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Part-Time Sick Leave as a Treatment Method?*

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Abstract
This paper analyzes the effects of being on part-time sick leave compared to full-time sick leave on the probability of recovering (i.e., returning to work with full recovery of lost work capacity). Using a discrete choice one-factor model, we estimate mean treatment parameters and distributional treatment parameters from a common set of structural parameters. Our results show that part-time sick leave increases the likelihood of recovering and dominates full-time sick leave for sickness spells of 150 days or longer. For these long spells, the probability of recovering increases by 10 percentage points.

Key words: part-time sick leave, selection, unobserved heterogeneity, treatment effects

JEL Classification: I12; J21; J28

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1 Introduction

During the second half of the 1990s, several countries changed their policies related to people with partially-reduced work capacity, providing support for what people are able to do rather than for what they are not (OECD, 2003). This involves policy re-orientation from passive compensation to active integration (e.g., changes in medical and vocational assessment toward work orientation and employer involvement). Ideally, people with partially-reduced work capacity should not leave the labor force but instead be supported to remain in, or find, appropriate jobs. Some countries (e.g., Australia, Denmark, Luxembourg, and the Netherlands) have chosen to have people with partially-reduced work capacity subject to participation or job-search requirements similar to recipients of unemployment benefits. Other countries (e.g., Sweden and Finland) have focused on the use of part-time sick leave instead of full-time sick leave, when possible. In Sweden, although it has been possible to be on part-time sick leave of 50% since the beginning of the 1960s (extended to also include 25% and 75% in July 1990), this policy did not receive much attention until the end of the 1990s. Part-time sick leave became a component of the action plan that the Swedish government set out in 2001 to increase health in the working life and to reduce sick leave by 50% by the end of 2008.

Despite the recent focus among policy makers, basically no previous theoretical or empirical research has evaluated the relative effects of part-time and full-time sick leave.[1] The aim of this paper is therefore to reduce this gap and analyze the effects of being on part-time sick leave compared to being on full-time sick leave on the probability of recovering (i.e., returning to work with full recovery of lost work capacity). To do this, we follow Aakvik et al. (2005) and estimate a discrete choice one-factor model that evaluates the effect of part-time sick leave when outcomes are discrete and responses to treatment vary among observationally identical persons. Additionally, we use this model to generate both mean and distributional treatment parameters from a common set of parameters.

[1] Nonetheless, we would like to refer to the results of the two previous studies on Swedish data that are closest to our research. Both estimated the effects of various types of rehabilitation programs on labor market outcomes of long-term sick people. Frölich et al. (2004)'s nonparametric matching estimates show that workplace training is superior to the other rehabilitation programs with respect to labor market outcomes, but compared to non-participation no positive effects are found. Heshmati and Engström (2001)'s estimates from a parametric selectivity model show that participation in vocational rehabilitation has positive effects on participants' health status and on their return to work, but they did not observe any evidence of selection on unobservable characteristics.

Our results show that it is important to control for unobserved heterogeneity, i.e., for the selection into part-time or full-time sick leave. The estimates show that part-time sick leave does have a positive effect, although only for a relatively small share of employees on sick leave (about 7-11%), and that a majority of the employees on sick leave (50-70%) return to work with full recovery of lost work capacity regardless of whether they were on part-time or full-time sick leave. This suggests that more sick employees should be on part-time sick leave instead of full-time sick leave. One implication of this result in terms of policy implications is that to improve the overall recovery effect of part-time sick leave, it is necessary to select into this treatment those who will gain the most from it rather than choosing less healthy persons (who are at a higher risk to leave the labor market permanently).

The study is organized as follows. The next section presents institutional settings of sick leave in Sweden, while Sections 3, 4, and 5 present the empirical specification, data, and the estimated results, respectively. The last section summarizes the paper and draws conclusions.

2 Institutional settings of sick leave in the early 2000s

People who are on sick leave part-time and work part-time have different institutional settings than those who just work part-time. There are international labor conventions that state provisions applicable to part-time workers.[2] A part-time worker is an employed person whose normal hours of work are less than those of comparable full-time workers. A comparable full-time worker refers to a full-time worker who has the same type of employment relationship, is engaged in the same or a similar type of work or occupation, and is employed in the same establishment, enterprise, or branch of activity. Full-time workers affected by partial unemployment (e.g., those with a temporary reduction in their normal working hours due to economic, technical, or structural reasons) are not considered part-time workers. However, these conventions do

[2] e.g., ILO's C175 Part-Time Work Convention; the provisions of the Equal Remuneration Convention, 1951; the Discrimination (Employment and Occupation) Convention, 1958; and the Workers with Family Responsibilities Convention and Recommendation, 1981; the Employment Promotion and Protection against Unemployment Convention, 1988; and the Employment Policy (Supplementary Provisions) Recommendation, 1984.

not refer to workers who have lost some of their working capacity and hence are not able to work their contracted hours.

In Sweden, both full-time and part-time workers can be on full- or part-time sick leave (since the beginning of the 1960s). The right to compensation of income loss due to sickness or disability is based on the medical evaluation of the person's loss of work capacity due to disease, sickness, or injury. Given the institutional framework, it is possible for a person who did not lose more than 75% of his or her work capacity to be on sick leave part-time and work part-time. The decision on the type of sick leave (i.e., full-time or part-time) is mainly based on a physician's evaluation of the patient's health status. It seems reasonable to expect the resulting judgment in the matter to be based on the patient's health status, job requirements, and work environment and characteristics. However, it has been observed that physicians often give in to patient demand for sick-listing, even in cases when the physician's own judgment speaks against sick-listing (Englund & Svärdsudd, 2000). The physician therefore seems to mediate between the patient's needs and the formal rules when writing the medical certificate.

Following the physician's evaluation, it is the social insurance office that decides whether an individual is entitled to compensation, and if so what type (i.e., 25%, 50%, 75%, or 100%). In most cases, the social insurance officers accept the recommendation of the physicians as final instead of using their own judgment (Hensing, Timpka, & Alexanderson, 1997). However, there is a clear distinction between these two deciding parties: the certifying physician determines to what extent disease or injury is impairing a patient's ability to perform his or her work, while the case manager at the local social insurance office formally determines whether the patient is entitled to monetary sickness benefits. Nevertheless, the social insurance officers do experience a lack of control over the decision process, as regulations and other stakeholders restrict their work (Ydreborg, Ekberg, & Nilsson, 2007).

Partial loss of work capacity is difficult to assess and therefore may give rise to misuse. It is not clear whether the part-time sick leave should be used in more difficult cases, in easier cases, or in both. The most difficult cases are expected to take the longest, and therefore one can expect that the patient might lose contact with his or her job, decreasing the probability of returning to work. Therefore, if a patient recovers gradually, it seems that a gradual return to work is beneficial in both the short- and long-term. This expectation is conditional on the patient receiving help in the form of treatment and/or information about how to take care of him- or herself. However, there are some diagnoses (e.g., musculoskeletal and mental disorders) for which part-time sick leave is a reasonable alternative, but it might be that the work situation of the patient does not allow for such solution.

Although part-time sick leave can fulfill the goal of keeping in contact with the job, it might also function as replaced leisure. In most cases, people on sick leave lose only a relatively small amount of money. In fact, the sickness insurance and the collective agreement replace 90% of the income lost due to sickness or disability. However, an annual income that exceeds 7.5 base amounts (which equaled SEK 297,750 in 2006) is not covered by the social insurance, but is covered by the collective agreement (usually up to a higher ceiling). This is most common in the other agreements than the Swedish Trade Union Confederation, LO. Losing a relatively small amount of money and/or appreciating more "time away from work" might make it difficult for some people to return to full-time work after recovering more than 75% of their work capacity. This is a moral hazard situation, which is relatively difficult to control given that there is no objective method or instrument to measure the work capacity of people. In this situation, one can in addition to patient misuse of the insurance also blame the physicians who evaluate these patients' work capacity and/or the social insurance officers who handle the cases. The insurer cannot have the same information as the patients and the physician, and therefore it seems that the decision is mainly based on the medical evaluation. The patient, who chooses to work part-time or full-time, makes the final decision. Therefore, the decision of the physician and the social insurance case manager may be evaluated as successful at least when the patient does the transition from full-time to part-time sick leave.

A problem is that not all jobs are suitable for a temporary or permanent part-time work solution since it might force employers to hire more people, reorganize the working arrangements for other employees, and/or the working place and working conditions. However, employers might be motivated to solve all these problems if there are economic incentives and/or rules or laws requiring them to do so.[3] For example, since 1992, employers have had to pay the sickness compensation for the beginning of each employee's sick leave period. This period, called the sick pay period, was 14 days from 1992 to 1996. From January 1997 to March 1998, it was 28 days, and in April 1998 it was reduced to 14 days again. It was increased to 21 days from June 2003 to January 2005, and decreased once again to 14 days in January 2006.

3 Empirical framework

3.1 The model and the estimation strategy

The point of departure is an employed individual with a diagnosed health condition and an accompanying reduced work capacity. This implies a choice between part-time or full-time sick leave. The choice of the degree of sick leave is a joint decision made by the individual, the employer, the physician, and the social insurance administrator, and from the previous section we know that they all do have a say in the final. However, this implies that there needs to be an agreement among the parties before a final decision can be made, meaning that the selection into a state of part-time or full-time sick leave can be represented by just one indicator.

The common objective of the four parties is to choose the alternative (the state of part-time or full-time sick leave) with the highest likelihood of recovery of the lost work capacity in the shortest amount of time. The relevant outcome is therefore a measure of the propensity to returning to work with full recovery of lost work capacity. A suitable structure for the empirical framework is for that reason a discrete choice switching regression model with an endogenous switch between the two states (Heckman, 1978; 1979), defined by the following equations:

$$Y_1^* = X\beta_1 + U_1, \quad Y_1 = 1 \; if \; Y_1^* \geq 0, \text{and } Y_1 = 0 \text{ elsewhere,} \qquad \text{(Part-time sick leave)} \quad (1)$$

$$Y_0^* = X\beta_0 + U_0, \quad Y_0 = 1 \; if \; Y_0^* \geq 0, \text{and } Y_0 = 0 \text{ elsewhere,} \qquad \text{(Full-time sick leave)} \quad (2)$$

$$D^* = Z\beta_D + U_D, \quad D = 1 \; if \; D^* \geq 0, \text{and } D = 0 \text{ elsewhere,} \qquad \text{(Selection rule)} \quad (3)$$

[3] The Swedish government offers some incentives for employers. Starting in January 2005, employers do not have to pay the contribution to the sickness insurance for employees who (1) are on part-time sick leave; (2) receive extended sickness compensation; (3) receive rehabilitation benefits; 4) are evaluated as having a high-risk of being long-term sick; or 5) receive sickness and activity compensation.

with (1) and (2) being equations for the potential outcome in each state and (3) an equation for the single index decision rule of sorting into either of the two states. More specifically, Y_1^* and Y_0^* are two latent measures for the propensity to return to work with full recovery of lost work capacity when being on part-time or full-time sick leave, respectively. D^* is a latent measure for the propensity to choose part-time sick leave. Hence, when D^* is large, the propensity to choose part-time sick leave is large, which is equivalent to having a small propensity to choose full-time sick leave, and vice versa when D^* is small. Each equation has its own stochastic component $(U_j, j = 1, 0 \text{ or } D)$, which allows for heterogeneity between individuals with the same observed characteristics. The decision on the degree of sick-leave is endogenous if the stochastic components of the outcome equations $(U_1 \text{ and } U_0)$ are correlated with the stochastic component of the selection equation (U_D).

One important extension of the basic model is to control for unobserved heterogeneity. This is solved by imposing a one-factor structure on the stochastic terms. The imposed factor is assumed to be common to the three equations. The factor loadings $(\theta_1, \theta_0, \theta_D)$ allow its importance to vary among the equations. The idea is that there exist unobservables captured by the unobserved factor ξ that are common to the three involved equations and this drives the correlation among them. The one-factor residuals are defined by:

$$U_1 = \theta_1 \xi + \varepsilon_1 \quad , \tag{4}$$

$$U_0 = \theta_0 \xi + \varepsilon_0 , \tag{5}$$

$$U_D = \theta_D \xi + \varepsilon_D . \tag{6}$$

From a technical point of view, the factor loadings serve the purpose of reducing the dimensionality of the problem. That is, instead of evaluating the covariances of a multivariate distribution, it is enough to integrate over just one dimension in order to estimate the variances and covariances among the residual terms of the main model. This possibility comes with the cost of an orthogonality assumption discussed in the model section. Using the factor loadings we may form product covariances, and since we have a factor loading for each equation, the sign of each covariance is free and governed by the data and the underlying correlation structure. Since the factor loadings can be used to implicitly calculate the covariances among the residuals they are also used as a summarizing measure for the effect from the unobservables that are relevant for each equation and cause a correlation among them. Had there been no correlation among the residuals, the covariances would be zero, and therefore also the factor loadings.

Since we allow the factor loadings to be different in each equation, we will also be able to separate the effect of the unobservables on the selection in to part-time sick leave from the effect on the output. That is, if the unobservables are important for the selection into a specific state but are of no major importance for an individual to recover, it will show up in the significance of the factor loadings in the selection equation and the output equations. This could be the case if the choice of state were a policy variable but the individual propensity to recover were unaffected by this measure on the unobservables.

For instance, if the degree of sickness and the propensity to recover differ among individuals with identical observable characteristics, the unobserables will have an important role. The degree of sickness and the propensity to recover would most likely be negatively correlated since the more sick an employee is initially the lower is his/her propensity to recover within a given time span. However, recovery time could also be affected by the degree of sick leave at the beginning of the spell. That is, to be severely sick and be placed on part-time sick leave might prolong the duration of the sick leave, since working could worsen the sickness. On the other hand, if the employee has a residual work capacity, working part-time might help avoid losing contact with the job and the labor market, which in itself could extend the sick leave. Hence, the degree of sickness and the choice of state are related and should be matched. In the present study, only 10 percent started their sickness spell on part-time leave, so the important question to answer is whether this number could be increased in order to decrease the length of sickness spells in general as well as decrease the welfare cost in the economy. Since the selection equation is a measure of the propensity to choose part-time sick leave, the unobservables will most likely have a relatively high value for those with a relatively low degree of sickness, while it will have a relatively low value if the degree of sickness is relatively high. If a high degree of sickness also implies a higher probability of choosing full-time sick-leave and the chosen state increases the likelihood to recover within a given time span, we expect the correlation between the selection residual and the outcome equation to be negative. Similarly, if individuals with a low degree of sickness are selected into part-time sick leave and this choice increases the likelihood of recovering, then the correlation between the degree of sick leave and probability to recover is negative.

The distributional assumption used is multivariate normal i.e., $(\varepsilon_1, \varepsilon_0, \varepsilon_D, \xi) \sim \mathrm{N}(0, I),$ where I is the identity matrix. With the imposed distributional assumption together with an exclusion restriction in the selection equation, we are able to define and identify the full distribution of $(U_1, U_0, U_D) \sim \mathrm{N}(0, \Omega),$ with Ω being the variance-covariace matrix of the error terms.

In order to define the likelihood function, we first need to consider a complication due to the unobserved factor. In order to account for its existence we have to integrate it out of the equations. Since we have assumed a parametric distribution of the unobserved factor, we integrate over its domain, assuming that $\xi \perp (X, Z).$ Since each equation is conditioned on the unobserved factor, essential for the selection to the two states, $(Y_1, Y_0) \perp (X, Z, \xi).$ This implies that $\Pr(Y \mid X, D, \xi) = \Pr(Y \mid X, \xi),$ which means that the selection equation and the outcome equations are unconditional probabilities in the likelihood function.[4] The likelihood function for the one-factor model can therefore be written as

$$L = \prod_{i=1}^{N} \int_{-\infty}^{\infty} \Phi(D_i \mid Z_i, \xi_i) \Phi(Y_i \mid X_i, \xi_i) dF(\xi_i), \tag{7}$$

with Φ being the standard normal cumulative distribution function and F an absolutely continuous distribution function which can be non-normal.

3.2 Effects of being on part-time sick leave

Given the model described above, we can now define the parameters of interest and estimate the effects of being on part-time sick leave compared to being on full-time sick leave on the probability of returning to work with full recovery of lost work capacity. One way of evaluating the relative merits of the two states for employees on sick leave would be to investigate the mean difference in the probability of recovering (i.e.,

[4] This integral is solved using the Gauss-Hermite quadrature with five points and nodes.

returning to work with full recovery of lost work capacity) within a given time span. Since we have a structural model, it is possible to estimate both the mean and distributional parameters of part-time sick leave.

3.2.1 Mean treatment parameters

The first basic parameter is the average treatment effect (*ATE*) of being on part-time sick leave compared to being on full-time sick leave. The effect is estimated on the whole group of employees on sick leave and measures the average potential impact on an individual randomly chosen from the population of employees on sick-leave. It measures how much an individual would gain or lose on average in terms of his or her probability of returning to work with full recovery of lost work capacity when starting a part-time sick leave instead of a full-time sick leave. The parameter is a measure of the mean difference in the probability of returning to work with full recovery of lost work capacity. It is defined in the following way:

$$ATE(X) = \int_{-\infty}^{\infty} [\Phi(Y_1 \mid X, \xi) - \Phi(Y_0 \mid X, \xi)] dF(\xi). \qquad (8)$$

Another important parameter is the treatment on the treated effect (*TT*), which measures the effect of part-time sick leave on those who actually were on part-time sick leave. *TT* describes the difference between the actual state and the counterfactual state, in case the individual had been chosen or sorted into full-time sick leave, and is defined as:

$$TT(X, Z) = \int_{-\infty}^{\infty} [\Phi(Y_1 \mid X, \xi) - \Phi(Y_0 \mid X, \xi)] dF(\xi \mid X, Z, D = 1). \qquad (9)$$

3.2.2 Distributional treatment parameter

The mean behavioral effects are informative, but more can be learned from analyzing the distribution of the effects related to the parameters of interest (*ATE* and *TT*). What proportion of those on part-time sick leave will recover (i.e., return to work with full recovery of the lost of the work capacity) compared to those on full-time sick leave, and what proportion will not recover? It would also be interesting to know what proportion will be indifferent between the two states in terms of potential outcome.

In this paper, the distributional parameter predicts the probability of four different events: successful, positive indifference, negative indifference, and unsuccessful. These events are identified by an indicator variable *I*, defined as the differences between the observed dependent variables of the outcome equations: $I = Y_1 - Y_0$. The fact that the dependent variables Y_1 and Y_0 are binary implies that *I* can take only three values (-1, 0, 1). $I = 1$ indicates a successful event (or a positive effect of part-time sick leave), which implies that part-time sick leave would result in recovery within a given time span, while the full-time sick leave would result in no recovery. When $I = 0$, we have an event of indifference (or no effect of part-time sick leave). This means that the individual would have the same outcome (recovery or not) in both states. This event can be further decomposed into two separate components: (1) positive indifference, which means that the individual will recover within a given time span, independently of the state; and (2) negative indifference, which means that the individual would not recover independently of the state. When $I = -1$, we have an unsuccessful event (or a negative effect of part-time sick leave), which implies that part-time sick leave would not result in recovery during a given time span, while the sickness spell would end in recovery in the case of full-time sick leave.

Using this indicator we can predict the probability of a successful event, an unsuccessful event and the events of indifference, in the following way:

$$ATE_{dist}\left[1(I = i) \mid X\right] = \int_{-\infty}^{\infty} \Phi(Y_1, Y_0, \xi)\, dF(\xi), \quad i = -1, 0, 1. \tag{10}$$

$$TT_{dist}\left[1(I = i) \mid X, Z, D = 1\right] = \int_{-\infty}^{\infty} \Phi(Y_1, Y_0, \xi)\, dF(\xi \mid X, Z, D = 1), \quad i = -1, 0, 1. \tag{11}$$

4 Data

This study uses the 2002 sample of the RFV-LS database of the National Agency of Social Insurance in Sweden. The database includes exact dates when sickness spells began and ended, as well as the states before and after sickness (work, education, unemployment, temporary, or permanent disability, etc.). It also contains information about individual characteristics (such as age, marital status, citizenship, etc.), the job (type of employer, occupation), the social insurance (local and regional office, the source of money, etc.), and the type of physician evaluating the health status of the employee (primary care, specialist, private, company physician and "other"). The sample also contains information about the sickness history in the year before (number of compensated cases and the duration of the longest spell). The 2002 sample includes 5,000 persons and is representative of all residents of Sweden registered with the social insurance office. Additionally, all persons in the sample started a sickness spell during 1-16 February 2001 and were 20-64 years old. Given the aim of this paper, to estimate the effect of part-time sick leave on the probability of returning to work with full recovery of lost work capacity within a given time span, we analyze only people who were employed the day before starting the selected sickness spell and did not receive any partial disability benefit, which implies that all analyzed spells are at least 15 days long. We also exclude a few special cases where employees on sick leave ended their spells because of incarceration, emigration, or participation in a rehabilitation program. This resulted in a sample of 3,607 employees.

One variable of major importance is the degree of sick leave at the beginning of an analyzed spell. Given that all spells are covered by the sickness insurance from the 15th day, the degree of sickness at the beginning of the spell actually refers to this day (the first day paid by the sickness insurance). Using this information, we create a part-time sick leave dummy, which takes the value 1 for all spells that started with 25%, 50%, or 75% sick leave; and the value 0 for all cases that started with 100% sick leave. Although it is common that a person works the rest of the time (i.e., the uncompensated time), this it is not always the case. Unfortunately, the data does not contain any information related to this. Table 1 presents descriptive statistics for all analyzed sickness spells and by the degree of sick leave in the beginning of a spell, and the health status at the end of a spell. The latter variable can take the following values: (1) recovered (i.e., the spell ended with full recovery of the lost work capacity); (2) not recovered (i.e., the spell ended with a partial or full disability benefit, which could be permanent or temporary); (3) censored (i.e., the spell has not ended at the end of the observation period). This last category of spells is considered when computing the mean and the median for all spells by using their lengths censored on March 1 (i.e., durations between 365 and 381 days). The descriptive statistics suggest that the spells that started as part-time are on average much longer than those that started as full-time, and they are more represented among those who were not recovered at the end of their spells (17%) than among those who were recovered (9%).

Table 1 Descriptive statistics of sickness spells by degree of sick leave

	All		Recovered		Not recovered	
	mean	median	Mean	median	mean	median
All spells	105.2	45.0	61.5	35.0	154.6	109.0
Sick-leave degree when spell started						
Full-time	99.8	42.0	59.3	34.0	150.5	104.0
Part-time	152.6	89.0	84.0	62.0	174.8	133.5
N	3607		2953		235	
% spells that started with part-time	10.4		8.9		17.0	

Using information about the health status at the end of a spell and the employment status (employee/unemployed/early-retired/disabled), we construct our outcome variable, which is a dummy variable that takes value 1 if the employee is back to work with full recovery of the lost capacity within a given period of days; and zero otherwise.

We choose to build our outcome variable for the first 30 days of sick leave, and then extend by steps of 30 days. This implies that the outcome variable at 30 days for those who started a spell with part-time sick leave (Y_{30}^{1}) takes the value one for those who ended their spells with full recovery of lost work capacity (any time) during this 30-day period and were recorded as working after the spell ended; and zero otherwise. The outcome variable at 60 days for those who started a spell with part time sick leave (Y_{60}^{1}) takes the value one for those who ended their spells with full recovery of lost work capacity any time during this 60-day period and were recorded as working after the spell ended; and zero otherwise. In the same way we construct the outcome variables at each 30th day, up to 300 days for both those who started with part-time $(Y_{30}^{1}, Y_{60}^{1}, Y_{90}^{1}, ..., Y_{300}^{1})$ and those who started with full-time sick leave $(Y_{30}^{0}, Y_{60}^{0}, Y_{90}^{0}, ..., Y_{300}^{0})$.

Table 2 presents the percentage of spells that ended with full recovery during periods of various lengths, for both those who started with part-time (column 1) and those who started with full-time sick leave (column 2). These descriptive statistics suggest that relatively more cases ended with full recovery of lost work capacity among those who started with full-time sick leave than among those who started with part-time sick leave, and there were relatively more cases that ended without full recovery among those who started with part-time sick leave. More descriptive statistics of the outcome variable are presented in Tables A1-A3 and Figures A1-A4 in the Appendix.

Table 2 Spells finished with full recovery*

Days since the spell began	Part-time (1)	Full-time (2)
≤ 30	16.53	37.00
≤ 60	33.60	58.66
≤ 90	45.87	68.29
≤ 120	53.33	72.90
≤ 150	59.47	76.36
≤ 180	62.67	77.69
≤ 210	65.87	79.73
≤ 240	66.67	80.97
≤ 270	68.27	81.78
≤ 300	68.80	82.12

* The difference between the mean values for full-time (2) and part-time (1) is statistically different from zero at the 1% level. The mean value for part-time (full-time) sick leave represents the percentage of the spells that ended with full recovery at the end of the analyzed period relative to the total spells that started with part-time (full-time) sick leave.

Another variable of major interest is the instrumental variable that causally affects the behavioral variable (selection into part-time or full-time) but does not have a direct causal effect on the outcome (returning to work with full recovery of lost work capacity). The choice of instrument is based on the fact that some employers have specific conditions related to the execution of a job task that makes it difficult to contend with part-time employment (usually small establishments, but sometimes even larger offices or labs that have only one employee who is able to perform specific tasks). The job simply requires full-time employee attendance in those cases. When this is the case, the employer cannot operate the business with an employee who can only work part-time (being on part-time sick leave the rest of the contracted work time), and therefore leaves the employee with the choice between working more than his/her work capacity allows, or being on full-time sick leave with a compensation that covers more than the lost work capacity. Hence, the probability of being on part-time sick leave or full-time sick leave differs among different employers. Although individuals might be aware of these differences among employers, knowledge of this fact should not be a driving force behind choosing a specific employer. Hence, it is not very likely that individuals act on this in the sense that ends up affecting the outcome variable. It is therefore plausible to say that some employers have a causal effect on an individual's propensity to be on part-time or full-time sick leave, while there should be no such direct effect related to the probability of recovering the lost work capacity within a given time span.

5 Results

5.1 The outcome and selection equations

Since we estimate the parameters of the one factor model for ten different time spans ranging from 30-300 days, the number of estimates is large. Therefore, we report the estimated parameters from each equation in the Appendix, and discuss the results only briefly but with a focus on the variables that are of special importance, i.e., the instrument and the factor loadings.

The selection equation for the propensity to be on part-time sick leave includes a number of variables that are important for a detailed analysis of sickness duration (e.g., diagnosis, type of prescribing doctor, and occupation), in addition to the usual socio-economic and demographic variables (e.g., age, gender, education, and region). The estimated coefficients (reported in Table A4 in the Appendix) are stable in level and statistical significance over the different time spans. Except for the time spans of 60 and 120 days, the precision of the coefficients for occupational type (the instrumental variables in our model) is good all over. The level of the coefficients does not deviate much for 60 and 120 days, so the precision deficiency is mainly related to the estimated standard errors. Since the choice of instrument is based on an identifying assumption, it is not possible to test whether it is a good instrument. Dropping the instrument to investigate whether the result will change would not do the job, since dropping variables with significant coefficients always have some effect on the result in a structural model.

The factor loading is not significant for spells shorter than 150 days, which is to say that the unobservables play a minor role in the selection process for cases that are shorter than 150 days. For cases between 150 and 240 days, the factor loading is significantly different from zero, which implies that the factor and therefore the unobservables do have a behavioral effect on the choice of part-time sick leave for sickness cases that require a longer recovery time to recuperate. One should keep in mind that the selection equation represents four parties, and that the unobservables are common among the three equations that drive the correlation among the residual terms. Even so, it is reasonable to assume that the four parities to some degree also are involved in the decision to classify an individual as fully recovered.

The factor loadings of both outcome equations are negative for almost all analyzed time spans, but are statistically significant only for the full-time equation for the time spans up to 90, 270 and 300 days (Tables A5 and A6 in the Appendix). Therefore, we cannot conclude that the unobservables decrease the probability of recovering for employees either in part-time or full-time sick leave. In contrast, almost all observable characteristics have a statistically significant effect on the probability of recovering for employees who started their spell with full-time sick leave. Although the outcome equation for part-time sick employees has much fewer parameters that are statistically significant, in most cases they have the same sign as in the full-time outcome equation.

Changing the state during an ongoing sickness spell could potentially affect the length of the spell. It has been argued that those who start their spells with full-time sick leave should start working part-time as soon as possible in order to preserve contact with the job. However, our results indicate that a change of the degree of sickness actually decreases the likelihood to recover for both part-time and full-time starters .

5.2 The treatment effects

Using the estimates from the main model, we are able to calculate the relative effects of part-time sick leave versus full-time sick leave, using the treatment parameters discussed in Sections 3.2.1 and 3.2.2.

5.2.1 The mean treatment effects

Table **3**3 and Figure 1 report the estimates for the *ATE* and *TT* parameters for different cut-off points. Except for 180 and 210 days (when it is positive, but almost zero), the *ATE* parameter is negative, suggesting a negative effect of part-time sick leave for a randomly chosen individual from the total sick leave population. That is, if part-time sick-listing were a general rule for the population of employees on sick leave, then the sickness spells would be longer. Individuals with sickness spells of up to 120 days would under those conditions extend their sick leave due to the sick-listing policy. Hence, part-time sick listing should not be imposed on individuals unrestricted.

Table 3 Mean treatment effects

	30	60	90	120	150	180	210	240	270	300
ATE	-0.1948	-0.1761	-0.0290	-0.1305	-0.0028	0.0040	0.0378	-0.0279	-0.0897	-0.0479
TT	-0.3924	-0.1470	-0.0739	-0.0852	0.0791	0.0905	0.1928	0.0663	0.1215	0.1307
TT-ATE	-0.1976	0.0290	-0.0449	0.0453	0.0819	0.0865	0.1550	0.0942	0.2112	0.1786
Correlations										
$C(U_1,U_D)$	-0.0141	-0.1100	-0.2899	-0.0781	-0.2643	-0.2746	-0.3139	-0.2063	-0.0526	-0.1268
$C(U_0,U_D)$	0.3682	-0.1202	-0.2008	-0.1419	-0.3436	-0.3476	-0.4740	-0.3244	-0.3870	-0.3960
$C(U_1,U_0)$	-0.0370	0.0234	0.3055	0.0278	0.1202	0.1272	0.1949	0.0920	0.1051	0.2480

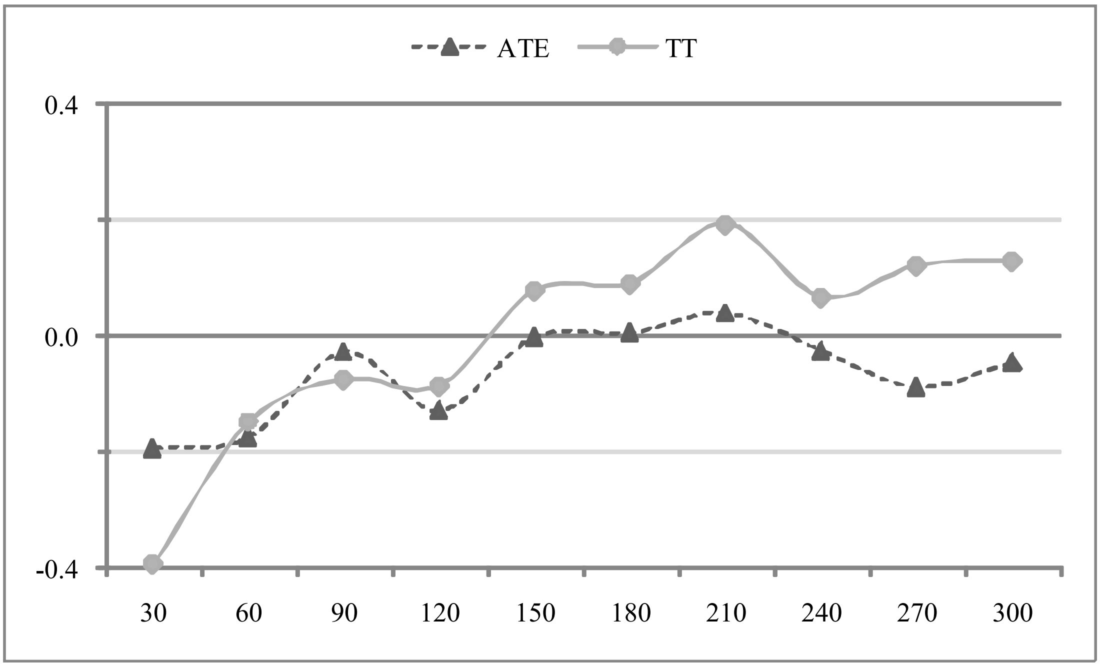

Figure 1 Mean treatment effects (ATE and TT) of part-time sick leave

Turning to the second parameter of interest, namely the measure for those who were actually sorted into part-time sick leave, we see a somewhat different picture even though it is slightly similar for shorter sickness spells. The estimated value of the TT parameter is negative up to 120 days, but positive for 150 days and above. The picture is similar to that of the previous parameter, but here part-time sick listing actually increases the likelihood of full recovery. Hence, selective judgment should be used when sorting people into part-time sick leave. There are of course several reasons for this result. One reason could be that maintaining contact with the job helps individuals return to a job full time. Being away from the workplace can isolate a person, with deteriorating self esteem as a result, which in turn makes it harder to return. Related to the inactivity is the resulting reduction in job-specific human capital that is also an effect of being disconnected from one’s work.

Table 3 also presents a measure for effect of selecting the appropriate individual into part-time sick leave (i.e., the difference between TT and ATE). The selection effect is negative up to 120 days, while it is positive for 150 days and above. This is reasonable since some individuals with severe illnesses will not recover unless they stay at home or at the hospital full time, which implies that forcing them to stay at work partially would worsen their health situation and consequently prolong their sick leave. Hence, unobserved factors play an important role for both short and long sickness spells.

The positive selection effect for longer sickness spells suggests that part-time sick leave does help some employees, particularly those with observed and unobserved characteristics that make them the least likely to return to work after losing contact with it (employees on full-time sick leave). However, in 2001 the actors involved in the selection process (the physician, the social insurance administrator, and the employer) only infrequently selected such individuals into part-time sick leave, which leaves room for efficiency improvements.

The correlation between the selection residual and the outcome of full-time sick leave equation is negative for all time spans, which suggests that a high degree of sickness implied a higher probability of being in full-time sick-leave and this state increased the likelihood to recover within a given time span.

Except the very short spells (i.e., less than 30 days), the correlation between the selection residual and the outcome of part-time sick leave equation is also negative, which suggests that individuals with a low degree of sickness were selected into part-time sick leave and this choice increased the likelihood of recovering.

5.2.2 The distributional effects

Table 4 and Figure 2 present the estimates for the distributional treatment effects with respect to the ATE and TT. We report four measures of the part-time sick leave effectiveness in the table, but only two for each parameter in the figure, to make the visual representation easier. We aggregated the positive effect and the positive indifference into a positive component, and the negative effect and the negative indifference into a negative component. Both the ATE and TT results show that there is a relatively high negative effect from part-time sick leave at the cut-off point of 30 days (31% and 46% respectively). After 60 days, the ATE results show that out of all employees who were on part-time sick leave, 13-17% gained and 13-22% lost from it, while more than half (52-70%) experienced no effect. This means that the larger group of employees on sick leave would have the same outcome (recovery or not) in both states. However, the share of employees with positive indifference (i.e., they recovered regardless of state) is increasing in time, from 8% at 30 days to about 60% after half of year, while the share of employees with negative indifference (i.e., not recovered indifferent of state) is decreasing in time (from about 50% at 30 days to about 8% after half a year). Except for 30 days, the TT values are always a little bit higher than the ATE values for both the positive and the negative effects and for negative indifference, but they are much smaller than the values for positive indifference.

It is interesting to observe that the share of those with a negative effect is about the same when the selection is random (the ATE parameters) as when the selection is restrictive (the TT parameters). This means that the share of those who would recover with full-time sick leave but not with part-time sick leave within a given time span is the same independent of whether selection is random or restrictive. The difference is instead that the share with no effect is somewhat larger when the selection is random, and the share with a positive effect is somewhat larger when the selection is restrictive. This suggests that there is potential for increasing the share of people on part-time sick leave as a means to reduce the budget cost, while some people should be on full-time sick leave.

Table 4 Distributional treatment effects on part-time sick leave

	ATE				TT			
	Positive	Indifference		Negative	Positive	Indifference		Negative
Days	Effect	Positive	Negative	effect	effect	Positive	Negative	effect
≤ 30	0.1161	0.0847	0.4882	0.3109	0.0681	0.1120	0.3595	0.4605
≤ 60	0.1485	0.2565	0.2705	0.3245	0.1603	0.1870	0.3476	0.3073
≤ 90	0.1612	0.4778	0.1709	0.1902	0.1637	0.2962	0.3027	0.2375
≤ 120	0.1451	0.4417	0.1376	0.2756	0.1829	0.3535	0.1958	0.2681
≤ 150	0.1687	0.5649	0.0950	0.1714	0.2667	0.3452	0.2185	0.1876
≤ 180	0.1665	0.5869	0.0840	0.1626	0.2703	0.3649	0.2022	0.1798
≤ 210	0.1688	0.6287	0.0716	0.1310	0.3316	0.3382	0.2116	0.1387
≤ 240	0.1468	0.6102	0.0683	0.1747	0.2491	0.4246	0.1572	0.1827
≤ 270	0.1293	0.5680	0.0837	0.2190	0.2719	0.4084	0.1693	0.1504
≤ 300	0.1252	0.6168	0.0850	0.1731	0.2615	0.4266	0.1810	0.1308

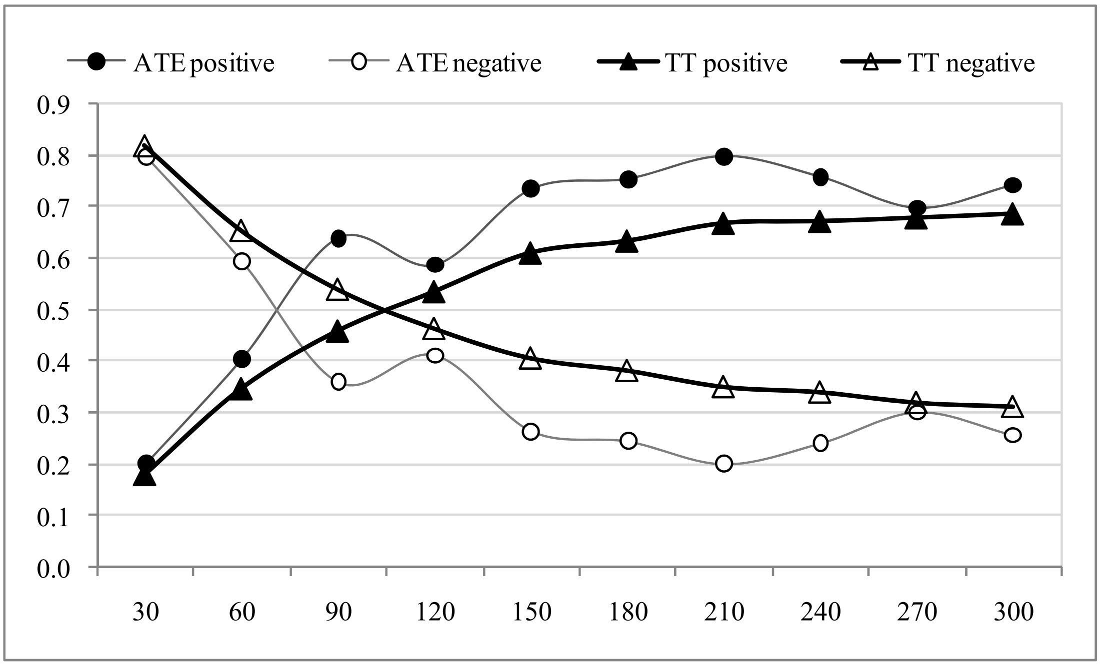

Figure 2 Distributional treatment effects of part-time sick leave

5.2.3 Sensitivity analysis

Unobserved heterogeneity is an important component in the one-factor control function model. It is therefore important to investigate how sensitive the results are to the assumptions imposed by the one-factor inclusion. In order to assess its influence on the results, we compare the estimates of our main model with the results from a number of alternative specifications for the treatment on the treated (TT). The first alternative estimator relaxes the distributional assumption made on the unobserved factor. We replace the normal factor assumption with a non-parametric distribution using a discrete factor approximation (Heckman and Singer, 1984).[5] The first two columns in Table 5 present the results for the two specifications. It can be seen that the distributional assumption of normality does generate results that are in line with those of the non-parametric distribution for sickness spells up to 150 days. For sick-leave spells longer than 150 days we found large deviations, where the estimates of the non-parametric approach increase drastically while the estimates of the parametric case remain stable. One important reason for the large deviation could be that the distribution of the unobserved factor extensively deviates from the normal distribution for sickness spells longer than 150 days. Another reason could be that the portion of part-time sick leavers who did not recover is very small for cases longer than 150 days, which makes the non-parametric approach unstable. Nevertheless, both approaches indicate that full-time sick leave is better for people with short sickness spells, and part-time sick leave increases the likelihood to recover for people with long-term spells, the break point being between 120 and 150 days.

The control function estimator with no unobserved heterogeneity should generate results similar to those of the matching estimator given that the instrument is valid. Comparing the no-factor model with a single-neighbour propensity score matching estimator, we see that they generate similar results, the no-factor estimates being slightly larger. These results show the importance of controlling for unobserved heterogeneity when the number of observed covariates is small. This also indicates that the propensity score estimator generates biased estimates, when not including all observed factors relevant for the selection. Finally, the results should be compared with observed mean differences in probability of leaving the sickness spell. As can be seen, the no-factor model, the propensity score estimator, and the simple mean difference in probability do not deviate too much, and it seems like unobserved factors are important and increase the effect of part-time sick leave for people with long-term sick-leave spells. That is, controlling for the existing correlation between the residual terms has a significant effect on the estimated value of the parameters of interest.

[5] The estimates based on the discrete factor approximation presented in Table 5 uses two discrete mass points. As an alternative, we used three discrete mass points, but the results turned out basically the same.

Table 5 TT effects from alternative model specifications

Days	Factor model estimates Normal factor (1)	Discrete factor approximation (2)	No factor (3)	Propensity score Matching (4)	Observed Mean difference (5)
≤ 30	-0.3924	-0.3266	-0.1826	-0.1653	-0.1994
≤ 60	-0.1470	-0.2047	-0.2277	-0.2106	-0.2446
≤ 90	-0.0739	-0.0636	-0.2025	-0.1840	-0.2233
≤ 120	-0.0852	0.0688	-0.1717	-0.1413	-0.1915
≤ 150	0.0791	0.1451	-0.1419	-0.1147	-0.1613
≤ 180	0.0905	0.5894	-0.1301	-0.1013	-0.1509
≤ 210	0.1928	0.7138	-0.1183	-0.0907	-0.1390
≤ 240	0.0663	0.7070	-0.1239	-0.0987	-0.1430
≤ 270	0.1215	0.7076	-0.1164	-0.0827	-0.1351
≤ 300	0.1307	0.1938	-0.1122	-0.0747	-0.1305

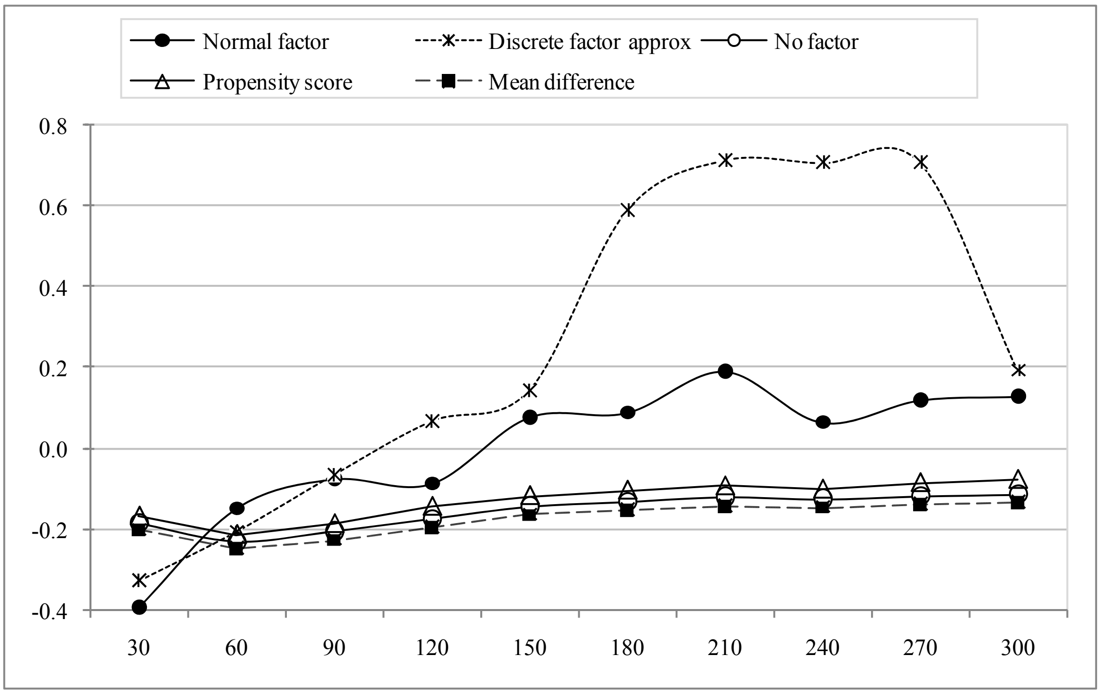

Figure 3 Mean TT effects on part-time sick leave using different specifications

We also compare the full model with the model where the factor loading in the selection equation is normalized to one. The signs of the factor loadings are the same in the two cases, and more importantly, the size of the implied correlation measures are comparable in size. We could not find any deviations that were significant.

6 Summary and conclusions

Part-time sick leave is one of the “inventions” that the Swedish government hoped would not only decrease the sickness absenteeism rates, but also help people not lose contact with their working places. Data from the National Agency of Social Insurance were used to assess the effect of part-time sick leave on the probability of returning to work with full recovery of lost work capacity. The estimates of a discrete choice factor model that accounts for the selection into the degree of sickness (part-time or full-time) show that the mean treatment effect of random assignment is negative for relatively shorter spells (i.e., ≤ 60 days) and almost zero for longer spells (i.e., 90-300 days). But the mean treatment effect of selective assignment (i.e., only for those who were actually “treated” with part-time) is negative for spells up to 120 days and then positive. This suggests that part-time sick leave could be used as a policy instrument for cases lasting longer than 120 days, and that the selection of cases should be restricted and directed to individuals with a health condition that allow for part-time work.

In a second step, we also estimated distributional effects based on the parameters of interest, to investigate how many people would gain from part-time sick leave and how many people would lose. The share of people who would lose is about the same for both random assignment and selective assignment. For random assignment, the share of those who would be indifferent between the states is somewhat larger compared to that for selective assignment, and for selective assignment the share of those who would gain from part-time sick leave is larger than for random assignment. In both cases, the shares are increasing over time, suggesting that part-time sick leave is more effective for long-term spells.

From a policy perspective, our results suggest that part-time sick leave is an effective means for longer cases, but that one should be more restrictive for shorter cases. Even so, the share of individuals who are indifferent between the states is large, in fact larger than 50 percent, which leaves room for budget savings.

References

Aakvik, A., Heckman, J. J., & Vytlacil, E. J. (2005). Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs. *Journal of Econometrics, 125* (1-2), 15-51.

Englund, L., & Svärdsudd, K. (2000). Sick-listing habits among general practitioners in a Swedish county. *Scandinavian Journal of Primary Health Care, 18* (2), 81-86.

Frölich, M., Heshmati, A., & Lechner, M. (2004). A microeconometric evaluation of rehabilitation of long-term sickness in Sweden. *Journal of Applied Econometrics 19* (3), 375-396.

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica, 46* (4), 931-959.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica, 47* (1), 153-161.

Heckman, J. (1981). The incidental parameters problem and the problem of initial conditions in estimating a discrete time–discrete data stochastic process. in C. Manski, D. & McFadden, Editors, *Structural Analysis of Discrete Data with Econometric Applications*. Cambridge, MA: MIT Press, 179-195.

Heckman, J., & Singer, B. (1984). A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica, 52* (2), 271-320.

Hensing, G., Timpka, T., & Alexanderson, K. (1997). Dilemmas in the daily work of social insurance officers. *Scandinavian Journal of Social Welfare*, 6, 301-309.

Heshmati, A., & Engström, L. (2001). Estimating the effects of vocational rehabilitation programs in Sweden. in M. Lechner, F. Pfeiffer, & (Eds.), *Econometric Evaluation of Labour Market Policies* (ss. 183-210). Heidelberg: Physica.

OECD (2003). Transforming Disability into Ability. Policies to promote work and income security for disabled people.

Ydreborg, B., Ekberg, K., & Nilsson, K. (2007). Swedish social insurance officers' experiences of difficulties in assessing applications for disability pensions - an interview study. *BMC Public Health, 7* (1), 128.

Appendix

Table A1 Mean values* by the degree of sick leave in the beginning of the spell and health status at the end of the spell

	Degree in beginning		Recovered		Not recovered	
	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time
Men	0.229	0.384	0.201	0.386	0.302	0.374
Women	0.771	0.616	0.799	0.614	0.698	0.626
SGIincome in 100 kr #	2.109	2.020	2.123	2.015	2.073	2.044
	(0.493)	(0.510)	(0.506)	(0.511)	(0.461)	(0.501)
Income from employment	2.099	2.005	2.110	2.001	2.071	2.021
(A-inkomst) in 100 kr	(0.518)	(0.539)	(0.537)	(0.539)	(0.468)	(0.537)
Age	45.104	43.744	43.071	43.037	50.264	47.349
	(11.519)	(11.425)	(11.331)	(11.478)	(10.364)	(10.441)
Age-dummies						
Age 16 – 25	0.029	0.066	0.041	0.075	0.000	0.019
Age 26 – 35	0.253	0.204	0.297	0.217	0.142	0.142
Age 36 – 45	0.197	0.265	0.212	0.268	0.160	0.247
Age 46 – 55	0.296	0.275	0.297	0.269	0.292	0.308
Age 56 – 64	0.224	0.190	0.152	0.171	0.406	0.285
Married	0.451	0.490	0.420	0.481	0.528	0.536
Born in Sweden	0.925	0.863	0.926	0.867	0.925	0.843
NUTS regions						
Stockholm	0.205	0.220	0.249	0.227	0.094	0.183
Östra Mellansverige	0.176	0.160	0.182	0.155	0.160	0.185
Småland med öarna	0.096	0.087	0.093	0.088	0.104	0.081
Sydsverige	0.115	0.132	0.097	0.133	0.160	0.128
Västsverige	0.184	0.187	0.186	0.186	0.179	0.192
Norra Mellansverige	0.099	0.107	0.093	0.107	0.113	0.108
Mellersta Norrland	0.056	0.045	0.045	0.046	0.085	0.045
Övre Norrland	0.069	0.062	0.056	0.059	0.104	0.077
Occupation with very little or no required education	0.061	0.084	0.063	0.081	0.057	0.098
Employer						
Private	0.413	0.511	0.409	0.515	0.425	0.489
Municipality	0.309	0.298	0.297	0.295	0.340	0.315
Occupation						
Legislators, senior officials and managers	0.040	0.032	0.037	0.033	0.047	0.028
Professionals	0.237	0.118	0.260	0.118	0.179	0.121
Clerks	0.123	0.109	0.138	0.110	0.085	0.100
Service and shop sales workers	0.179	0.262	0.164	0.264	0.217	0.249
Craft and related trades workers	0.067	0.118	0.056	0.119	0.094	0.111
Plant/machine operators & assemblers	0.051	0.125	0.048	0.125	0.057	0.126
Elementary occupations	0.296	0.227	0.294	0.223	0.302	0.245
At least one previous sick leave	0.301	0.218	0.275	0.212	0.368	0.251
Diagnosis						
Mental disorder	0.211	0.170	0.227	0.154	0.170	0.249
Circulatory organs	0.024	0.038	0.011	0.035	0.057	0.053
Musculoskeletal	0.371	0.319	0.323	0.305	0.491	0.389
Pregnancy and delivery complications	0.075	0.028	0.093	0.032	0.028	0.006
Injuries and poisoning	0.053	0.095	0.059	0.101	0.038	0.064
Other	0.261	0.345	0.283	0.366	0.208	0.238
Physician						
Primary care	0.485	0.467	0.502	0.477	0.443	0.413
Company	0.163	0.095	0.160	0.078	0.170	0.179
Private	0.128	0.125	0.123	0.123	0.142	0.138
Specialist (at the hospital)	0.224	0.313	0.216	0.322	0.245	0.270
Changed degree of sick leave	0.184	0.201	0.171	0.183	0.217	0.294
Interactions						
Private x Primary care	0.203	0.219	0.204	0.225	0.198	0.189
Musculoskeletal x Company physician	0.080	0.038	0.063	0.029	0.123	0.087
Mental disorder x Specialist	0.027	0.027	0.026	0.021	0.028	0.055
	375	3232	269	2702	106	530

*Standard deviations are also reported within parentheses for continuous variables. NUTS stands for the Nomenclature of Territorial Units for Statistics. #The benefit amount is based on a theoretical income, *sjukpenninggrundande inkomst* (SGI), which is calculated based on current or previous earnings. The lowest possible SGI is 24 percent of the base amount, set yearly by the government. The highest possible SGI is 7.5 times the base amount.

Table A2 Detailed description of the analyzed spells

Sick leave in the beginning	Status at the end	Total	Failed	Censored	% censored
Full-time	Not full recovery or censored	530	196	334	63.02
Full-time	Full recovery	2702	2690	12	0.44
Part-time	Not full recovery or censored	106	40	66	62.26
Part-time	Full recovery	269	262	7	2.60
Total		3607	3188	419	11.62

Table A3 Spells finished without full recovery*

Days since the spell began	Part-time (1)	Full-time (2)
≤ 30	2.67	1.24
≤ 60	4.53	2.60
≤ 90	4.80	2.94
≤ 120	4.80	3.22
≤ 150	5.60	3.47
≤ 180	5.87	3.74
≤ 210	6.13	3.99
≤ 240	6.40	4.02
≤ 270	6.93	4.73
≤ 300	8.27	5.01

*The difference between the mean values for part-time (1) and full-time (2) is statistically different from zero at the 1% level. The mean value for part-time (full-time) represents the percentage of spells ended without full recovery at the end of the analyzed period relative to the total spells that started as part-time (full-time). There are also censored spells at the end of all analyzed periods.

Table A4 The estimated parameters of the selection equation for different cut points

	≤ 30 days	≤ 60 days	≤ 90 days	≤ 120 days	≤ 150 days	≤ 180 days	≤ 210 days	≤ 240 days	≤ 270 days	≤ 300 days
Factor loading	0.4046	1.1412	0.4853	0.8130	1.7582 ***	1.7355 ***	1.7968 ***	1.6327 **	0.4902	0.5038
Men (CG: Women)	-0.4068 ***	-0.5872	-0.4305 ***	-0.4962	-0.7989 ***	-0.7933 ***	-0.8153 ***	-0.7473 **	-0.4229 ***	-0.4252 ***
Swedish-born	0.0075	0.0169	0.0125	0.0139	0.0360	0.0338	0.0367	0.0273	0.0096	0.0090
Age-groups (CG: 16-24 years)										
25-34	-0.1095	-0.1813	-0.1548	-0.1636	-0.3655	-0.3724	-0.4566	-0.3383	-0.1849	-0.1913
35-44	-0.3935 ***	-0.5753	-0.4488 ***	-0.5032	-0.8379 **	-0.8533 **	-0.9499 ***	-0.8108 **	-0.4806 ***	-0.4898 ***
45-54	-0.2350 *	-0.3306	-0.2673 **	-0.2977	-0.4920 *	-0.5052 *	-0.5766 *	-0.4827	-0.2946 *	-0.3017 *
55-64	-0.0995	-0.1619	-0.1433	-0.1492 *	-0.2931	-0.3040	-0.3919	-0.2912	-0.1707	-0.1780
Married	-0.1610 **	-0.2297	-0.1672 ***	-0.1953	-0.2826 **	-0.2800 **	-0.2740 **	-0.2700 **	-0.1630 **	-0.1629 **
Stockholm	-0.2195 ***	-0.2925	-0.2114 ***	-0.2437	-0.3501 **	-0.3503 **	-0.3415 **	-0.3395 **	-0.2068 **	-0.2082 **
Income$^{\#}$ (in Thousands kronor)	-0.1046 *	-0.1430	-0.0980 *	-0.1189	-0.1881	-0.1797	-0.1702	-0.1741	-0.0961	-0.0950
Sick leave previous year	0.2371 ***	0.3322	0.2404 ***	0.2800	0.4488 **	0.4410 **	0.4517 **	0.4217 **	0.2356 ***	0.2378 ***
Diagnosis										
Mental disorder	0.0133	0.0187	0.0155	0.0157	0.0436	0.0429	0.0483	0.0358	0.0157	0.0188
Musculoskeletal	0.1323 *	0.1742	0.1261 *	0.1483	0.2463	0.2443	0.2525	0.2331	0.1324	0.1344
Physician (CG: primary care)										
Company	-0.0267	-0.0404	-0.0354	-0.0316	-0.0635	-0.0646	-0.0651	-0.0545	-0.0281	-0.0291
Private	-0.1456	-0.2167	-0.1590	-0.1800	-0.2872	-0.2838	-0.2919	-0.2679	-0.1571	-0.1564
Specialist	-0.3495 ***	-0.4925	-0.3646 ***	-0.4194	-0.6262 ***	-0.6258 ***	-0.6317 ***	-0.5938 **	-0.3533 ***	-0.3545 ***
Occupation (CG: Professionals)										
Legislators, senior officials	-0.2938	-0.4456	-0.3098 *	-0.3662	-0.6320	-0.6159	-0.6156	-0.5385	-0.2674	-0.2756
Clerks	-0.6492 ***	-0.8640 *	-0.6034 ***	-0.7251	-1.1022 ***	-1.0863 ***	-1.0906 ***	-1.0476 **	-0.6068 ***	-0.6047 ***
Service and shop sales work	-0.9481 ***	-1.3215	-0.9523 ***	-1.1144	-1.8005 ***	-1.7678 ***	-1.7779 ***	-1.6732 **	-0.9310 ***	-0.9349 ***
Craft and related trades	-0.7515 ***	-1.0197	-0.7310 ***	-0.8643	-1.3568 ***	-1.3217 ***	-1.3415 ***	-1.2826 **	-0.7394 ***	-0.7438 ***
Plant/machine operators	-1.0310 ***	-1.4431 *	-1.0409 ***	-1.2197	-1.8696 ***	-1.8459 ***	-1.8711 ***	-1.7759 ***	-1.0286 ***	-1.0289 ***
Elementary occupations	-0.4978 ***	-0.6961	-0.4960 ***	-0.5871	-0.9585 **	-0.9366 ***	-0.9533 ***	-0.8921 **	-0.4930 ***	-0.4961 ***
Municipality sector	-0.2023 **	-0.2977	-0.2199 ***	-0.2439	-0.3570 **	-0.3553 **	-0.3545 **	-0.3368 *	-0.2026 **	-0.2034 **
Interactions										
Private*Primary care	-0.1785 *	-0.2469	-0.1868 **	-0.2088	-0.2812	-0.2827	-0.2795	-0.2712	-0.1737	-0.1744
Musculoskeletal*Company	0.3457 *	0.4975	0.3666 **	0.4165	0.6837	0.6774	0.7096 *	0.6469	0.3616 *	0.3646 *
Mental disorder*Specialist	0.2305	0.3154	0.2332	0.2718	0.3898	0.3912	0.3853	0.3851	0.2414	0.2359
Log-likelihood	-3133.3	-3244.3	-3162.3	-3077.2	-2987.6	-2940.5	-2857.1	-2807.4	-2764.0	-2744.4

Notes: CG stands for comparison group, and $^{\#}$ the income refers to the income qualifying for sickness allowance (SGI). The estimate is significant at the 10% level (*), at the 5% level (**), and at the 1% level (***). These notes hold for all tables of estimates.

Table A5 The estimated parameters of the full-time equation

	≤ 30 days	≤ 60 days	≤ 90 days	≤ 120 days	≤ 150 days	≤ 180 days	≤ 210 days	≤ 240 days	≤ 270 days	≤ 300 days
Factor loading	5.1401	-0.1691	-0.5181 ***	-0.2308	-0.4304	-0.4380	-0.6458	-0.4114	-1.8446 ***	-1.8541 ***
Men (CG: Women)	0.0830	0.1251 *	0.1040	0.0689	0.0757	0.1036	0.1599	0.1274	0.2578	0.2734
Swedish born	0.2184	0.1864 ***	0.2098 ***	0.2302 ***	0.1882 **	0.1304	0.1756 **	0.2027 **	0.4064 **	0.4253 **
Age/10	-0.3568 *	0.1807 **	0.3374 ***	0.3271 ***	0.3887 ***	0.4282 ***	0.5363 ***	0.5059 ***	1.0498 ***	1.0561 ***
Age-squared/100	0.0281	-0.0281 ***	-0.0509 ***	-0.0506 ***	-0.0590 ***	-0.0645 ***	-0.0792 ***	-0.0749 ***	-0.1569 ***	-0.1593 ***
Married	0.0547	-0.0097	0.0123	0.0092	0.0174	0.0274	0.0285	-0.0003	0.0067	0.0190
Income[#] (in Thousands kronor	0.1792	0.0151	0.0439	0.0360	0.0404	0.0373	-0.0198	0.0059	-0.0194	-0.0234
NUTS-regions (CG: Övre Norrland)										
Stockholm	-0.0383	0.2260 **	0.2345 **	0.3446 ***	0.3706 ***	0.3506 ***	0.3584 **	0.3704 ***	0.8599 **	0.9056 ***
Östra Mellansverige	0.2568	0.1992 *	0.1380	0.2126 *	0.2378 *	0.2402 *	0.2074	0.1738	0.3943	0.4927
Småland med öarna	0.4090	0.2735 **	0.2276 *	0.2517 **	0.3120 **	0.3265 **	0.3276 **	0.3264 **	0.6594 *	0.7029 **
Sydsverige	0.4831 *	0.2718 **	0.3103 ***	0.4851 ***	0.4563 ***	0.4412 ***	0.3563 **	0.3523 ***	0.7701 **	0.7920 **
Västsverige	0.2296	0.2112 *	0.1880	0.2943 ***	0.3073 **	0.2796 **	0.2576 *	0.2520 **	0.5682 *	0.5681 *
Norra Mellansverige	0.3014	0.1027	0.1857	0.2694 **	0.3380 **	0.3266 **	0.3370 **	0.3356 **	0.7333 **	0.7407 **
Mellersta Norrland	0.5039	0.1682	0.2225	0.3555 **	0.3869 **	0.3498 **	0.3729 **	0.3644 **	0.8149 *	0.8208 *
Sick leave previous year	0.0208	-0.0951	-0.1549 **	-0.1439 **	-0.1658 **	-0.1635 **	-0.1789 **	-0.1390 *	-0.3175 **	-0.2997 *
Diagnosis (CG: Injuries & poisoning)										
Mental disorder	-0.2110	-0.4265 ***	-0.5143 ***	-0.4831 ***	-0.4378 ***	-0.4351 ***	-0.4107 ***	-0.3499 ***	-0.7700 **	-0.7941 **
Circulatory organs	1.0168 ***	-0.0851	-0.2262	-0.2877 *	-0.3347 **	-0.3103 *	-0.3335 *	-0.3776 **	-0.8445 **	-0.8824 **
Musculoskeletal	0.2710	-0.1053	-0.1746	-0.1698 *	-0.2053 *	-0.1579	-0.1595	-0.1789	-0.4044	-0.4283
Pregnancy and delivery complications	-0.3958	0.0541	0.1000	0.1826	0.2463	0.3067	0.4475 *	0.6102 **	0.9722 *	0.9244 *
Other	1.2651 ***	0.2929 ***	0.2273 ***	0.1011	0.0629	0.0880	0.1131	0.0640	0.1042	0.1196
Physician (CG: primary care)										
Company	-1.7217 ***	-0.5836 ***	-0.5254 ***	-0.4504 ***	-0.5093 ***	-0.4301 ***	-0.4524 ***	-0.4304 ***	-0.8137 ***	-0.7876 **
Private	-0.6503 ***	-0.1766 *	-0.1283	-0.1098	-0.1183	-0.0946	-0.0782	-0.1214	-0.3072	-0.2276
Specialist	-1.1477 ***	-0.2814 ***	-0.1472 *	-0.0545	0.0099	0.0521	0.0836	0.0496	0.1160	0.1417
Private sector	0.0340	-0.0708	-0.0178	0.0029	-0.0062	-0.0490	-0.0049	0.0337	0.0529	-0.0094
Occupation with little or no required education	0.1223	-0.0442	0.1126	0.0869	0.0241	0.0085	-0.0834	-0.0388	-0.0971	-0.1192
Changed degree of sick leave	-6.9965	-1.0889 ***	-0.9046 ***	-0.6507 ***	-0.5166 ***	-0.4634 ***	-0.4947 ***	-0.3932 ***	-0.7546 ***	-0.7380 ***
Interactions										
Private*Primary-care	-0.1875	0.0900	0.0170	0.0089	-0.0009	0.0437	-0.0133	-0.0760	-0.1628	-0.1023
Musculoskeletal*Company	0.9175 **	0.1475	-0.0461	-0.1432	-0.1765	-0.2784	-0.3601 *	-0.3171 *	-0.5296	-0.5424
Mental disorder*Specialist	0.0189	-0.1079	-0.4505 **	-0.2967 *	-0.5103 ***	-0.5312 ***	-0.5730 ***	-0.5712 ***	-1.1316 ***	-1.0818 ***

Table A6 The estimated parameters of the part-time equation

	≤ 30 days	≤ 60 days	≤ 90 days	≤ 120 days	≤ 150 days	≤ 180 days	≤ 210 days	≤ 240 days	≤ 270 days	≤ 300 days
Factor loading	-0.0377	-0.1478	-0.8880	-0.1247	-0.3192	-0.3342	-0.3849	-0.2493	-0.1204	-0.2937
Men (CG: Women)	-0.1839	-0.3370	0.0617	-0.0356	-0.2468	-0.2814	-0.2714	-0.3634 *	-0.2799	-0.2320
Swedish born	0.3660	0.0347	0.2221	0.1477	0.2109	0.1279	0.1688	0.1909	0.2700	0.3185
Age/10	-0.0509	0.1767	0.5057 ***	0.3707	0.3677	0.3543	0.5112	0.4161	0.3638	0.5109
Age-squared/100	-0.0051	-0.0365	-0.0993	-0.0809 *	-0.0759	-0.0743	-0.0903 *	-0.0794	-0.0761	-0.0957
Married	-0.0187	0.0028	-0.0193	-0.0729	0.0177	-0.0176	-0.0483	-0.0266	-0.0787	-0.0428
Income[#] (in Thousands kronor	0.0206	0.1216	0.2186	0.1407	0.2215	0.2523	0.1704	0.1680	0.1741	0.2145
NUTS-regions (CG: Övre Norrland)										
Stockholm	0.2052	0.6080 *	0.8091	0.8635 ***	1.1070 ***	1.1358 ***	0.9455 ***	0.9020 ***	1.0700 ***	1.0029 **
Östra Mellansverige	-0.0070	0.4883	0.7883	0.6429 **	0.7086 **	0.6570 **	0.5845 *	0.5620 *	0.6722 **	0.5421
Småland med öarna	-0.1354	0.2868	0.6635	0.4141	0.5051	0.4600	0.2312	0.3778	0.5460	0.4352
Sydsverige	-0.1824	0.1926	0.2594	0.4035	0.3860	0.4881	0.3710	0.3472	0.3895	0.2367
Västsverige	0.3051	0.5041	0.7980	0.6688 **	0.6549 **	0.6674 **	0.5136	0.4979	0.5765 *	0.5215
Norra Mellansverige	-0.4178	0.3140	0.2763	0.2237	0.3442	0.5436	0.2848	0.3368	0.4721	0.4508
Mellersta Norrland	-0.0945	0.1854	0.5828	0.4461	0.4012	0.3042	0.2652	0.2234	0.2829	0.1890
Sick leave previous year	-0.0734	-0.1426	-0.3153	-0.1510	-0.2643	-0.2088	-0.2191	-0.2325	-0.2344	-0.2290
Diagnosis (CG: Injuries & poisoning)										
Mental disorder	-0.7645 **	-0.4455	-0.2398	-0.1529	-0.1034	0.0063	-0.0181	-0.0283	-0.1589	-0.3630
Circulatory organs	-0.9483	-0.7420	-0.3329	-0.4405	-0.3788	-0.4109	-0.5508	-0.5514	-0.6701	-0.8641
Musculoskeletal	-0.8702 **	-0.7221 **	-0.6871	-0.5406 *	-0.4168	-0.3219	-0.3465	-0.3300	-0.4511	-0.6293 *
Pregnancy and delivery complications	-0.8280 *	-0.2250	-0.4381 ***	-0.2876	-0.1997	0.2202	0.2168	0.1679	0.0133	-0.1696
Other	-0.8354 **	-0.6431 **	-0.5813	-0.3304	-0.0441	0.0284	-0.0213	-0.0134	-0.2039	-0.3550
Physician (CG: primary care)										
Company	-0.7897 *	-0.5496 *	-0.3727 ***	-0.2641	0.0094	-0.0467	0.1280	0.1380	0.2816	0.4270
Private	-0.3839	-0.4838 *	-0.4923	-0.0962	-0.1129	-0.2133	-0.1229	-0.1327	-0.2408	-0.2306
Specialist	0.0328	-0.3125	-0.3661	-0.0863	-0.2670	-0.2673	-0.1564	-0.1710	-0.3146	-0.2710
Private sector	0.3494	0.4159 *	0.1788	-0.1140	0.0247	0.0426	0.0473	0.0889	0.0091	0.0147
Occupation with little or no required education	-0.1852	0.0244	-0.0019	-0.2345	0.3593	0.2758	0.2376	0.1848	0.1434	0.1664
Changed degree of sick leave	-0.9718 ***	-0.7279 ***	-0.7547	-0.5640 ***	-0.5437 ***	-0.4308 **	-0.2300	-0.2485	-0.2544	-0.3122
Interactions										
Private*Primary-care	-0.2362	-0.4852	-0.2081	0.0604	-0.1270	-0.1338	-0.0229	-0.0290	-0.0682	-0.0729
Musculoskeletal*Company	0.6546	0.2530	-0.1978	0.0802	-0.4488	-0.3420	-0.3328	-0.2346	-0.4654	-0.6106
Mental disorder*Specialist	-0.2377	-0.6813	-0.5589 **	-0.7446	-0.6330	-0.4345	-0.0562	-0.0338	-0.0554	0.2359

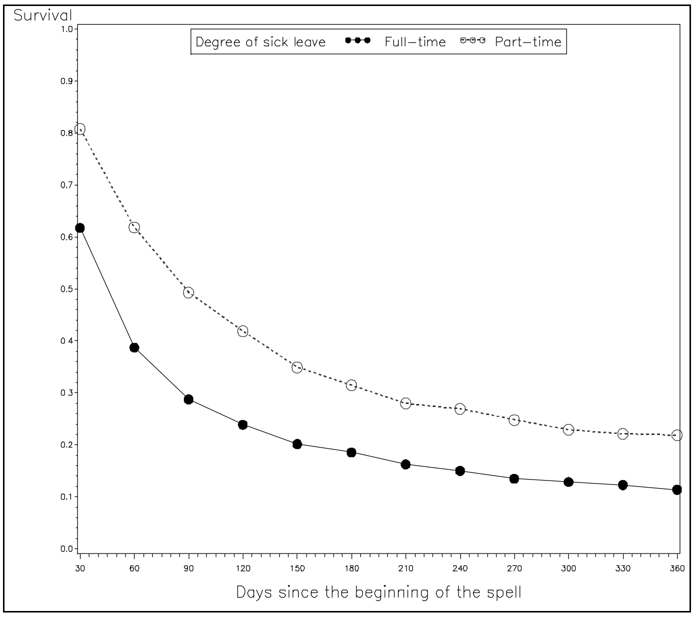

Figure A1 Survival plots by sick leave

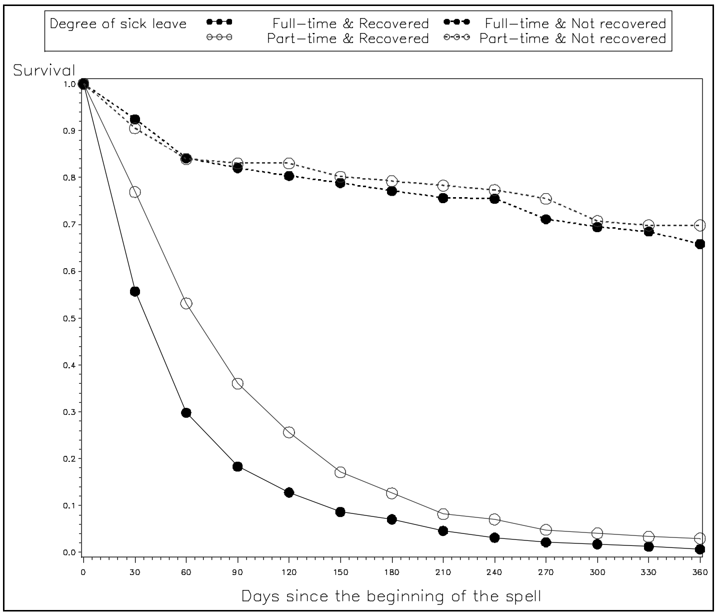

Figure A2 Survival plots by sick leave and health status

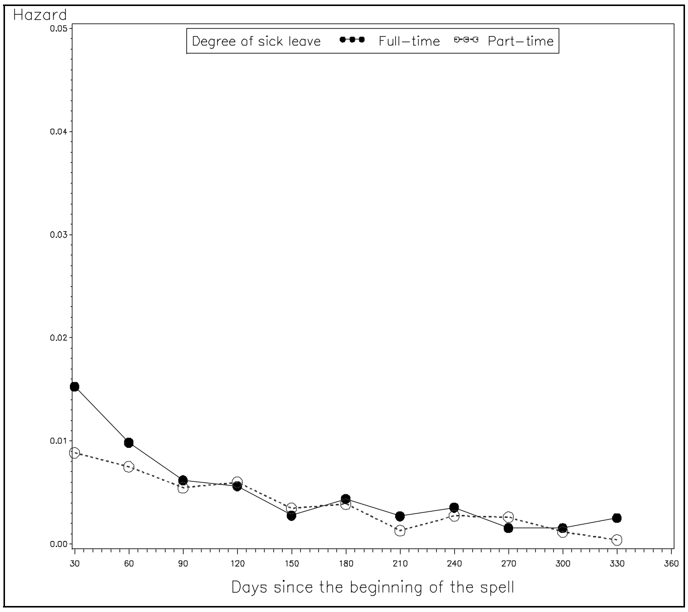

Figure A3 Hazard plots by sick leave

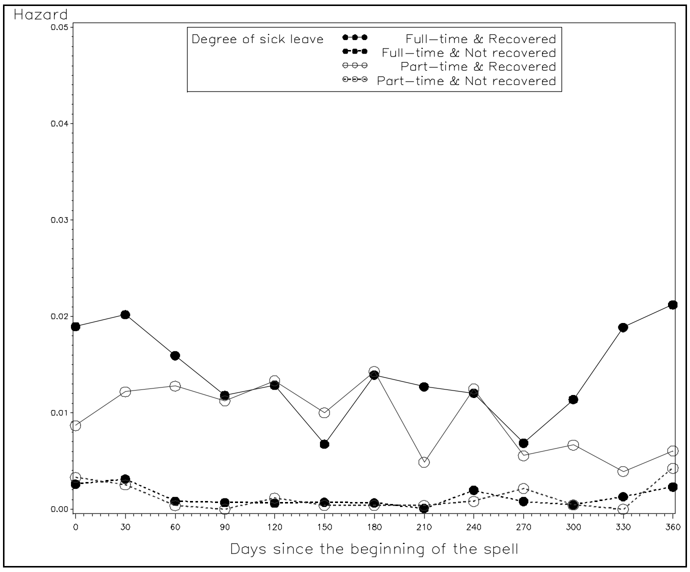

Figure A4 Hazard plots by sick leave and health status