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How to evaluate the impact of part-time sick leave on the probability of recovering*

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Abstract
This paper presents an econometric framework for analyzing part-time sick leave as a treatment method. We exemplify how the discrete choice one-factor model can address the importance of controlling for unobserved heterogeneity in understanding the selection into part-time/full-time sick leave and the probability to fully recover from a reduced work capacity. The results indicate that part-time sick listing increases the probability to recover compared to full-time sick listing when the expected time to recover is longer than 120 days.

Key words: part-time sick leave, discrete choice model, selection, unobserved heterogeneity.

JEL Classification: I12; J21; J28

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1 Introduction

People may be absent from their job due to their own or another family member's *sickness*, due to death in the family, or due to other strictly personal reasons. Although these situations imply loss of income for the individual, she or he can avoid the income loss if there is an insurance that covers the situation in question. In some countries (e.g., all of Scandinavia), it is even possible to combine work and sick leave when an employee's normal work capacity is reduced by at least 25% (which is covered by the sickness insurance). This combination is considered to be a re-orientation from passive compensation to active integration, but not much empirical evidence exists for it. Despite the recent focus among policy makers, no previous theoretical or empirical research has evaluated the relative effects of part-time and full-time sick leave. The aim of this article is therefore to reduce this gap and analyze the effects of starting the sick leave on part-time (compared to full-time) 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.[1] The rest of presents the empirical framework (Section 2), the data and some institutional settings (Section 3), some results (Section 4), and conclusions (Section 5).

2 Empirical framework

The point of departure is an employed individual with a diagnosed health condition and an accompanying reduced work capacity. In the Scandinavian countries, this implies a choice between two states: to be on part-time or full-time sick leave. Even though it is of policy relevance to have information about which state generally generates the highest probability to recover from the reduced work capacity, previous literature does not provide robust theoretical or empirical evidence in this regard. As a suitable structure for the empirical framework, Andrén and Andrén (2008) suggest a discrete choice switching regression model with an endogenous switch between the two states (Heckman, 1978; 1979), defined by the following equations:

[1] The present article is a short version of Andren and Andrén (2008) who use an econometric framework to analyze the effects of being on part-time sick leave compared to being on full-time sick leave.

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

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

$D^* = Z\beta_D + U_D,\ D = 1\ if\ D^* \geq 0,$ and $D = 0$ elsewhere, (Selection rule) (3)

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. 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 and full-time sick leave, respectively. D^* is a latent measure for the propensity to choose part-time sick leave. Each equation has its own stochastic component $(U_j,\ j = 1, 0, \text{or } D),$ which allows for heterogeneity among individuals with the same observed characteristics.

One important extension of the basic model is to control for unobserved heterogeneity, as proposed by Aakvik et al. (2005). This is solved by imposing a factor structure with factor loadings on the stochastic terms. The one-factor residuals are defined by:

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

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

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

The idea is that there exist some unobservables captured by the unobserved factor ξ that are common to the three involved equations and that drive the correlation among the residual terms (U_1, U_0, U_D). Each equation has its own factor loading $(\theta_1, \theta_0, \theta_D)$ attached to the factor. The factor loadings are important since they control for any potential correlation among the residual terms. Using the factor loadings, we may form product covariances $(Cov(U_1, U_D) = \theta_1\theta_D, Cov(U_0, U_D) = \theta_0\theta_D, Cov(U_1, U_0) = \theta_1\theta_0)$, 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.[2]

[2] This is possible under the assumption that $(\varepsilon_1, \varepsilon_0, \varepsilon_D, \xi) \sim N(0, I)$ with I being an identity matrix.

The likelihood function for the one-factor model is defined as

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

with $\Pr(.)$ being the standard normal cumulative distribution function and F an absolutely continuous distribution function that can be non-normal.[3]

3 Data and some institutional setting

The present study uses the 2002 sample of the RFV-LS database of the Swedish Social Insurance Agency, which includes 5,000 persons (aged 20-64 years) who started a sickness spell during 1-16 February 2001. Given the aim of this paper, we analyze only people who were employed the day before starting the selected sickness spell and did not receive any partial disability benefit. We exclude a few special cases where employees on sick leave ended their spells because of incarceration, emigration, or participation in a rehabilitation program. This results in a sample of 3,607 employees. The descriptive statistics of all variables used in the empirical analysis are presented in Appendix A1.

In Sweden, both full-time and part-time workers can be on full- or part-time sick leave. 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 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 the disease, sickness, or injury. Although part-time sick leave can fulfill the goal of keeping in contact with the job, it might also function as replaced leisure. A problem is that not all jobs are suitable for a temporary 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.

The first step in this analysis is to define a treatment and a comparison group. Given that all sickness spells are at least 15 days long (due to the fact that all employees are covered by the sickness insurance only from the 15th day), we use the degree of sickness on the 15th day (or the *first* day paid by the sickness insurance) to define the

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

two groups: (1) the treatment group (part-timers), with sickness spells that started with 25%, 50%, or 75% sick leave and (2) the control group (full-timers), with spells that started with 100% sick leave.

The second step involves constructing the outcome variables for the potential outcome equations. They are constructed using information about the employment status of the individuals at the end of their sickness spells, and take a value of 1 when recovered (i.e., the spell ended with full recovery of the lost work capacity) and a value of 0 when not recovered (i.e., the spell ended with a partial or full disability benefit, which could be permanent or temporary) or censored (i.e., the spell has not ended at the end of the observation period). We choose to build the outcome within given periods, with cut-off points starting at 30 days, and then extend by steps of 30 days, which is the usual time between appointments with a general practitioner or a specialist or with social insurance officers. This allows us to draw conclusions about the effect of part-time sick leave on the probability to recover compared to the effect of full time sick leave, and how it changes over time.

The third step involves constructing an exclusion restriction or an instrument that is to be included in the selection equations and that works as an identifier of the treatment effects.[4] Since some employers cannot conveniently fill certain positions with part-time employment (common in small establishments, but also in offices or labs that have only one employee specialized in certain tasks), we choose the occupational categories as instruments. It is plausible to say that some employers have a causal effect on the 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.

[4] The use of an exclusion restriction in selection models is important for the performance of the estimator. When no exclusion restriction is imposed, the identification of the treatment effect depends entirely on the non-linearity of the model, which usually has non-desirable effects on the estimate. The exclusion restriction is imposed on the output equations and the instrument placed in the selection equation.

4 Results

Table 1 reports the estimates for the average treatment effect (*ATE*),[5] and the treatment on the treated (*TT*),[6] of being on part-time sick leave compared to being on full-time sick leave at different cut-off points.[7] The difference between *TT* and *ATE* is a measure of the selection effect that results from selecting or sorting appropriate individuals into part-time sick leave and full-time sick leave. Had there been no selection and the assignment to part-time sick leave had been random, then the selection effect would have been zero and *ATE* and *TT* would have been the same.

Table 1 Mean treatment effects

	≤ 30	≤ 60	≤ 90	≤ 120	≤ 150	≤ 180	≤ 210	≤ 240	≤ 270	≤ 300
ATE	-0.1919	-0.2050	-0.0315	-0.1469	-0.1184	-0.1319	-0.0552	-0.1475	-0.1178	-0.0633
TT	-0.4679	-0.1252	-0.0590	-0.0552	0.0655	0.0788	0.3394	0.0513	0.0712	0.1043
TT - ATE	-0.2761	0.0798	-0.0275	0.0917	0.1840	0.2107	0.3946	0.1988	0.1890	0.1677

The ATE parameter is negative all over, suggesting a negative effect of part-time sick leave for a randomly chosen individual from the population. That is, if part-time sick listing would have been a general rule for the population of employees on sick leave, the sickness cases would generally have been longer. Hence, part-time sick listing should not be thought as a first-best choice for all.

The estimated *TT* parameter shows negative values up to 120 days, but is positive at 150 days and above, suggesting that selective is used when sorting people into part-time sick leave. There could of course be several reasons for this result, for example, that maintaining contact with one's job helps the individual return to the job full time. After all, being away from the work place may have an isolating effect and

[5] *TT* is 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:

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

[6] *ATE* is a measure of the mean difference in the probability of returning to work with full recovery of lost work capacity, and is defined as: $ATE(X)=\int_{-\infty}^{\infty}\left[\Pr(Y_1 \mid X,\xi)-\Pr(Y_0 \mid X,\xi)\right]dF(\xi).$

It is interpreted as the mean effect on a randomly chosen individual in the population of sick listed.

[7] While the mean treatment effects are interesting, more can be said by investigating the distribution of the treatment effects. With the distributional treatment parameters, we can predict the probability of a successful event, an unsuccessful event, and the event of indifference. For example, how many gain from part-time sick leave and how many lose, i.e., prolong their sick leave, as a result of being selected into the "wrong" state. For more details, see Andrén and Andrén (2008).

consequently lead to a deteriorating self esteem, which in turn may make it harder to return. Another issue related to inactivity is the resulting reduction in job-specific human capital.

The results indicate that when the expected time to recover is longer than 120 days, the probability to recover from the lost work capacity is higher in the state of part-time sick leave compared to full-time sick leave.

5 Summary and conclusions

The estimates of a discrete choice factor model that takes into account the selection into different degrees of sickness (part-time and full-time) show that the mean treatment effect for selective assignment (i.e., only for those who were actually "treated" with part-time) is negative within 120 days (or less) and positive afterwards. This suggests that part-time sick leave could be used as a policy instrument for cases where the expected time to recover is longer than 120 days, and that the selection of cases should be restricted and directed to individuals with health conditions that allow for part-time work.

From a policy perspective, our results suggest that part-time sick leave is effective for longer cases but that one should be more restrictive for shorter cases.

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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
SGI-income 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 small or not requirement of the level of 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
Clarks	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 given birth 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 the sickness degree	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 amount of benefit is based on a theoretical income, *sjukpenninggrundande inkomst* (SGI), which is calculated based on current or earlier earnings. The lowest possible SGI is 24 percent of a base amount that is set every year by the government. The highest possible SGI is 7.5 times the base amount.