table 5 in the Appendix.

Table 3: Results from the discrete time hazards model. Significant on at least 10 per cent level in at least one model. Boldface numbers indicate significant results.

	WA $\rightarrow$ W			W $\rightarrow$ WA		
Covarite	Coeff	S.E.	p-value	Coeff	S.E.	p-value
			Personal Characteristics			
DIV	-0.0978	0.0768	0.2032	**0.2565**	**0.0762**	**0.0008**
AGE	**-0.0116**	**0.0025**	**0.0000**	**-0.0047**	**0.0024**	**0.0501**
DISAB	**-0.4312**	**0.1227**	**0.0004**	**0.2938**	**0.1042**	**0.0048**
NRCH	-0.0358	0.0267	0.1801	**-0.0878**	**0.0268**	**0.0011**
FEMALE * AGE	0.0018	0.0031	0.5584	**-0.0051**	**0.0030**	**0.0914**
			Economic Incentives			
w	**0.0058**	**0.0025**	**0.0193**	**-0.0061**	**0.0026**	**0.0166**
R	0.0020	0.0014	0.1519	0.0003	0.0013	0.8204
HOLI	**-0.3467**	**0.0894**	**0.0001**	**-0.6002**	**0.0858**	**0.0000**
t^c	0.0017	0.0034	0.6117	**0.0066**	**0.0033**	**0.0480**
FEW	**-0.1270**	**0.0556**	**0.0224**	0.0796	0.0547	0.1459
MORE	**-0.2125**	**0.0684**	**0.0019**	-0.0415	0.0665	0.5322
REFORM	-0.0265	0.0578	0.6471	**-0.3934**	**0.0456**	**0.0000**
w * FEMALE	-0.0058	0.0036	0.1039	**0.0090**	**0.0036**	**0.0123**
R * FEMALE	**-0.0025**	**0.0014**	**0.0813**	0.0017	0.0014	0.2330
FEMALE * REFORM	0.0480	0.0762	0.5289	**-0.1462**	**0.0768**	**0.0570**
			Work Environment			
SMOKE	-0.0005	0.0431	0.9909	**0.1080**	**0.0424**	**0.0109**
SHAKE	**-0.1964**	**0.0685**	**0.0041**	0.0749	0.0663	0.2587
LIFT	**0.0816**	**0.0431**	**0.0581**	0.0118	0.0432	0.7847
SWEAT	-0.0246	0.0413	0.5514	**0.1087**	**0.0398**	**0.0063**
REP	-0.0205	0.0407	0.6145	**0.1163**	**0.0403**	**0.0039**
MBM	**-0.1010**	**0.0401**	**0.0117**	-0.0150	0.0391	0.7021
UBP	0.0556	0.0427	0.1927	**0.0945**	**0.0417**	**0.0234**
RISK2	0.0411	0.0354	0.2463	**0.0582**	**0.0339**	**0.0860**
			Health Status			
TBC	-0.1465	0.3701	0.6923	**0.7761**	**0.2997**	**0.0096**
HARTP	**-0.2676**	**0.1466**	**0.0679**	**0.3386**	**0.1383**	**0.0144**
HBLOOD	**-0.2466**	**0.0722**	**0.0006**	0.0546	0.0696	0.4330
STOMACH	-0.0177	0.0987	0.8577	**0.2225**	**0.0975**	**0.0224**
HEMORR	0.0244	0.0816	0.7650	**0.1751**	**0.0776**	**0.0240**
LBROCK	**-0.4543**	**0.2489**	**0.0680**	-0.3717	0.2368	0.1164
CANCER	**-0.6656**	**0.2155**	**0.0020**	-0.1743	0.1949	0.3711
PREGNANT	**-0.3238**	**0.1215**	**0.0077**	**-0.2479**	**0.1221**	**0.0424**
			$D(t^a)$			
CLOCK	**-0.0794**	**0.0401**	**0.0474**	**0.1101**	**0.0388**	**0.0045**
UNEM	0.0218	0.0166	0.1894	**-0.0409**	**0.0173**	**0.0183**

preferences for much work absence may have a lower wage rate as a result of forgone on-the-job training. A similar argument is that workers with preferences to be frequently absent from work may earn less as they are less likely to be promoted or be permanently employed as they are less productive. Finally, it can be hypothesized that workers with inferior health are likely to be less productive and also likely to be more frequently absent as their health force them to be absent from work. All this will generate spurious correlation between the hourly wage rate and the duration and incidence of work absence.

Fortunately, the reform of the sickness insurance introduces an exogenous variation in the cost of being absent from work. This enables us to get an estimate of the effect of a change in the cost of being absent that is not influenced by unobserved heterogeneity. The interpretation of the parameter of the REFORM indicator is different from that of the wage rate parameter. As was pointed out in Section 4, individual income will on average decrease as an effect of the reform. Assuming work absence to be a normal good, this will decrease the demand from being absent. That is, the ceteris paribus effect of the increased cost and decreased income will work in the same direction. We will, thus, expect to observe a negative parameter for the REFORM indicator in the model for the incidence of work absence spells (W $\rightarrow$ WA) and a positive sign on this parameter for the duration of the work absence spell (WA $\rightarrow$ W).

Turning to the results, it can be seen in Table 3 that the parameter estimate for the hourly wage variable came out significantly positive when analyzing the WA $\rightarrow$ W hazard and significantly negative in the equation for the W $\rightarrow$ WA hazard. The parameter estimate of the female wage rate interaction is positive and significant for the W $\rightarrow$ WA hazard and negative and almost significant for the WA $\rightarrow$ W hazard. Adding the parameter for the interactions with the parameters for the wage rate variables, it turn out that these parameter estimates are insignifican different from zero for the female sub-sample for both hazards.

These results implies that the substitution effect for the males is larger than the income effect and that the workers with relatively high wage rates on average make a faster transition back to work in a work absence spell and that they on average have a lower incidence of work absence spells. For the female sub-sample, the substitution effect equals on average the income effect and the incidence as well as the duration of work absence spells are indepent of the wage rate.

The parameter estimate for the REFORM indicator is significantly negative for the W $\rightarrow$ WA hazard and not significant for the W $\rightarrow$ WA hazard. The female interaction is significant negative for the W $\rightarrow$ WA hazard. That

Table 4: Results from the stratified analysis (Semi-parametric estimation method).

	WA → W			W → WA		
Covariate	Coeff	S.E.	p-value	Coeff	S.E.	p-value
HOLI	-0.1649	0.1344	0.2199	-1.0244	0.1284	0.0000
REFORM	-0.0066	0.0983	0.9462	-0.5112	0.0804	0.0000
FEMALE * REFORM	0.0539	0.1247	0.6655	-0.1249	0.1026	0.2233
UNEM	0.0450	0.0501	0.3694	-0.0764	0.0471	0.1046

is, the results indicate that the increased cost of work absence decrease the incidence of work absence and that the effect is larger among the females than among the males.

To sum up, for the W → WA hazard the parameter estimate for the wage rate is lower for males than for females and the parameter estimate for the REFORM indicator is higher for males compared to females. This result can be rationalized if the income effect is larger for the female sub-sample. The opposite results, holds for the WA → W hazard and again this can be rationalized if the income effect is larger for the female compared to male sub-sample.

Comparing the result of the REFORM indicator to those obtained from the stratified analysis and reported in Table 4, it can be seen that the point estimates are very similar: The parameter estimate for the change in the incidence of work absence spells after the reform is significant and negative; the estimate of the interaction between the reform and female indicator variables is negative, although not significant.

The estimates of the effect of the reform are also in accordance with the findings in the non-parametric analysis discussed in Section 3. We saw that the intensity, compared with the pre-reform intensity, to leave a WA spell increased for the first two days in a spell and then decreased after day seven. These results can, at least partially, be explained by the design of the reform: The relative cost of short absence spells increased much more compared to long spells. Furthermore, in general, it seems plausible that short absence spells are more sensitive to economic incentives compared to long spells, as the health deficiency causing long spells in general are more severe.[13]

The parameter estimates for the non-labor income are of the expected signs, except for the males in the WA → W spells. The only significant

[13] As mentioned in Section 2, the Swedish sickness insurance requires a certificate from a physician for absence spells longer than seven days.

parameter, however, is the female interaction for the WA $\rightarrow$ W spells. It can be noted that the difference between men and women with respect to the non-labor income parameters for both WA $\rightarrow$ W and WA $\rightarrow$ W hazards, are in accordance with the gender differences in the income effect found for the wage rate and REFORM indicator parameters.

Following the study of Dunn and Youngblood (1986), we are able to investigate to what extent work absence is used to adjust to the desired number of hours of work. Assuming that workers are restricted to choose to be contracted for a certain number of hours of work, like e.g. "half time" or "full time", in order to keep a regular employment, even if their desired number of hours of work may be much less. In the interview of the SLLS the individuals are asked wether or not they are content with their actual number of hours of work. The dummy-variable FEW takes the value one if the worker states that she would prefer to work fewer hours; MORE takes the value one if she would prefer to work more hours. Table 3 shows that the estimates are both significantly negative for the WA $\rightarrow$ W hazard, i.e. those who are not satisfied with their work hours have a lower intensity to return from a work absence spell. For FEW this seems plausible and confirms the Dunn and Youngblood (1986) results. An explanation to the parameter estimate for the MORE indicator can be a confusion on wether or not the question refer to actual or contracted work hours. The effect of the FEW and MORE on the hazard of leaving the work state has the expected signs, however insignificant. In the W $\rightarrow$ WA model we find a positive and significant effect of the contracted working time, t^c. Hence, people with longer hours of work have on average more frequent work absence spells.

Finally, the results, in both the analysis, show that workers are less likely to begin work absence spells during the summer holiday in July. That is, by not entering a work absence spell, the worker avoids the cost of the excess in the sickness insurance. The decreased transition out of work absence spells is likely to be caused by the fact that fewer short work abence spells are started during this period.

6.2 Personal Characteristics

The estimates for the age variable shows an interesting pattern. The estimate for the transition out from a work absence spell is negative. This result confirms earlier studies and can be the result of the decline of the worker's health over the life-cycle and/or that the penalty of lower future earnings of being absent decreases with age, as the time period when these decreased labor earnings is collected is shorter

The estimate for the transition into a work absence spell complicates the picture since the estimate is again significantly negative. One possibly explanation for this pattern may be differences in preferences between younger and older individuals. The younger workers may, as they have preferences to invest more in their health, demand shorter work absence spells than older workers. Another explanation is that we have heterogeneity within the sample that we have not controlled for. The older workers can be polarized into one group with relative long work absence spells, explaining the results for the transition out of work absence, and a second group with very few work absence spells, explaining the result for the transition into work absence. It can also be seen, as the parameter estimate for the interaction with the indicator variable FEMALE, is significantly negative, that this pattern is even mor pronounced in the female sub-sample.

The estimates of the indicator variables of other personal characteristics, number of children (NRCH), divorced (DIV) and physical handicapped (DISAB), all give plausible and significant results that have also been obtained in previous empirical studies.

6.3 Health status

As expected, several of the indicator variables measuring differences in the workers health status are shown to be important determinants of work absence behavior. It can be seen that five health indicators are significantly different from zero in each of the two proportional hazard models. In the non-parametric study of Section 3 it was found that exits from work absence is more dependent on the health status indicators than exits from work. It can be seen that somewhat different health deficiencies are important in influencing the two different transitions. The factors influencing the transition from work absence are HARTP, HBLOOD, PREGNANT, LBROCK, and CANCER whereas the determinant incidence of work absence spells are TBC, HARTP, STOMACH, HEMORR, and PREGNANT.

These results give a clear pattern: The health deficiencies influencing the length of the work absence spell have the character of permanent health deficiencies. The health problems affecting the exits from work spells are primarily problems that fluctuates in intensity, e.g. general problems with the stomach or hemorrhoids. The only significant parameter estimate that has the unexpected sign is the parameter for PREGNANT in the W $\rightarrow$ WA transition. This estimate suggest that having pregnancy problem would decrease the exits from the work state. One reasonable explanation to this is that during the last two month of the pregnancy the worker has the option of taking maternity leave in advance and, thus, use another insurance.

6.4 Work Environment

We use two different types of measures for work environment. First, subjective measures of job characteristics. Second, two measures of occupational specific measures of risk exposure: RISK1 measuring the risk of work accidents and RISK2 measuring the risk of work related illnesses. Three job characteristics variables came out significant for the work absence spells: SHAKE, LIFT, and MBM. Four job characteristics variables (SMOKE, SWEAT, REP and UBP) and one measure of risk exposure (RISK2) are significantly different from zero in the proportional hazard model for the incidence of work absence spells.

All the parameter estimates, except the one for LIFT, have the expected sign in the sense that presence of a risk or inconvenience on the work place leads to higher rate of work absence. The explanation to the estimate for the LIFT variable is likely to be that persons who sort themselves into jobs with heavy lifting are likely to be relatively strong in a broad sense, and therefore more likely to recover faster from work absence spells. The fact that more work environment variables are significant for the incidence of work absence spells compared to the model for duration of the spells supports the result obtained in the non-parametric estimate of the survival functions.

The finding that bad working conditions and high exposure to risk increases the incidence of work absence spells may seem trivial, but it has an economic importance. Calculations on investments in improved work environment that ignore benefits from lower incidence of work absence spells may be misleading. Furthermore, the design of most social insurances, like the Swedish sickness insurance, are such that all pay the same premium, irrespective of the risk exposure of utilizing the insurance. This is not the case on a perfect insurance market. In absence of all sickness insurances, it is reasonable to assume that compensating wage differentials would be higher. Although further research are required to assess the magnitude of these compensating wage differentials, the results obtained in this study suggests that the sickness insurance may counteract economic incentives for the employers to improve work conditions.

6.5 Control and Rate of Unemployment

Following the discussion of Section 4, the penalty function $D(t^a)$ is specified as a liner function of the unemployment rate (UNEM) and the two indicator variables measuring wether or not there is a punch clock at the worker's job (CLOCK) and if the worker has flexible work hours (FLEX). This specification are of course limited by the availability of data. As the local unemployment rate changes over the year, in particular in 1991 in Sweden, and as we have access to monthly data for the local unemployment rate, we are able to include this variable in the stratified analysis.

It can be seen in Tables 3 and 4 that all parameter estimates for the unemployment rate have the expected signs. The parameters in the stratified analysis are larger in absolute values than in the fully parametric models. The only significant estimate is for the discrete time hazard model for the incidence of work absence spells. The corresponding estimate in the stratified analysis is, however just insignificant.[14] That the parameter in the stratified analysis is not significant is due to the lower power of this approach.

The estimates for the CLOCK indicator variable, indicating presence of a punch clock at the workers work place, has exactly the opposite from what was hypothesized. A possible explanation for this result is that the punch clocks are primarily used when other forms of control is not possible, e.g. in large firms. The result indicate that the other form of control is more efficient in decreasing the rate of work absence. This results may also reflect the fact that unplanned work absence may be more easily recorded with a punch clock. The parameter estimates may therefore indicate that the measure of work absence do in fact not include all forms of unscheduled absence from work.[15]

6.6 Overall Male-female Differences

There are several aspects of male-female differences in work absence behavior. It is evident from Tables 1 and 2 that women on average have higher work absence compared to men in our data-set. This is also true for aggregate Swedish statistics: In 1991 the average number of work days compensated by the sickness insurance was 19.3 for men and 25.8 for women (see Socialförsäkring, 1992). The gender difference in the rate of work absence has emerge as almost a "stylized fact" in all industrialized economies (see Paringer, 1983). There is also a gender difference in the pattern of spell length: In 1991, 47.9 per cent of all work absence spells for women consist of spells on one or two days (see Socialförsäkring, 1992). The corresponding figure for men is 39.4 per cent.

It is not obvious how these differences can be explained. In our dataset there are some differences among the explanatory variables. The largest differences can be foun in the group classified as Economic Incentives. The

[14] These two estimates are different, using the standard error from the parametric model, at the 4 per cent level.

[15] In the time-use study (SAF, 1986) it was found that about 97.1 % of all unscheduled work absence for blue collar workers is covered by the sickness insurance.

females in the sample have on average 16 percent lower hourly wage rate and on average 24 per cent higher daily non-labor income. The women in the sample work one average one hour less each day than the males.

The difference in the hourly wage rate as well as in non-labor income obviously contribute to the male-female differences in work absence behavior observed on the aggregate level. The effect of the hourly wage rate on both the incidence as well as the duration of work absence spells is insignificantly different from zero for the females. It is, thus, not obvious, departing from our estimates, that the gender difference in the work absence behavior would decrease if we made the thought experiment that the hourly wage rate of women increased to the same level as for men. As noted above, our estimates shows that women have a relatively high income effect that counteracts the substitution effects on higher cost of being absent from work. However, our estimates suggest that a further reduction of the replacement level in the sickness insurance would decrease the gender difference in work absence.

There are no unambiguous evidence that women have inferior health compared to men. A commonly used health indicator is the mortality rate. It is well known that women have lower mortality rates in all age-groups. Predictions from Statistics Sweden for the period between 1991 and 1995 give a prediction of remaining lifetime at age 16 (the minimum age for being insured by the sickness insurance) of 65.50 years for girls and 60.21 years for boys. However, in studies on self assessed health status, the most common result is that women have inferior health (see Lundberg et al., 1997).

There are eight health status variables that were significant in the analysis. For three of these conditions the proportion experiencing it are the same between the females and males. In three conditions the males are experiencing a higher proportion than the females and for two of the conditions the females have a higher proportion (PREGNANT and LBROCK). A careful examination of the health status indicators used in this study shows that there are some small gender differences. A somewhat larger proportion of the women, 25.5 per cent compared to 20.5 for men, have at least one indication of health problem among the indicator variables for health status. To sum up, there are little evidence from our sample that supports the view that the females have inferior health than the males, that can explain the gender difference in work absence.

Another alternative is that male-female differences in work absence can be explained by differences in work environment. However, this explanation do not seem to be very plausible since men in general have inferior work environment compared to the women. Both risk indices RISK1 for work accidents as well as RISK2 for work related diseases, is much higher for men. compared to women. From Table 3 we can see that we have eight significant parameters for the variables measuring the work environment. For only one of these eight variables (MBM) are the proportion that experience this work condition higher for the females than for the males.

The overall male-female differences in work absence behavior found primarily in the non-parametric analysis, i.e. that women on average have more frequent but shorter work absence spells, can be given an economic interpretation. It is a well known fact from studies in health economics that women on average consume more health care services than men. Sindelar (1982) interpret this consumption as investments in health and the observed differences can be explained by differences in preferences. The same interpretation can be given work absence spells (see Paringer, 1983): The worker may choose to be absent from work in order to recover faster from temporary illnesses, or to decrease the probability to get more permanent health problem. That is, the results indicate that women may, as they have preferences to invest more in their health, also demand more short work absence spells.

7. Discussion

What can be learned from this study on the effect of economic incentives (in a broad sense) on work absence and about econometric modelling of work absence behavior? Although a relatively rich set of results were obtained, it should be stressed that most of these have also been found in previous studies. However, let us summarize what we believe are the new results.

The importance of modelling state dependence in the work absence behavior can be seen from the results. Several of the variables considered did not have the same effect on the incidence of work absence spells as on the duration of these spells. Let us mention two examples. First, the effect of physical age on the exit rate from work absence back to work is negative, implying higher aggregate work absence rates. The effect of age on the exit rates from work to work absence is also negative, implying *lower* aggregate work absence rate. Second, a significant effect of the reform of the sickness insurance on the exit rate from work to work absence is estimated, while no effect on the exit rate from work absence can be detected. That is, an econometric method that only considers the frequency of work absence can not distinguish between these two different effects.

Several interesting differences between men and women were found. A fundamental issue in this context is to determine to what extent the observed male-female difference in the aggregate work absence rate can be attributed to differences in health or is due to economic incentives. The answer to this question following the result of this study is that a large part of the difference can be attributed to economic incentives.

The main results are robust to the different methods used. The estimates of the effect of the reform is very similar in the non-parametric, the semi-parametric as well as in the fully parametric model. The results from the semi-parametric model is obtained under less restrictive assumptions on parametric form and unobserved heterogeneity compared to the parametric model. The similarity in the results of the effect of the reform, unemployment, holiday and interactions indicates that the parameters from the fully parametric model is not severely biased due to unobserved heterogeneity.

Finally, our study contains an explicit policy analysis as the reform of the sickness insurance is included. The results show that the reform led to a sharp decrease in the number of short work absence spells. This effect can, also, be seen from aggregate data. The result that the exit rate from work absence is not affected by the reform can, on the other hand, not be seen in aggregate data. If short work absence spells serves as investment in health, our results indicate that a complete analysis of the reform may include a long term inverse effect of the reform, the negative effect on the general health status of the workers.

REFERENCES

Allen, S. G., "An Empirical Model of Work Attendence," *Review of Economics and Statistics*, 63 (1981a), 77-87.

Allen, S. G., "Compensation, Safety, and Absenteeism: Evidence From the Paper Industry," *Industrial and Labor Relations Review*, 34 (1981b), 207-218.

Aronsson, T. and J. R. Walker, "The Effects of Sweden's Welfare State on Labor Supply Incentives," in R. B. Freeman, B. Swedenborg and R. Topel, eds., *The Welfare State in Transition* (Chicago: Chicago University Press, 1997).

Barmby, T., C. Orme and J. Treble, "Worker Absence Histories," *Labour Economics* 2 (1995), 53-66.

Broström, G., "Cox regression: Ties without tears," manuscript submitted to *Lifetime Data Analysis* (1998).

Cassel, C., P. Johansson and M. Palme, "A Dynamic Discrete Choice Model of Blue Collar Worker Absenteeism in Sweden 1991," Stockholm School of Economics, Working Paper No. 129 (1996).

Dunn, L. F. and S. A. Youngblood, "Absenteeism as a Mechanism for Approaching an Optimal Labor Market Equilibrium: An Empirical Study," *Review of Economics and Statistics* 68 (1986), 668-674.

Fritzell, J. and O. Lundberg, "Vardagens Villkor. Levnadsförhållanden i Sverige Under Tre Decennier," (Stockholm: Brombergs Förlag, 1994).

Heckman, J. J., "Statistical Models for Discrete Panel Data," in C. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data*, 114-178. Cambridge, Mass.: MIT Press (1981).

Kalbfleisch, J. D. and R. L. Prentice, *The Statistical Analysis of Failure Time Data*, (New York: Wiley, 1980).

Lancaster, T., *The Econometric Analysis of Transition Data*, (Cambridge: Cambridge University Press, 1990).

Lantto, K., "Optimal Deterrents to Malingerence," Ph. D. Thesis, Department of Economics, Stockholm University (1991).

Lundberg, L, M. Johannesson, D.G.L. Isaksson, and L. Borgquist, "Health State Utilities in a General Population in relation to Age Gender and Socio-econmic Factors," Mimio, Stockholm School of Economics (1997).

McCullagh, P., and J. A. Nelder, *Generalized Linear Models*, (London: Chapman and Hall, 1983).

Paringer, L., "Women and Absenteeism: Health or Economics?," *AEA Papers and Poceedings* 73 (1983), 123-127.

SAF, "Tidsanvändningsstatistik," *Svenska Arbetsgivareföreningen* (1986).

Sindelar, J., "Differential Use of Medical Care by Sex", *Journal of Political Economy* 90 (1982), 1003-1019.

Socialförsäkring 1991 och 1992, Sveriges oficiella statistik, Riksförsäkringsverket, Stockholm (1992).

Willis, R., "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," in O. Ascenfelter and R. Layard. eds., *Handbook of Labor Economics*, (Amsterdam: North-Holland, 1986).

Appendix: All parameter estimates

	WA → W			W → WA		
	Personal Characteristics					
Covariate	Coeff	S.E.	p-value	Coeff	S.E.	p-value
Female	0.2485	0.1672	0.1372	0.1024	0.1549	0.5085
MARR	-0.0751	0.0481	0.1190	-0.0206	0.0479	0.6663
DIV	-0.0978	0.0768	0.2032	0.2565	0.0762	0.0008
AGE	-0.0116	0.0025	0.0000	-0.0047	0.0024	0.0501
DISAB	-0.4312	0.1227	0.0004	0.2938	0.1042	0.0048
NRCH	-0.0358	0.0267	0.1801	-0.0878	0.0268	0.0011
FEMALE * AGE	0.0018	0.0031	0.5584	-0.0051	0.0030	0.0914
	Economic Incentives					
w	0.0058	0.0025	0.0193	-0.0061	0.0026	0.0166
R	0.0020	0.0014	0.1519	0.0003	0.0013	0.8204
HOLI	-0.3467	0.0894	0.0001	-0.6002	0.0858	0.0000
t^c	0.0017	0.0034	0.6117	0.0066	0.0033	0.0480
FEW	-0.1270	0.0556	0.0224	0.0796	0.0547	0.1459
MORE	-0.2125	0.0684	0.0019	-0.0415	0.0665	0.5322
REFORM	-0.0265	0.0578	0.6471	-0.3934	0.0456	0.0000
w * FEMALE	-0.0058	0.0036	0.1039	0.0090	0.0036	0.0123
R * FEMALE	-0.0025	0.0014	0.0813	0.0017	0.0014	0.2330
FEMALE * REFORM	0.0480	0.0762	0.5289	-0.1462	0.0768	0.0570
	Work Environment					
NOISE1	0.0116	0.0661	0.8603	-0.0295	0.0771	0.7026
NOISE2	-0.0187	0.0411	0.6487	0.0498	0.0491	0.3096
SMOKE	0.0015	0.0430	0.9721	0.1309	0.0502	0.0092
SHAKE	-0.1396	0.0678	0.0395	0.0213	0.0779	0.7843
POISON	0.0457	0.0579	0.4302	0.0425	0.0662	0.5213
LIFT	0.0570	0.0431	0.1858	0.0997	0.0516	0.0531
HARD	-0.0713	0.0429	0.0966	0.0580	0.0511	0.2565
SWEAT	-0.0001	0.0416	0.9980	0.1167	0.0477	0.0143
EXHM	0.0509	0.0381	0.1811	0.0119	0.0452	0.7932
STRESS	-0.0132	0.0384	0.7309	-0.0607	0.0452	0.1796
REP	-0.0093	0.0408	0.8192	0.0901	0.0479	0.0602
MBM	-0.1066	0.0402	0.0081	-0.0212	0.0475	0.6557
UBP	0.0445	0.0425	0.2944	0.0954	0.0505	0.0591
RISK1	-0.0496	0.0303	0.1022	0.0428	0.0335	0.2018
RISK2	0.0273	0.0357	0.4446	0.0512	0.0409	0.2102
	Health Status					
STRUMA	-0.1166	0.1675	0.4863	0.2538	0.1583	0.1089
TBC	-0.1465	0.3701	0.6923	0.7761	0.2997	0.0096
HARTP	-0.2676	0.1466	0.0679	0.3386	0.1383	0.0144
HBLOOD	-0.2466	0.0722	0.0006	0.0546	0.0696	0.4330
STOMACH	-0.0177	0.0987	0.8577	0.2225	0.0975	0.0224
HEMORR	0.0244	0.0816	0.7650	0.1751	0.0776	0.0240
LBROCK	-0.4543	0.2489	0.0680	-0.3717	0.2368	0.1164
ABROCK	-0.1295	0.0792	0.1023	0.1116	0.0771	0.1476
MENTAL	-0.0106	0.2795	0.9697	-0.4876	0.3208	0.1285
CANCER	-0.6656	0.2155	0.0020	-0.1743	0.1949	0.3711
DIABETIC	-0.0797	0.1334	0.5503	0.1354	0.1376	0.3253
NEURO	0.0901	0.2445	0.7125	-0.2389	0.2571	0.3527
PREGNANT	-0.3238	0.1215	0.0077	-0.2479	0.1221	0.0424
	$D(t^a)$					
FLEX	-0.0339	0.0384	0.3768	0.0251	0.0382	0.5108
CLOCK	-0.0794	0.0401	0.0474	0.1101	0.0388	0.0045
UNEM	0.0218	0.0166	0.1894	-0.0409	0.0173	0.0183