UNIVERSITY OF OSLO
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Sick leave and economic incentives

New evidence from personell data

Master Thesis

Master of Economic Theory and Econometrics

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Of course, I take complete responsibility for any mistakes and unclear content.

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Daniel Bergsvik

1. Introduction

Each working day, a considerable part of the labor force in many industrialized countries is on sick leave. Sick leave constitutes an extensive cost to society. This cost compromises not only neglected and deferred work, but also substantial expenditures on sickness insurance. In Norway, the sick leave rate has been around 6 to 7% in the last years according to Statistics Norway. In 2008, public expenditures on sickness insurance were about 2.4% of the Norwegian mainland GDP. However, sick leave varies a lot within and between countries, and so its associated costs (Barmby et al. 2002, Bonato and Lusinyan 2004). The search for reasons behind the variation of sickness absence is thus easily motivated.

The aim of this thesis is to search for economic incentives related to absenteeism at the firm level. Personell data of a large Norwegian group of companies is examined. The analysis compromises both employer and employee behavior. First, focus is on possible responses of the firm to sickness absence. In particular, it is tested if a relation between sick leave and earnings can be established. Does a firm respond to sick leave by refusing future pay rise? In addition to this question, several aspects of the employees' absence behavior are considered. A closer look is taken at the correlation of sick leave with wage levels and tenure, and if absence behavior changes when an employee leaves the firm. The other central question is whether sickness absence is subject to moral hazard.

The results of the analyses performed in this study indicate that economic incentives at the firm level indeed are important for sick leave behavior. First, it is verified that sick leave affects pay rise. Employees are penalized for being absent, even for low rates of sick leave. Sickness absence in the interval 3 to 5% is estimated to reduce pay rise by around 1.4% relative to those with less than 1% absence. Absence rates above 5% are predicted to be relatively penalized by around 2% less extra pay rise. Moreover, sick leave seems to increase in the time before an employee leaves the firm. This is taken as an evidence for moral hazard problems. However, the results of other tests do not support a moral hazard interpretation.

Several of the questions addressed in this thesis can be related to the existing literature on sick leave. Similar to this analysis, recent economic research on absenteeism has primarily focused on financial incentives. Trends and changes in absenteeism are tried to be explained by possible rewards and penalties associated with sickness absence. Most of the work is empirical, and the incentives which gained most interest were related to sickness insurance institutions and employer responses. The next chapter will give a selected review of this literature.

The impact of sick pay systems is obviously necessary to assess. Insurance against the risk of income loss under absence may clearly have an disincentive effect on attendance. This has been verified several times, at least for Sweden (Johansson and Palme 1996, 2005). A less generous sick pay system resulted in significantly lower sick leave rates. In Norway, however, the public insurance system guarantees a replacement rate of normally 100% from the first day of absence. In general, since this implies a strong disincentive for work, high absence rates are predicted. Indeed, Norwegian sick leave rates are among the highest in Europe (Bonato and Lusinyan 2004), but more striking is that the system is far from fully exploited.

Moreover, abuse of sick leave institutions appears actually to be easy. In Norway and other countries, short absence spells are allowed to be self-certified. Basically based on trust, employees can declare themselves to be incapable of work and stay at home. Together with full income replacement, this seems at first view to be a free lunch. When absence involves no cost and no monitoring, the incentive to attend at work for daily earnings deteriorates. Hence, other incentives than those related to sickness insurance institutions must play an important role as well. Otherwise the observed patterns remain unexplained. This is also one of the reasons why this thesis is concerned with incentives provided at the firm level.

The workplace is certainly important for absence behavior. The employees' sick leave is likely to interrelated with rewards and penalties provided by employers. Absenteeism is costly for firms. Work remains undone, and in several countries, including Norway, firms have to cover the income replacement of shorter spells. Obviously, employers want to reduce sick leave, and various forms of responses to higher sick leave are possible. Shirking might cause dismissal, and individuals with high absence rates could be the first to be signed of in periods of downsizing or be rejected permanent positions (Henningsen and Hægeland 2008, Ichino and Riphahn 2005). However, such responses are harsh, and dismissals are often strongly regulated by law. Such reactions are therefore less likely to observe.

Wage setting and promotions could be another disciplinary device used by firms in order to contain absenteeism. At least wages are negotiated frequently and might thus be an applicable mechanism of control. Employees with high sick leave rates could be penalized by receiving lower pay rise and being refused promotion. Vice versa, employees with lower absence rates may be rewarded with a wage increase. Hansen (2000) and Markussen (2009) suggest such absence penalties imposed by firms, and this thesis postulates a similar relationship. The work of Hansen and Markussen is thus comparable to this study, but methods and data differ. While they use administrative data, this thesis estimates the relation between sick leave and earnings directly at firm level employing personell data, including accurate measures of self-certified sick leave.

If pay rise is used as a disciplinary device, absence behavior may change when an employee leaves the firm. When the employee quits anyway, the incentive to be present and receiving a possibly higher pay rise vanishes. Whether such an effect exists or not will be tested in this study. Moreover, any change in risk of being penalized could possibly have an effect. Ichino and Riphahn (2005) postulated, for instance, that the end of probation possibly triggers higher sick leave. This hypothesis is retested here by considering the effect of tenure. Whether start or end of an individual's occupational career is associated with different sick leave rates can indicate possible moral hazard behavior. In addition, it also supports the theory that employers are likely to penalize sickness absence through their wage setting.

The search for economic incentives related to absenteeism is performed by employing different statistical models. The possible relation between sick leave and pay rise is examined by discrete choice and censored regression models. While logit models estimate the probability of receiving a pay rise, tobit models estimate the size of the reward. Regarding absence behavior, incidence and duration are considered. The influence of the variables mentioned above on sick leave incidence is treated by logit models as well. Incidence is modeled as probability of starting a new absence spell. Absence duration is treated by proportional hazard models. Because duration models are less common in economics, a short introduction is given in the chapter on the empirical strategy.

This analysis differs from many previous approaches by using personell data. The impact of sick leave on earnings and the effect of other incentives can be examined directly. The personell data is retrieved from a larger group of companies in Norway. Daily records of employees' work absence, together with data on pay rise, workplace and demographic characteristics, provides a well-suited basis for analyzing individual absence behavior. The advantage of personell data is that the individual decision to start and stop an absence spell can be studied directly. The possible effect of incentives related to sick leave are examined on an individual level. In addition, the measures of sick leave, including self-certified sick leave, are highly accurate.

2. Sick leave in the economic literature

The effect of economic incentives on sick leave has been examined in numerous empirical and theoretical studies. Economists began in earnest to be interested in absenteeism in the 1980s. First, traditional labor market models were applied to explain absence behavior from a supply side point of view. Later, also the role of the demand side was included in the analyses. The responses to the cost of being absent for the employer and employee could then be considered more integrated.

The cost of being absent is determined both directly through the sick pay scheme, if existent, but also indirectly through responses of the employer. Both types of costs together with their induced incentives are discussed in the literature. Several studies focus on the effect of changes in the replacement rate on sick leave. A Swedish reform in the early nineties, which allowed to identify the relation between economic incentives and absenteeism, was the point of departure. Showing that a correlation between sick leave and its cost exists, these studies concluded that sickness insurance institutions may be subject to moral hazard. Research focusing on incentives at the firm level came to a similar conclusion.

2.1 Work absence and the labor market

The first economic studies of absenteeism looked at labor supply decisions under contractual constraints and considered consequences for labor demand. The static neoclassical labor supply model was the framework of choice for discussing an employee's absence decision. Contrary, the role of the production process was found to be critical for assessing the impact of absenteeism for labor demand. Both directions of research assumed that work absence to some extent is voluntary and that no income replacement is paid. Thus, absenteeism does not arise because an employee is not capable of work, but because an employee chooses to be absent and abstains from income. The terminology reflects this position. The terms *sick leave* or *sickness absence* are rarely found in the early articles.

2.1.1 Work absence and labor supply

Examples of studies focusing on labor supply are the empirical works by Allen (1981), and Dunn and Youngblood (1986). These analyses treat work absence exclusively as a labor supply decision on part of the worker. Deviation from contractual hours occurs when an employee's marginal utility of leisure exceeds the marginal wage. Work absence was seen as a mechanism for approaching an optimal labor market equilibrium. In its most rigorous way, this argument along contractual constraints is laid out in the theoretical work by Brown and Sessions (1996).

In order to test the optimal labor supply hypothesis, Allen (1981) estimates several absence likelihood equations on a sample of workers with self-reported measures of days absent. He finds that the wage level is negatively related to work absence. Those who have a higher wage, and thus more to abstain, are less likely to be absent. The results are, however, questionable. The wage effect is only significant in equations omitting personal and industrial characteristics. Moreover, when Allen divides the data into blue collar and white collar subgroups, a wage effect does only appear for blue collar workers, and only if accompanied by an insignificant dummy variable describing whether sick leave is payable. On the other hand, some supportive evidence for a negative correlation between wage rates and absence is also found by e. g. Chaudhury and Ng (1992), and Drago and Wooden (1992)

Dunn and Youngblood (1986) construct a measure of the marginal rate of substitution of income for leisure from survey data. This measure is employed in a tobit regression on the absence frequency. A positive, slightly significant coefficient on the difference between wage and the marginal rate of substitution is estimated. This estimated effect is taken as evidence that work absence is a way of approaching an optimal labor market equilibrium. This is also supported by the recent work of Barmby et al. (2002). Comparing sickness absence in different countries, absence is positively correlated with higher usual hours of work. Higher hours of work may be related to a higher marginal rate of substitution of income for leisure.

2.1.2 Work absence and labor demand

Labor supply may be interrelated with labor demand. Studying work absence without considering the demand side can therefore give misleading results. This was emphasized by Barmby and Treble (1989, 1991). They suggest that a possible reason for the difficulty in interpreting the empirical results regarding work absence and labor supply can be addressed to an identification problem. High absence rates, may induce various reactions of the employer. Therefore, when demand side effects are present, it can be difficult to disentangle their effect on work absence from the effect of labor supply.

In one of the first economic analysis of work absence and labor demand, the role of the production process is highlighted. Weiss (1985) argues that absenteeism is more costly for firms using an assembly-line type production. In such a production process a certain amount of workers is needed to operate, and absence is obviously associated with a cost, even if no replacement is paid. The expected marginal value of an employee decreases as the propensity to be absent increases. Weiss postulates thus an efficiency wage type relationship for employees working along an assembly line.

This argument is generalized by Coles and Treble (1993, 1996). They point out that when employees are complements in production, work absence reduces productivity stronger, and a firm may pay higher wages to reduce non-attendance. Hence, worker reliability requires a wage premium. A trade off between wage costs and work absence arises, and depending on the firm's production technology different adaptions are possible. This may also provide an explanation of some of the wage and absence rates variation observed in the labor market.

Another efficiency wage effect is highlighted by Carlin (1989) and Barmby et al. (1994). In order to discourage absence, a firm may respond by monitoring. As monitoring is costly, an optimal level of absence is defined. Thus, the firms permits an optimal amount of absence. Barmby et al. (1994) show that an optimal response to increased monitoring cost may be raising wages relative to sick pay.

2.2 The costs of absence and moral hazard

Sick leave is associated with costs. A sick pay scheme, which may be publicly or internally regulated, sets a direct cost of being absent. The higher the replacement rate, the lower is obviously the cost of being absent and the incentive to reduce sick leave decreases. Recent research, especially on a Swedish reform in 1991, has confirmed that incentives resulting from sick pay schemes are important.

On the other hand, many countries in Europe have a generous sickness insurance system without experiencing high sick leave rates. See, for example, Barmby et al. (2002) and Bonato and Lusinyan (2004) for an international comparison of work absence rates. Sickness insurance systems are far from fully exploited. In particular, Germany has both a generous sickness insurance system, but also low absence rates. Hence, other incentives to reduce absenteeism may play a role as well, and economic research focused on the effect of sick leave on wages and employment. Pay rise and employment may be disciplinary devices with respect to sickness absence.

In the economic literature on absenteeism, the term *moral hazard* is often employed to summarize the result that sick leave is influenced by economic incentives. In general, moral hazard is defined as the phenomenon that individuals protected from risks may behave differently from the way they would behave if fully exposed to the risks. In this context, moral hazard denotes thus how individuals possibly would chance absence behavior if exposed differently to costs and risks associated with sick leave. Moral hazard means not that sick leave actually is abused, but rather emphasizes the importance of economic incentives when considering absenteeism.

2.2.1 Incentives related to sick pay schemes

Barmby et al. (1991, 1995) were the first to examine how employees adjust their absence behavior under a sick pay scheme. They analyze data of daily absence records at two manufacturing plants operated by the same firm. The firm assigns three different grades conditional on the number and types of absence records. Each worker's sick pay rate is determined by these grades. Using this data, Barmby et al. set up a Weibull duration model and a random effects logit model and estimate how such a sick pay scheme affects absence behavior. Approaching a lower grade seems to have a negative effect on absence duration. However, in the logit model which estimates the probability of being absent, the revealed effects are hard to interpret. While moving towards the second grade seems to have a disincentive effect on the probability of being absent, approaching the third grade has no significant effect at all.

Several studies examine the effects of changes in the Swedish sickness insurance system. In 1991, the replacement level of the compulsory sickness insurance was reduced markedly. The replacement level was set from 90% to 65% of daily earnings for the first three days and from 90% to 80% for the days four to 89. An insured employee could, however, still be absent from work for up to eight successional days without a certificate from a physician. The reform allowed researchers to identify directly economic incentives that affect work absence.

In the first article, Johansson and Palme (1996) use the exogenous reform effect to estimate a demand function for absence by a count data regression model. Individual data on absence behavior is aggregated over one year, and the variation in virtual income and the cost of being absent is employed to estimate the effect of economic incentives on work absence. For the male subsample, their results indicate a negative relationship between absence and its associated cost. On the other hand, for the female subsample the relationship is positive. Virtual income when a worker is absent has a negative effect.

Later, Johansson and Palme (2002, 2005) and Broström et al. (2002) get similar results. They study work and absence spells by Kaplan-Meier techniques and different duration models. Again, they show that the cost of being absent significantly affects works absence behavior. The cost has a significant negative impact on the incidence, while impact on spell duration appears to be weaker. The change in the pattern of the replacement rates is exploited. When absent under the new regime, an individual has the choice of returning to work, and possibly start a new spell, or continue being absent. When continuing, the individual gets a gradually higher replacement rate from day four and day 90. Johansson and Palme (2005) show the duration of spells longer than 90 days increased. These results are taken as an evidence for moral hazard problems being present.

Henrekson and Persson (2004) analyzes the effect of several Swedish sickness insurance reforms using time series from 1955 to 1999. In this time period, numerous changes in the compensation level were made. The Henrekson and Persson find that reforms entailing more generous replacement rates for work absence can be associated with higher sick leave, and vice versa. Interestingly, the impact of the 1991 reform is insignificant in their first regression. Therefore, the authors examine a more narrow time period employing regional panel data which gives significant effects with the expected sign. Thus, absence behavior seems to be affected by changes in the sickness insurance system.

2.2.2 Incentives related to employer responses

While the analyses of changes in the Swedish sickness insurance system showed how sick leave behavior significantly is influenced by economic incentives, the approaches could not explain why generous sick pay schemes are not exploited to the full extent. Sick leave must be subject to other incentives. Recent research proposes both earnings and unemployment to be affected by sickness absence. Employers may respond to high absence rates by wage cuts or reduced pay rise. Moreover, employees who are more absent could have less secure positions.

Two studies analyze the impact of sick leave on wages. Hansen (2000) investigates the relation between short-term absences and wages using Mincer regressions. He argues that short-term absence may signal the level of commitment to the job, and thus be related to the wage level. In order to control for the effect of motivation, an instrument for absence duration is constructed exploiting the Swedish 1991 reform. Hansen finds a significant negative effect of days absent on women's wage. One day of sick leave reduced the wage rate by 0.2%. On the other hand, the relationship is insignificant for men.

Markussen (2009) employs Norwegian administrative data to estimate a relation between sickness absence and earnings as well. Using an indicator of the physicians' lenience as an instrument for sick leave, Markussen controls in this manner for work motivation and health status. He finds that one day of extra sickness absence reduces future earnings by 0.3%. In addition, the first absence day has a negative impact on the wage of even 0.6%. In a restricted sample, covering only full-time employed individuals, the cost of an extra absence day is estimated to be 0.06%. These results are taken as evidence for a causal effect of sick leave on earnings.

Hesselius (2007) examines whether sick leave influences the probability of becoming unemployed. Similar to Hansen, he suggests that the utilization of sick leave implies a signaling of productivity. Having more sick leave may therefore imply for an employee to be assessed as less productive and more expensive. This may, in turn, lead to dismissal. Employment duration is analyzed by a Cox proportional hazard model, and measures of absence duration and incidence are included in the regression. The results indicate that a transition into unemployment appears to be significantly correlated with the number of sick leave spells and their average length.

Another way of investigating whether unemployment is correlated with sick leave is to consider the absence behavior over the business cycle. This is the approach of Askildsen et al. (2005). They employ a fixed effects logit model on Norwegian administrative data to estimate the probability of absence. First, their results indicate a negative impact of unemployment. This impact becomes even stronger in a restricted sample, which covers only workers present in the whole data period of six years. Therefore, Askildsen et al. conclude that the procyclical variation in absenteeism is caused mainly by established workers, not by a different labor force composition. This result can be interpreted as an evidence of moral hazard. Since those individuals in the restricted sample are likely to be better insured against the risk of becoming unemployed, they demand more sick leave.

Finally, the result that employment protection can have a negative impact on sick leave is also found by Ichino and Riphahn (2005). They uses personnel data from an Italian bank to estimate the effect of probation on absenteeism. In Italy, the end of probation is associated with the begin of a strict firing protection. Controlling for individual and seasonal effects, Ichino and Riphahn show that the end of probation has a significant effect on weekly days of absence for both men and women. Particularly for men, the number of absence days increases significantly. For men, the begin of strict firing protection is also the most likely break point in the series of work absence. This test, however, fails for females. Nevertheless, the work by Ichino and Riphahn shows in clear way that moral hazard behavior may occur in the sick leave system.

3. Data and institutions

3.1 The group of companies

This thesis considers personell data of a Norwegian group of companies situated in Oslo. The group comprises 13 power and venture capital companies. The period of observation covers five years, from 2004 until 2008. Not every company is observed for the whole period due to merger and outsourcing. The group of companies has a monthly average of 892 employees. In total, 1166 different employees are observed. The sizes of companies varies from having ten until more than 200 employees. Roughly, one third of the employees are women.

Daily time records which count hours worked, overtime, sick leave etc. of each employee are available. These time records can be employed to construct accurate sick leave rates and spell patterns for each individual. In addition, there are monthly observations on earnings, tenure, contractual working hours and demographic variables. Among other things, any possible pay rise can be retrieved from this data.

3.1.1 Pay rise

In the group of companies, wages are bargained collectively and adjusted every year on given dates, usually in June. Individual pay rises, however, on top of the collectively agreed rates are possible and are realized together with the latter. Around one quarter of the employees in the group receive such an individual wage increase. The collectively bargained rates are known, while the exact additional individual increases are unknown. Since the individual and collectively agreed part of the pay rises are realized jointly, they can easily be calculated. See table 3.1 for some descriptive statistics on extra pay rise.

Table 3.1 gives also some descriptive statistics on the employees' absence rates. The statistics are calculated using the panel of preceding sick leave rates observed at each years wage adjustment. Since this gives means, standard deviations and percentiles for individual absence behavior, the values differ from the absence statistics for the whole group. The average monthly absence rate in the group of companies is 5.9% in the period of observation. The physician-certified rate is 4.1%, and self-reported absence is 1.0%. A time series of monthly

Table 3.1: Descriptive statistics

	Mean	Std. dev.	25%	50%	75%
Sick leave rate:					
Total sick leave	0.051	0.109	0	0.012	0.045
Physician certified, 100%	0.034	0.093	0	0	0.022
Physician certified, graded	0.006	0.035	0	0	0
Self certified	0.011	0.016	0	0.003	0.016
Extra pay rise	0.027	0.057	0.004	0.011	0.28
Tenure in months	201.727	149.490	59	213	309
Overtime rate	0.027	0.049	0	0	0.034
Age	47.397	11.057	39	48	57
Parttime	0.09				
Female	0.34				

Means, standard errors and percentiles are calculated using all employee records in the period 2004 – 2008 observed at each years wage adjustment. The individual absence and overtime rates are calculated for the periods between wage adjustments.

absence rates is given in figure 3.1.1.

3.2 Sickness insurance institutions

Sick leave can either be self-certified or physician-certified. Both absence types are present in the data. In the group of companies under study, spells of self-certified sick leave can last up to eight successional days. However, the sum of self-certified sick days cannot exceed 24 days within 12 months, and after eight absence days, single or successional, an employee must be present for at least 16 days before self-certification is again allowed.[1] Each employee is entitled to use self-certification after two months of tenure.

Contrary, there are no limits regarding physician-certified spells. Physician-certified absence may be 100% with respect to contracted working hours or graded, i. e. less than full-time Graded sick leave denotes a combination of part-time working and sick leave. In general, individuals with long-lasting or recurrent diseases, who are capable of work, though not fulltime, are on this type of sick leave. Because precise starting dates are not given, its duration and scope are hard to identify, and graded sick leave is ignored in this thesis. Moreover, graded sick leave accounts for only a small fraction of total sickness absence, see table 3.1. Transitions from self-certified spells to physician-certified spells of both kinds may occur.

In Norway, the replacement ratio is normally 100% from the first day of absence, irrespective of the type of sick leave. This is covered by the employers in the first 16 days, after wich

[1] In the group of companies, the right to use self-certification is extended compared to the law-regulated standard of maximum three days and four spells within twelve months. This is due to the companies participation in an intervention program aimed at reducing sick leave and increasing the average retirement age.

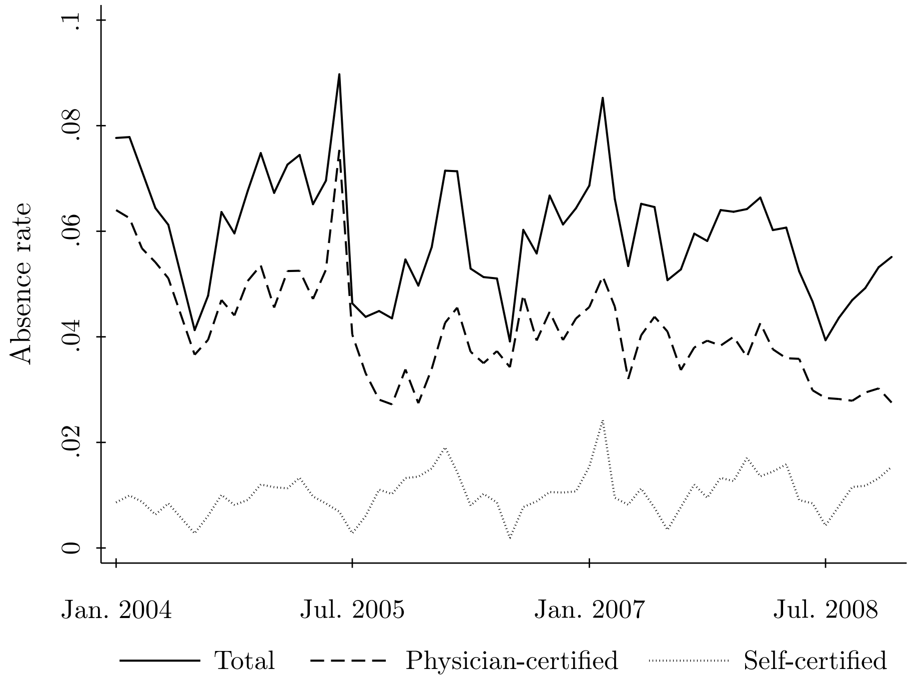

Figure 3.1: Time series of sick leave rates in the group of companies

the social security system pays the replacement up to a ceiling of around 400.000 NOK (in 2008), while employers in many cases add the amount necesary to ensure full replacement. This also applies for the group of companies under study. The maximum duration of sickness benefits is one year. After this period an individual must either go back to work or participate in a rehabilitation program. However, in data available, all uncensored sick leaves spells are less than a year.

4. Empirical strategy

Three aspects of sick leave and its relation to variables of interest are considered. In the first section, several approaches for modeling the relation between pay rise and sick leave are discussed. Then, in the second section, various ways of modeling the possible relation between the incidence of absence and some explanatory variables are examined. Finally, a short introduction on duration models is given. These models are employed to focus on the length of sick leave spells. The results of estimation are presented in the next chapter.

4.1 Pay rise and sick leave

Each year, together with the collectively agreed wage increase, the employees can receive an additional pay rise. This extra pay rise is negotiated individually. The probability of receiving such a pay rise can be considered using logistic regression. Since the size of the extra pay rise is known, it can alternatively be examined by a censored regression model.

4.1.1 Logit models

In order to test the hypothesis that there is a link between sick leave and pay rise, a first approach may be to divide the workers into two different groups depending on whether or not they get an additional individual pay rise. For convenience, call them winners or looser, indicated by 1 and 0. Individual sick leave rates in the periods between wages are renegotiated are taken as a measure of absence.

A logit model is applied to estimate the probability of belonging to the group of winners,

$$Y_{it} = \mathbf{1}_{\{\boldsymbol{\beta}'\boldsymbol{x}_{it}+\epsilon_{it}>0\}}, \qquad \Pr(Y_{it}=1|\boldsymbol{x}_{it}) = \frac{e^{\boldsymbol{\beta}'\boldsymbol{x}_{it}}}{1+e^{\boldsymbol{\beta}'\boldsymbol{x}_{it}}}. \tag{4.1}$$

As explanatory variables, $\boldsymbol{x}_{it}$, four categorical dummies representing different sick leave rates and several control variables are employed. Having less than 1% sick leave is taken as a reference category. In general, due to the danger of parametric mispecification, all continuous variables are rather represented by categories which allow for nonlinear relationships. As controls, categorical dummies for wage level, tenure, overtime rate and age are included, in addition to single dummies for company, year, sex and part-time. The wage level is represented by four company-specific wage quantiles with the first quantile as reference category. These quantiles have been calculated for each period before a possible pay rise is realized. By representing the wage levels in this way, they become comparable through time.

Wage quantiles are included in the regression in order to control for the possible effect that high-paid employees not only are less sick but also receive more pay rise. Tenure is important because newly-employed individuals may be considerably different from those who are tied to the companies for a longer time. For example, receiving a pay rise in the first year is unlikely, but sick leave may be extraordinary low under probation as well. Therefore, four tenure-interval dummies are added. Overtime rates have also to be taken into consideration. High overtime rates can cause both frequent sickness absence and pay rise. Furthermore, working part-time may be associated with less frequent extra pay rise, while the employees' health status could vary from those working full-time. Since sick leave rates vary substantially over age and sex, nine age-interval dummies and a dummy for females are included. Finally, sick leave rates and pay rise also vary over companies and years. Therefore, ten company dummies and four year dummies are included in the model.

The data set is an unbalanced panel. Due to hiring and dismissal, not every worker $i = 1, \ldots, n$ is present in the sample period $t = 2004, \ldots, 2008$. However, it is important to recognize the panel structure and take it into account. In general, the panel structure would require to specify the intragroup disturbances ϵ_{it} and ϵ_{is} to be freely correlated, whereas disturbances across groups are assumed uncorrelated. This problem can, in principal, be solved by an effects model. Such a model respecifies the disturbance as $\epsilon_{it} = u_i + v_{it}$, where unobserved individual-specific effects are captured by the term u_i. Depending on whether or not the individual heterogeneity u_i is correlated with some of the explanatory variables, a fixed or random effects model can be applied, see e. g. Greene (2003, chap. 21.5) for a discussion on effects models.

Low work motivation, for instance, is unobserved and may cause both higher absence rates and no extra pay rise. As a consequence of not controlling for motivation, the estimator may be biased and inconsistent. Given that motivation is constant over time, employing a fixed effects logit model could solve the problem. It estimates a fixed motivation parameter for each employee. However, the fixed effects logit model has some major shortcomings as, among others, pointed out by Wooldridge (2002, chap. 15.8). Since the estimator relies on estimating a constant for each employee with only a few observations, these individual-effects estimators are inconsistent. The estimator for the coefficients relies on these inconsistent estimators and will be inconsistent as well. This problem is usually denoted as the incidental parameter problem with reference to Neyman and Scott (1948).

The log-likelihood function for the fixed effects model is

$$\ell = \sum_{i=1}^{n} \sum_{t=1}^{T_i} \log \Pr(Y_{it} = 1 | u_i + \boldsymbol{\beta}' \boldsymbol{x}_{it}), \tag{4.2}$$

where $\Pr(Y_{it} = 1|u_i + \boldsymbol{\beta}'\boldsymbol{x}_{it})$ is defined analogously to eq. (4.1).

A fixed effects model can only identify the effect of variables that change within individuals. Variables that do not vary within individuals can statistically not be separated from the individual-specific effect u_i. Hence, the impact of sex on pay rise cannot be estimated. In addition, a problem between pay rise and the wage quantiles arises. As wages are downward rigid, moving to a higher wage quantile is caused by extra pay rise. A downward movement is likely to occur when not receiving a pay rise. It is easier to move upwards, when in the lower quantiles, but more difficult in the third and impossible in the fourth quantile. For downward movements, it is the other way round. Since only those individuals who move between categories contribute in the fixed effects model, the higher quantiles will be biased negatively and the lower quantiles positively.

This problem do not occur in the random effects model. The random model treats individual heterogeneity as a random variable drawn from known distribution, usually the normal distribution. Using this approach, there is no problem related to incidental parameters, but none of the explanatory variables can be correlated with u_i. This is a strong assumption which easily fails to be met, e. g. if work motivation affects sick leave as suggested above. On the other hand, if the underlying assumptions of the random effects model are satisfied, the estimator is consistent and efficient.

The log-likelihood function for each individuals T_i observations is

$$\ell_i = \int_{-\infty}^{+\infty} \left[\sum_{t=1}^{T_i} \Pr(Y_{it} = y_{it} | u_i + \boldsymbol{\beta}' \boldsymbol{x}_{it}) \right] f(u_i) \mathrm{d}u_i, \tag{4.3}$$

where $f(u_i)$ denotes the density function of the random heterogeneity term.

Results for the effect of total sick leave on extra pay rise can be found in table 5.1. Table 5.2 displays the estimation results for models substituting total sick leave with physician-certified and self-certified sick leave, respectively.

4.1.2 Tobit models

The binary model above neglects the information that is contained in the different levels of additional pay rise. For example, as a consequence of being more absent than other employees, pay rise may be lower, but not zero. Incorporating such information can be done by employing a tobit model. The lower limit for the individual pay rise is zero. Thus, it is a limited dependent variable, continuous for positive values, but censored at zero. The ordinary least squares estimator would be biased in this case, whereas the tobit estimator handles the censoring. In general, the tobit model can be written as

$$y_{it} = \begin{cases} \boldsymbol{\beta}'\boldsymbol{x}_{it} + \epsilon_{it} & \text{if } \boldsymbol{\beta}'\boldsymbol{x}_{it} + \epsilon_{it} > 0 \\ 0 & \text{if } \boldsymbol{\beta}'\boldsymbol{x}_{it} + \epsilon_{it} \leq 0, \end{cases} \tag{4.4}$$

where y_{it} now denotes the left-censored variable. Let each ϵ_{it} be independent normally distributed with variance σ. The likelihood function for each observation is then given by

$$\mathcal{L}_{it} = \begin{cases} \frac{\phi((y_{it} - \boldsymbol{\beta}'\boldsymbol{x}_{it})/\sigma)}{\sigma} & \text{if } y_{it} > 0 \\ 1 - \Phi\left(\frac{\boldsymbol{\beta}'\boldsymbol{x}_{it}}{\sigma}\right) & \text{if } y_{it} = 0. \end{cases} \tag{4.5}$$

For each nonlimit observation, the likelihood is the height of the density representing the probability of obtaining this observation. For each censored observation, the likelihood is equals the probability of getting an observation below or equal the zero limit.

A random effects tobit model is easily implemented, and allows for intragroup correlation of the disturbance $\epsilon_{it} = u_i + v_{it}$. The same strong exogeneity assumption on u_i as in the logit case apply. A fixed effects estimator, however, is not available for tobit models in common statistical packages. Greene (2004) shows that also this fixed effects estimator suffers from a similar bias as in the logit case. The estimation results for the tobit model can be found in table 5.1 and 5.2.

4.2 Sick leave incidence

One way of looking at the incidence of sickness spells and their relation to variables of interest, is to model the probability of starting a new spell. Conditional on attendance the previous recorded working day, such a probability model can be estimated by similar logit models as in the section above. Binomial logit models are used to examine the probability of starting any kind of sickness absence, whereas a multinomial logit model is employed to consider the choice between physician-certified and self-certified sick leave.

4.2.1 Logit models

Being absent or not is a binary outcome which may be fitted by an logistic regression. Explanatory variables are categorical dummies for wage quantiles, tenure and the time before quit, in addition to some control variables. The controls for age and company are identical with those included in the logit and tobit models of extra pay rise.

The wage quantiles are also constructed identically. Due full income replacement under absence it is assumed that there is no direct relationship between the wage level and sick leave. Company-dependent wage quantiles may however serve as proxies for different types of jobs and the employees' position in the organizational hierarchy. Tenure and time before quit are added to the regression in order to inspect if there exist a moral hazard problem related to the period of probation or the period before leaving the company. for some unknown reason.

Two intervals of the time before quit are included in the model, twelve to six months and six or less months. More than twelve months is the base category. In general, those who leave can be more sick than others, but it may be unlikely that such a selection is present only in the last six months. If individuals who quit on average have another health status, it is expected to be revealed in both time intervals. In addition, eleven age-interval dummies control for any age-specific effects that may appear, as many leave due to retirement. Furthermore, if most of the employees quit at a specific point in time, for instance in June, the quit variables could wrongfully capture a calendar time effect. Thus, dummies for calendar months must be included, otherwise the results could be biased. The estimation results for the logit models can be found in table 5.3

4.2.2 Multinomial logit models

When starting a new sick leave spell, an employee has the choice between self-certification and obtaining a medical certificate from a physician. Contrary to the binary choice between work attendance and sick leave, this is a situation with several choices which can be modeled using a multinomial logit model. Let 1 denote physician-certified absence, while 2 denotes the choice of self-certified sick leave. Naturally, the base category, 0, is no absence. The probability of choosing alternative $j = 0, 1, 2$ is modeled as

$$\begin{aligned} P_{0it} &= \Pr(Y_{it} = 0|\boldsymbol{x}_{it}) = \frac{1}{1 + e^{\boldsymbol{\beta}'_1\boldsymbol{x}_{it}} + e^{\boldsymbol{\beta}'_2\boldsymbol{x}_{it}}}, \\ P_{kit} &= \Pr(Y_{it} = j|\boldsymbol{x}_{it}) = \frac{e^{\boldsymbol{\beta}'_j\boldsymbol{x}_{it}}}{1 + e^{\boldsymbol{\beta}'_1\boldsymbol{x}_{it}} + e^{\boldsymbol{\beta}'_2\boldsymbol{x}_{it}}}, \quad k = 1, 2. \end{aligned} \tag{4.6}$$

It is important to include a constant term in the vector of coefficients $\boldsymbol{\beta}_j$, otherwise the logit model is subject to an important restriction called *independence from irrelevant alternatives*. Basically, in multinomial logit models, all probability ratios such as $P_{1it}/P_{0it} = \exp(\boldsymbol{\beta}'_j\boldsymbol{x}_{it})$ are independent from other choice alternatives. In this case, this seems unrealistic because self-certified and physician-certified sick leave may be close substitutes. By adding a constant term, however, the estimation procedure will come up with a value so that the probabilities do not exhibit this restriction (Train 1986). The log-likelihood function for the multinomial logit model is just a generalization of that for the binomial logit model,

$$\ell = \sum_{i=1}^{n} \sum_{j=0}^{J} \log \Pr(Y_{it} = 1 | u_i + \boldsymbol{\beta}' \boldsymbol{x}_{it}). \tag{4.7}$$

Effects models for the multinomial logit which account for the panel structure of the data are not available or computational challenging. While a fixed effects variant does not seem to be existent, at least not in most standard statistical software packages, a random effects model is not possible to fit within a reasonable amount of time. Hence, only a model without individual effects is fitted. Results from maximum likelihood estimation are found in table 5.3.

4.3 Sick leave duration

Another way of looking at sick leave, is to consider the length of spells. Duration models can be employed to examine whether sick leave duration is related to the same variables of interest considered in the the section above.

4.3.1 Basics concepts and notation

Let T be a positive random variable representing absence duration. T is also known as *survival time*. It has cumulative density $F(t) = \Pr(T \leq t)$, and its probability density function is $f(t) = \mathrm{d}F(t)/\mathrm{d}t$. The complement of the cumulative density function, $\bar{F}(t) = 1 - F(t)$, is called *survival function*. The survival function gives the probability that the spell is at least of duration t. The probability that a spell ends in the next short interval Δt, given that it has lasted until time t can be characterized by the *hazard rate*. It is defined as

$$\lambda(t) \equiv \lim_{\Delta t \to 0^+} \frac{\Pr(T \in [t, t + \Delta t) | T \geq t)}{\Delta t}. \tag{4.8}$$

$\lambda(t)$ can be interpreted as the rate at which spells are completed after duration t, given that the spell lasts at least until t. The hazard rate can also be expressed in terms of the distribution functions and survival function, and vice versa,

$$\lambda(t) = \frac{f(t)}{1 - F(t)} = -\frac{\mathrm{d}\log(1 - F(t))}{\mathrm{d}t} = -\frac{\mathrm{d}\log(\bar{F}(t))}{\mathrm{d}t} \quad \Leftrightarrow$$
$$\bar{F}(t) = \exp\left(-\int_0^t \lambda(u)\mathrm{d}u\right), \qquad t \geq 0.$$

Since the hazard function generally is more interesting for the analysis than the survival function, it is normally this part which is modeled directly.

4.3.2 Proportional hazards models

Several functional forms for the hazard have been suggested, e. g. exponential, Weibull and lognormal.[1] In particular, the first two specifications are part of the popular *proportional* hazard family, and it is assumed that the hazard has a functional form of this family. In general, a proportional hazard model is described by

$$\lambda(t|\boldsymbol{x}) = \lambda_0(t)\exp(\boldsymbol{\beta}'\boldsymbol{x}), \tag{4.9}$$

where $\lambda_0(t)$ is called *baseline hazard*. It determines the shape of the hazard function, while $\exp(\boldsymbol{\beta}'\boldsymbol{x})$ scales it. This implies that only the level of the hazard function is allowed to differ across observations, and absolute differences in $\boldsymbol{x}$ imply proportionate differences in in the hazard at each t. Hence, its name. The parametrization $\lambda_0(t) = \alpha t^{\alpha-1}$, $\alpha > 0$, gives the Weibull model.

However, different parametric specifications of the hazard give different estimators and possibly misleading results when choosing the wrong form. Therefore, rather than assuming a specific parametrization for $\lambda(t)$, a semiparametric approach has become popular. Cox (1972) introduced a hazard model where the baseline hazard is left unspecified and showed that the effect of the explanatory variables could be estimated by partial likelihood.

Let there be K distinct end times. At each of those time points T_k, let R_k be the set of individuals who have not yet ended their spell, while D_k is the set of d_k individuals who exit. The probability of the latter, conditional on the risk set R_k, is

$$P_k = \frac{\prod_{i\in D_k}\exp(\boldsymbol{\beta}'\boldsymbol{x}_i)}{\left[\sum_{i\in R_k}\exp(x_i)\right]^{d_k}}, \tag{4.10}$$

where the baseline hazard cancels out due to the conditioning. The log-likelihood can now be written as

$$\ell = \sum_{k=1}^{K}\left\{\sum i \in D_k \boldsymbol{\beta}'\boldsymbol{x}_i - d_k \log\left[\sum_{i\in R_k}\exp(x_i)\right]\right\} \tag{4.11}$$

Results from maximum likelihood estimation of the semiparametric Cox model can be found in table 5.4.

4.3.3 Unobserved heterogeneity

If all differences among individuals are captured by the observed explanatory variables, no unobserved heterogeneity is present. This may be unlikely, and Lancaster (1979) and Vaupel

[1]See e. g. Greene (2003, chap. 22.5) and Kiefer (1988) for an overview.

et al. (1979) introduced for this reason a stochastic heterogeneity variable in the proportional hazard model. First, wrongfully ignoring unknown heterogeneity over-estimates negative duration dependence, because subjects with high individual-specific hazards will complete spells faster. Positive-duration dependence is analogously under-estimated. Second, failure to control for unobserved heterogeneity can produce severe bias in the estimates on the explanatory variables. The proportionate response of the hazard to variation in each regressor at any duration is weakened (Lancaster 1990, chap. 4).

Let all unobservable heterogeneity be captured by the random variable V, and let its particular realization v enter multiplicatively into eq. (4.9) as the other terms, so that

$$\lambda(t, \boldsymbol{x}|v) = \lambda_0(t) \exp(\boldsymbol{\beta}'\boldsymbol{x})v. \tag{4.12}$$

Unobserved heterogeneity is either assumed to follow a parametric distribution or it is specified nonparametrically as by . Eq.(4.12) is referred to as a *mixed* proportional hazard model. In table (5.4), estimation results can be found for the parametric Weibull model. The random effects Weibull model is calculated assuming that heterogeneity follows a gamma distribution. See e. g. Gutierrez (2002) for a formal derivation of the maximum likelihood estimator.

4.3.4 Discrete time models

Under the proportional hazard assumption, a discretization of the time scale allows for easy methods for estimating flexible hazard functions (Jenkins 1995). This discretization is not inconsistent with an underlying continuous process. A discrete time proportional hazard model was originally introduced by Kalbfleisch and Prentice (1973) and Prentice and Gloeckler (1978), and later extended by Meyer (1990) and Han and Hausman (1990).

Suppose durations are only observed in T disjoint time intervals of equal length. Let the t'th interval be defined as $[t, t+1)$. The discrete time (interval) hazard is defined as the probability that a spell is completed in the interval ending before $t+1$, given that it has lasted until t, i. e. $\lambda_t = \Pr(T < t+1 | T \geq t, v)$. Using the survival function, the interval hazard can be written as

$$\begin{aligned} \lambda_t &= 1 - \bar{F}(t|v)/\bar{F}(t+1|v) \\ &= 1 - \exp\left[-\int_t^{t+1} \lambda(\tau|v)\mathrm{d}\tau\right] \end{aligned} \tag{4.13}$$

If the underlying continuous hazard $\lambda(t)$ is assumed to belong to the mixed proportional hazard class, as specified by eq. (4.12), and is integrable, then eq. (4.13) can be rewritten. Furthermore, if the explanatory variables are assumed to be constant within intervals, this yields

$$\begin{aligned}\lambda_t &= 1 - \exp\left[-v\exp(\boldsymbol{\beta}'\boldsymbol{x}_t)\int_t^{t+1}\lambda_0(\tau)\mathrm{d}\tau\right]\\ &= 1 - \exp\left[-\exp(u + \boldsymbol{\beta}'\boldsymbol{x}_t + \gamma_t)\right],\end{aligned} \tag{4.14}$$

where $\gamma_t \equiv \log\int_t^{t+1}\lambda_0(\tau)\mathrm{d}\tau$ and $u \equiv \log(v)$. Such a specification of the discrete hazard rate is also called *cloglog* model. Alternatively, eq. (4.14) can be rewritten as

$$\log(-\log[1-\lambda_t]) = u + \boldsymbol{\beta}'\boldsymbol{x}_t + \gamma_t, \tag{4.15}$$

which is known as an *complementary log-log* transformation.

In general, the distribution of u among individuals is unknown. Therefore, in order to account for unobserved heterogeneity, it is often assumed that u follows a normal or gamma distribution with mean one. Meyer (1990), for instance, employs the model above by assuming a gamma distribution for u. See table 5.4 for results from maximum likelihood estimation of a cloglog model with normal random effects. The construction of the likelihood equation is shown many in textbooks on *generalized linear models*[2], for example Skrondal and Rabe-Hesketh (2004).

[2]The cloglog model with random effects is a *generalized linear mixed model* belonging to the binomial family with cloglog link function.

5. Results

Following the same structure as the previous chapter on the empirical strategy, the results concerning sick leave and pay rise are considered first. Thereafter follow the results and discussion of the models on the probability of starting a new sick leave spell. Finally, the estimates of the duration models are presented.

5.1 Sick leave and pay rise

The effect of sick leave on extra pay rise is examined by logit and tobit models. The results are displayed in table 5.1 and 5.2. Table 5.1 shows estimates on the effect of total sick leave, while table 5.2 shows estimates on the effect of physician-certified and self-certified absence, respectively.

5.1.1 Total sick leave

Consider first the impact of total sick leave on individual pay rise. The estimates of the simple logit model without individual heterogeneity clearly suggest an effect of total sick leave on pay rise. All categories for sick leave have negative coefficients and these become stronger both in size and significance the higher the absence rate. At 3 to 5% sick leave, the impact becomes statistically significant at a 5% level. For example, an average male employee in the largest company and in the second wage quantile would have a probability of 32.2% of getting a pay rise in 2007 if his sick leave stayed below 1%. Increasing his sick leave to the category 5 to 7%, reduces the probability to 21.0%. It is 19.7% if the rate is higher than 7%.

The same effect seems also to be present in the fixed effects variant of the logit model. The coefficients have the same sign and similar size. The impact of sick leave on extra pay rise appears thus not to be seriously biased due to individual heterogeneity. Unobservable effects such as work motivation seem to have less importance if assumed constant over time. However, except for the coefficient on the highest sick leave rate, none of the coefficients are significant on a 5% level. Such a reduction in significance could be expected. First, because the sample size is almost halved. In addition, recover that in the fixed effects model only those individuals

Table 5.1: Determinants of extra pay rise

	Logit model 1		Logit model 2		Tobit model	
Sick leave rate:						
0.00 − 0.01						
0.01 − 0.03	−0.0380	(0.1127)	−0.0754	(0.1568)	−0.0092*	(0.0038)
0.03 − 0.05	−0.3472*	(0.1494)	−0.3401	(0.2139)	−0.0143**	(0.0055)
0.05 − 0.07	−0.5787**	(0.2016)	−0.4936	(0.2675)	−0.0200*	(0.0080)
0.07 +	−0.6479***	(0.1374)	−0.5720**	(0.2109)	−0.0214***	(0.0053)
Wage quantiles:						
1st quantile						
2nd quantile	−0.4574***	(0.1204)			−0.0159**	(0.0053)
3rd quantile	−0.4693***	(0.1204)			−0.0152**	(0.0054)
4th quantile	−0.9964***	(0.1371)			−0.0318***	(0.0080)
Tenure:						
0 − 1 year	−0.9896***	(0.2076)	−0.2615	(0.8643)	−0.0157	(0.0086)
1 − 3 years	0.3651*	(0.1759)	0.8581	(0.7851)	0.0204**	(0.0067)
3 − 5 years	0.4777**	(0.1797)	0.6590	(0.7077)	0.0205**	(0.0069)
5 − 10 years	0.1041	(0.1413)	0.0957	(0.6139)	0.0095	(0.0054)
10 + years						
Overtime rate:						
no overtime						
0 − 0.02	0.0530	(0.1278)	−0.1445	(0.1916)	−0.0030	(0.0047)
0.02 +	0.5119***	(0.1043)	0.4566*	(0.2011)	0.0098**	(0.0037)
Part time	−0.3153*	(0.1525)	−1.0228	(0.6653)	−0.0092	(0.0055)
Female	0.0299	(0.1081)			0.0036	(0.0043)
Individual effects	No effects		Fixed effects		No effects	
Log likelihood	-1685.150		-637.575		540.926	
Observations	3043		1795		3043	
uncensored					1052	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parenthesis. Robust standard errors allowing for correlation within individuals are reported in the tobit model. The logit models estimate the probability of getting an extra pay rise, while the tobit model takes extra pay rise, censored at zero, as left-hand side variable. Additional control variables, not displayed above, are nine categorical dummies for age, ten dummies for company, year dummies and a constant. Sick leave rates are calculated for the period between each years wage adjustment. Furthermore, wage quantiles are company dependent. Random effects models give essentially the same estimates as the respective models without effects. Logit employed on the subsample from the fixed effects model gives similar results compared to estimation on the whole sample.

who change categories contribute in estimation. At lower sick leave rates, individuals do not changes categories often.

A random effects model gives essentially the same estimates on sick leave as the model without effects. A Hausman test, however, rejects the possibly efficient random effects model over the fixed effects model. On the other hand, this test assumes the fixed effect estimator to be consistent. This consistency assumption is somewhat problematic as discussed above. Nevertheless, only the fixed effects model can capture unobservable heterogeneity which is correlated with some the explanatory variables. For this reason, the fixed effect model is favored and displayed in table 5.1. At least for the sick leave rates, the fixed effect variant of the logit model gives some evidence that unobservable individual heterogeneity is not a serious problem. Hence, unobservable motivation effects, which could have been correlated with both sick leave and pay rise, appear not to bias the impact of sick leave on additional pay rise.

The negative impact of sick leave on pay rise is even clearer in the tobit model. The estimated coefficients in the tobit model have also direct interpretation. While in the previous models the data is fitted to a nonlinear logistic curve, the tobit model is linear for all positive pay rises, but censored at zero. Thus, for all positive values, i. e. realized wage increases, its interpretation is similar to a linear regression model. For example, having a sick leave rate of 5 to 7% gives a 2% lower individual pay rise. A sick leave rate above 7% reduces pay rise by 2.14%. When an employee should have received the mean pay rise of 2.7%, being more than 5% absent is predicted to almost elapse this extra pay rise. The effects are significant, even at the lowest level of absence, 1 to 3%, where an almost 1% pay rise reduction is estimated.

A random effects tobit model gives statistically identical estimates of the impact of sick leave. However, the logit models indicate that there is no strong heterogeneity bias on absence rates. A simple tobit model seems therefore appropriate. In addition, standard errors are chosen to be robust with respect to correlation within individuals.

Finally, these findings can also be related to some of the results in the contemporary economic literature on sick leave. Recently, both Hansen (2000) and Markussen (2009) have assessed the impact of sickness absence on earnings. Recover that, Hansen estimated, though only for females, a significant reduction of the the wage rate by 0.2% for each day of absence. Markussen shows that future earnings on average are reduced by 0.6% the first day and by 0.3% each following day. This study suggests, at least for low absence rates, similar reductions.

For example, seven days of sick leave equal approximately an absence rate of 3%. While Hansen and this study then predict a reduction of 1.4% for seven absence days, Markussen estimates an average reduction of 2.4%. Similarly, an absence rate of 6% is estimated to reduce future earnings by 2% in this study and by 2.8% in Hansen's analysis. Markussen (2009), on the other hand, predicts the reduction to be even 4.5%. Hence, for low sick leave rates which are representative for most employees, these three studies are comparable.

5.1.2 Other covariates

Although the primary focus is on the relation between sick leave and pay rise, other interesting observations can be made on the estimated models. Both the simple logit model and the tobit model reveal that the wage level is important for additional wage increase. The estimated pattern is striking. The higher the wage level, the lower is the probability of receiving an extra pay rise. The tobit model predicts that an individual in the second and third quantile will get on average 1.59% and 1.52% lower pay rise, respectively. At the highest wage levels, additional pay rise is on average reduced by 3.18%.

These results are controlled for tenure and age, so it seems that the wage policy of the group of companies has an equalizing profile. Whether this is intended or not remains questionable. An alternative explanation may be that the employer cares about the total cost of extra pay rise. Each employee's pay rise is considered in percentage, and the total cost for the companies depends thus on the employees previous wage levels. Distributing more pay rises to those in the higher wage quantiles is more costly than favoring those in the lower quantiles. Hence, if the group of companies is concerned about the total cost of the additional pay rises, there is an incentive to distribute more of the pay rises to the lower quantiles.

The effect of tenure on additional pay rise is somewhat as expected. The results show that it is unlikely that a newly-employed individual receives a pay rise. The simple logit model shows a strong negative effect in the first year of work. Also the random effects model and the tobit model estimate a negative impact. However, the coefficient is not significant at a 5% level, and in the logit model with random effects the coefficient is much lower. The latter indicates that unobservable heterogeneity with respect to the effect of tenure may be important.

For the second until the fifth year, the tobit model estimates an extra pay rise of about 2.5%. Also the logit model without individual effects predicts a higher probability of receiving a wage increase. The random effects model proposes somewhat stronger, though insignificant, effects. These results suggest that the first years after probation are important for additional pay rise. The wage-tenure curve seems to be steep in the beginning, while it becomes more flat after five years.

5.1.3 Physician-certified and self-certified sick leave

In table 5.2, the estimated effects of physician-certified and self-certified absence are displayed. Analogous models as above have been fitted to the data with total sick leave substituted with the two sick leave types, respectively. The estimates on the other covariates are almost identical to the results from table 5.1. For this reason, these estimates are not displayed in table 5.2.

Physician-certified sick leave appears to reduce individual pay rise, at least if above 5%.

Table 5.2: The effect of physician-certified and self-certified sick leave on pay rise

	Logit model 1		Logit model 2		Tobit model	
Physician-certified sick leave rate						
0.01 − 0.03	−0.1241	(0.1627)	−0.0838	(0.2134)	−0.0060	(0.0050)
0.03 − 0.05	−0.3249	(0.1919)	−0.2410	(0.2705)	−0.0113	(0.0070)
0.05 +	−0.6221***	(0.1305)	−0.5188**	(0.1818)	−0.0169***	(0.0050)
Self-certified sick leave rate						
0.01 − 0.02	−0.0701	(0.1130)	−0.0654	(0.1538)	−0.0085*	(0.0041)
0.02 − 0.03	−0.2308	(0.1622)	0.0875	(0.2323)	−0.0133*	(0.0060)
0.03 +	−0.3483*	(0.1486)	0.2454	(0.2248)	−0.0148*	(0.0067)
Individual effects	No effects		Fixed effects		No effects	
Observations	3043		1795		3043	
uncensored					1052	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ and standard errors in parenthesis. Robust standard errors allowing for correlation within individuals are reported in the tobit model. The effect of the physician-certified and self-certified sick leave rate on extra pay rise has been estimated separately. The models are analogous to the model reported in table (5.1) and control variables are identical. Logit on the subsample from the fixed effect model gives clearly different estimated coefficients for self-certified sick leave than for the whole sample, while they are almost identical for physician-certified sick leave.

The estimated coefficients on lower rates have the expected sign and decrease as expected with higher absence rates. The coefficients are, however, not different from zero at a 5% level of significance. The picture is similar for all three models, and the results from the fixed effect model are similar to the logit model without any individual heterogeneity. The latter indicates again that it not erroneous to stick to models without individual effects. On the other hand, the fixed effects model shows how robust the result related to 5% absence is.

The size of the effect can be illustrated by looking at the changes in probability. The simple logit model estimates that going from 1% or less to more than 5% absence, the probability of receiving a pay rise in 2007 decreases from 31.0% to 19.4% for an average male employee in the largest company having a wage in the second quantile. The tobit model, which estimates the reduction directly, predicts that the employee's extra pay rise escaped with 1.69%.

For self-certified sick leave, a more complicated picture emerges. In the logit model without individual effects, the estimated coefficients have the expected sign and decrease with higher sick leave. However, only the highest rates, more than 3%, are statistically significant. Contrary, the estimates of the fixed effects model are peculiar. Although far from significant, higher self-certified sick leave rates appear to be positively correlated with pay rise.[1] On the

[1] A possible explanation may be that the reduced fixed effect sample is too different from the original data. This seems to be confirmed when the reduced sample is employed in a simple logit model. The resulting estimates on subsample are very different from the estimates on the whole sample.

other hand, the results from the tobit model support the hypothesis that employees are punished for being absent, especially if self-certified. Using robust standard errors, all rates are significant and decreasing with higher self-certified absence. For example, having more than 3% sick leave without a medical certificate is estimated to reduce individual pay rise by 1.48%.

Note that the assessed sick leave rate intervals are different in the two models. Since the average physician-certified sick leave rate is higher than the average rate for self-certified sick leave, it also requires wider categories compromising higher absence rates. Comparing the two models in table 5.2 uncovers thus a remarkable pattern. While documented sickness absence is significantly penalized first if above 5%, self-certified absence is found to be penalized already at 1%. According to the tobit models, a physician-certified absence rate between 1 and 3% cuts definitely not an extra pay rise, while a self-certified rate in the same interval apparently does. Since self-certification is more vulnerable to abuse than physician-certified absence, the result that undocumented sickness absence is penalized harder by withholding extra pay rise may not be surprising.

To sum up, sick leave has obviously a negative impact on the probability of receiving an additional pay rise. The higher the sick leave, the lower is the predicted probability, and the lower is the realized extra wage increase, if any. Unobserved heterogeneity seems not to affect this result. Moreover, the sick leave type does matter. Self-certified absence is penalized at lower levels than physician-certified sick leave. Both results indicate that the group of companies, intentional or not, employs extra pay rise as an incentive mechanism to reduce sick leave.

5.2 Sick leave incidence

The incidence of sickness absence is studied by modeling the probability of starting a new spell. Logit models are applied, and the results can be found in table 5.3. The probability of starting *any* kind of spell, physician-certified or self-certified, is modeled by binomial logit models with and without individual effects. The results of the simple logit model which not accounts for individual heterogeneity are displayed in the first column. The results of the fixed effects variant are given in the second column.

According to a Hausman test, the random effects logit model is found to be statistically not identical to the fixed effects model. In this case, the fixed effects model is considered as consistent and efficient, and thus preferred over the non-consistent random effects variant. However, the same irresolvable consistency problem with respect to the fixed effect logit estimator as mentioned above arises. On the other hand, many observations for each individual will strengthen the consistency of the fixed effects estimator.

The probability of choosing a *specific* kind of spell is examined by a multinomial logit model. In the third column in table 5.3, the estimated coefficients and its standard errors for physician-certified absence are displayed, while the fourth column shows the same for self-certified absence. An effects model could due to computational constraints not be fitted within a reasonable time.

5.2.1 Wage level

Consider the simple logit model without individual heterogeneity displayed in the first column in table 5.3. As in the previous models, the first company-dependent wage quantile is taken as a reference category. At first view, the relation between wage and the probability of starting a new spell appears intricate to explain. While the probability increases significantly in the second wage quantile, it decreases in the fourth quantile by almost the same amount. The impact of the third wage quantile is statistically not different from the first. Hence, the effect of the wage level appears to be nonlinear, hardly explained by a single or an unidirectional effect.

The wage level is expected to have no direct impact on the probability of starting a new absence spell. In general, as the replacement ratio in Norway is 100% from the first day of absence, the employees do not face a direct financial loss linked to their wage level when on sick leave. In the previous section, however, it is claimed that sick leave is penalized by receiving lower pay rise. If the utility function is concave over income, a marginal pay rise will result in higher utility gains in the lower wage quantiles than in the upper quantiles. The incentives to reduce sick leave incidence should therefore be higher at lower wage levels. This can explain why the probability of starting a spell rises in the second quantile. On the other hand, the reason why wage levels above the median appears to be negativly correlated with spell incidence remains unexplained.

Employees having higher wage levels may be substantially different from those receiving less wage. A selection mechanism can be easily set up. Generally, high wage levels are associated with specific job types, promotions and, of course, extra pay rise. The latter is already being seen to be partly determined by the sick leave rate, and it is not unlikely that also promotions are influenced by the absence behavior of an individual. Moreover, high paid jobs often require higher education, which also represents a selection. Markussen et al. (2009) show that educational attainment sharply reduces the rates of entry into absence. This supports the argument that high paid employees are substantially different with respect to absence, and suggests a selection mechanism as well. Hence, employees at the higher wage levels may to some extent have a high wage level due to less sickness absence.

The fixed effects model does not reveal if such a reasoning can be right. The model's estimates are displayed in the second column of table 5.3. None of the coefficients on the wage quantiles are significant, and the estimates which are significant in the other model are

Table 5.3: Probability of starting a new spell and choice of absence type

	Logit models				Multinomial logit model			
	Logit model 1		Logit model 2		Physician-certified		Self-certified	
Wage quantiles:								
1st quantile								
2nd quantile	0.1340***	(0.0340)	0.0078	(0.0586)	0.0330	(0.0573)	0.1918***	(0.0422)
3rd quantile	−0.0065	(0.0349)	0.0171	(0.0717)	−0.1466*	(0.0589)	0.0724	(0.0433)
4th quantile	−0.1495***	(0.0366)	−0.0298	(0.0752)	−0.2179***	(0.0609)	−0.1068*	(0.0457)
Tenure:								
0 – 1 year	−0.2396***	(0.0611)	−0.3183	(0.2120)	−0.3699***	(0.1081)	−0.1586*	(0.0741)
1 – 3 years	−0.1763**	(0.0542)	−0.2505	(0.1983)	−0.4492***	(0.1001)	−0.0577	(0.0652)
3 – 5 years	−0.1086*	(0.0550)	−0.1185	(0.1807)	0.0290	(0.0908)	−0.1573*	(0.0686)
5 – 10 years	−0.2337***	(0.0460)	−0.2876	(0.1567)	−0.4580***	(0.0822)	−0.1218*	(0.0557)
10 + years								
Time before quit:								
0 – 6 months	0.1265**	(0.0471)	0.0430	(0.0608)	−0.0231	(0.0824)	0.2016***	(0.0573)
6 – 12 months	0.0977	(0.0552)	0.0423	(0.0636)	0.0834	(0.0913)	0.1027	(0.0690)
12 + months								
Female	0.4403***	(0.0299)			0.6920***	(0.0500)	0.3048***	(0.0371)
Individual effects	No effects		Fixed effects		No effects			
Log likelihood	-35069.797		-30501.827		-39027.628			
Observations	638835		559865		638835			

* p < 0.05, ** p< 0.01, *** p< 0.001 and standard errors in parenthesis. Additional control variables, not displayed above, are categorical dummies for age, dummies for company, month, and a constant. Wage quantiles are company dependent. Employing the logit estimator on the subsample from the fixed effects model gives similar results compared to estimation on the whole sample. A random effects model gives essentially the same estimates as the as respective model without effects.

now much weaker. The fixed effects model alone indicates therefore no relation between wage and the incidence of absence spells. Comparing both approaches, the fixed effect logit model suggests at first view that individual heterogeneity biases the results of the logit model, but the interpretation is more complex.

Recover again that in the fixed effects model any relation between wage and incidence is identified only by those individuals who change categories. Variables that do not vary within individuals can statistically not be separated from the fixed effect term. While a possible effect of weaker incentives at higher wage levels, as outlined above, is not affected by this estimation property, the possible effect of selection, however, will vanish. For example, low-paid employees with a low absence incidence, and who later due to selection receive pay rises, do not contribute to the quantile estimates because the their absence behavior will be captured by the individual heterogeneity term. This can explain, why also the fourth quantile has become insignificant.

The multinomial logit model, which is used to examine the probability of starting a specific type of spell, resembles a similar pattern as the simple logit model. The probability of starting a physician-certified spell is significantly lower at wage levels above the median. For self-certified spells, the probability is significantly higher in the second wage quantile and lower in the fourth quantile. While the pattern for higher wages is similar to the results of the binomial logit models, it becomes also evident that the higher sick leave incidence in the second quantile is driven by self-certified absence. Whether this higher self-certified absence in the second quantile is a general phenomena or not is uncertain. An individual effect, as seen in the binomial models, is likely.

5.2.2 Tenure

The effect of tenure on the probability of starting a spell is intricate to interpret as well. Relative to those who have been tied to the companies for more than ten years, newly-employed individuals are less likely to start a new absence spell. For example, an average female employee in the largest company, in the second wage quantile and with more than ten years of tenure would have a probability of 1.49% of starting a spell in February. This probability is conditioned on attendance the previous recorded working day. With only less than one year of tenure the value falls to 1.23%. The impact of tenure also falls in the next two intervals, but becomes clearly stronger with five to ten years.

In the random effects model, the effect of different times of tenure on the probability of starting a new spell is stronger for all intervals, but the effect of three to five years is insignificant. Thus, it seems that unobservable heterogeneity with respect to the effect of tenure is present.

Ignoring the last tenure-interval of five to ten years, the pattern could be interpreted as a revelation of a moral hazard problem related to probation or temporary positions. As soon as the period of probation is passed or a temporary position becomes permanent, the incentive to show reliability with respect to sick leave deteriorates, and the probability of starting new spells increases. Higher sick leave has normally no consequences for the employee's position, but may be result in receiving less extra pay rise, as seen above.

Since the probability of being absent is predicted to be lowest in the first year of tenure, such a theory is at first view supported by the models. However, because also employees with five to ten years of tenure have a significantly lower probability of starting a spell, moral hazard may not be the only explanation, if at all.

Interestingly, a somewhat similar pattern as in the previous models is estimated by the multinomial logit model as well. The estimates on the probability of starting a new physician-certified spell show that the impacts of the first, second and fourth tenure-intervals are negative and decreasing, whereas the effect of three to five years of tenure is insignificant. In the results describing the probability of starting a new self-certified spell, the second coefficient is statistically not different from zero, while the other coefficients are negative and quite similar in size. As above, these results do not indicate that there is a moral hazard problem related to the transition from temporary positions or probation to permanent positions.

5.2.3 Time before quit

Two interval dummies for the time before quit are included in the logistic regression. Their purpose is to investigate if there arises a moral hazard problem with respect to sick leave when an individual leaves the company. In the last months before quit, an employee may have weaker incentives to be present at work because lower sick leave unlikely is rewarded, and sick leave hardly can be penalized. The employee leaves the company anyway. Thus, a higher sick leave is expected.

In the simple logit model, displayed in the first column of table 5.3, the probability of starting a new spell seems indeed to be higher in the last six months. Contrary, in the last twelve to six months no significant increase in incidence is predicted. This weakens the argument that those who leave are not in the best of health. In addition, this result is controlled for sex, age and calendar months. A selection and calendar time bias, which may arise when dealing with the time before quit, must therefore be small.

In the logit model which accounts for individual heterogeneity, there is not a significant higher sick leave incidence in the time before quit. The estimated coefficient for the last six months is now much smaller and thus statistically not different from zero at a 5% level. Comparing this result with the significant estimate of the simple logit model, a possible interpretation is that only some of the employees are sicker than others in the time before quit, but not that many employees to make it a general pattern. While those who have a higher incidence are biasing the estimate in the first logit model, this individual heterogeneity is wiped out in random effects model.

Considering the multinomial logit model, more interesting observation can be made. While the probability of starting a physician-certified spell statistically is not different in an employee's last 12 months compared to the time before, the probability of self-certified spells increases significantly in the last six months. This indicates indeed a strong moral hazard problem. If the population of employees who leave generally are more sick than others, the probability of starting a physician-certified spell should be expected to be positive as well. However, as neither this coefficient is significant, nor for both types of spells the six to twelve months before quit, it seems that self-certification is abused.

An effects model which accounts for individual heterogeneity could not be estimated. Therefore, it is unknown whether this effect is a general observation, valid for most of the employees, or if only some individuals seem to abuse self-certification, but more extensively. The binomial random effects model suggests the latter. On the other hand, the effect of the last six months on physician-certified spells is estimated to have a negative sign. This weakens the effect on the total probability of starting a new sick leave spell in this period. Hence, an increased incidence of self-certified sick leave in the last six months can be a general pattern, not only an individual.

5.3 Sick leave duration

Sick leave duration is studied by three different proportional hazard models. The results are displayed in table 5.4. While the semiparametric Cox model makes no assumption on the baseline hazard, the Weibull and cloglog model allow for individual heterogeneity. The random effects in the Weibull model are gamma distributed, and a normal distribution is chosen in the cloglog model. Since both the baseline hazard and the possibility of individual effects are expected to influence the estimates, three different models can indicate whether problems regarding these assumptions arise.

5.3.1 Wage quantiles

Surprisingly, the wage level appears not to affect sick leave duration. In all three model and except for one single coefficient, the estimates on the company-dependent wage quantiles are statistically not significant at a 5% level. This is in sharp contrast to the results for the probability of starting a new absence spell. While the wage level to some extent seems to determine how likely an individual starts a spell, the length of the spell is not influenced by being in a particular wage quantiles.

In the Cox model, the second wage quantile has a significant negative impact on the hazard of ending a spell. This result has no obvious interpretation. There may exist a relation to

Table 5.4: Sick leave duration

	Cox model		Weibull model		Cloglog model	
Wage quantiles:						
1st quantile						
2nd quantile	-0.0845^{*}	(0.0348)	0.0216	(0.0509)	0.0087	(0.0456)
3rd quantile	-0.0205	(0.0336)	0.0442	(0.0555)	0.0241	(0.0473)
4th quantile	-0.0415	(0.0355)	0.0076	(0.0612)	0.0121	(0.0527)
Tenure:						
0 – 1 year	-0.0514	(0.0590)	-0.0317	(0.1023)	-0.1392	(0.0918)
1 – 3 years	-0.1129^{*}	(0.0533)	-0.1641	(0.0950)	-0.2617^{**}	(0.0847)
3 – 5 years	-0.0322	(0.0526)	-0.1563	(0.0916)	-0.1687^{*}	(0.0799)
5 – 10 years	-0.0822	(0.0441)	-0.0917	(0.0827)	-0.1061	(0.0741)
10 + years						
Time before quit:						
0 – 6 months	-0.0556	(0.0408)	-0.2526^{***}	(0.0529)	-0.1704^{***}	(0.0497)
6 – 12 months	-0.1544^{**}	(0.0519)	-0.2536^{***}	(0.0609)	-0.1592^{**}	(0.0594)
12 + months						
Female	0.0944^{**}	(0.0292)	0.1338^{*}	(0.0660)	0.1785^{***}	(0.0503)
Self-certified	0.8559^{***}	(0.0279)	1.7154^{***}	(0.0299)	1.4567^{***}	(0.0346)
Individual effects	No effects		Random effects		Random effects	
Log likelihood	-59553.862		-10260.587		-14255.928	
Observations	39087		39087		39087	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ and standard errors in parenthesis. Additional control variables, not displayed above, are categorical dummies for age, dummies for company, month, and a constant. Gamma random effects in the Weibull model. Gaussian random effects in the cloglog model.

the higher probability of starting a spell, as detected above. However, the coefficients on the quantiles in the Weibull model and cloglog model have different sizes and signs. Although not significant, it indicates that unobservable heterogeneity may be important in this case. Therefore, this result from the Cox model must be considered with caution.

5.3.2 Tenure

The effect of tenure on spell length is more consistent. All coefficients are somewhat similar in size and have the same sign. In all three models, the negative impact on the hazard is highest at one to three years of tenure, and decreases thereafter. The effect of the second tenure-interval is significant in both the Cox model and the cloglog model. In addition, the third tenure-interval is significant in the cloglog model. In the Weibull model, however, all estimated coefficients on tenure are insignificant, but this model makes also the strongest assumptions on the baseline hazard.

At one to three years of tenure, the negative impact on the hazard may be related to the probability of starting a spell. The logit models above showed that individuals are less likely to begin a spell in this tenure-interval. It is not surprising, when the probability of going into sick leave is lower, then those who begin are maybe more sick as well. A selection mechanism may be present. Contrary, no significant effect of tenure on spell duration is found for newly-employed individuals. Those with less than a year of tenure are predicted to be less likely to start a spell. It follows that, if a newly-employed individual becomes sick, a more serious sickness must be expected, and thus a longer absence duration. No evidence for longer absence durations in the first year is however found in the results.

5.3.3 Time before quit

To examine if individuals change their absence behavior in the time before leaving the company, two time-interval dummies, which cover the last year before quit, are included in the models. In all duration models, the estimated effects on the hazard have the same sign and are similar in size. The impact of the two intervals in the two random effects models appears also to be identical, while the coefficient on the last six months in the Cox model is insignificant.

Having less than a year left, it seems that the probability of returning to work is lower. This fits well with the results for the probability of starting a new spell. The logit models revealed that moral hazard behavior related to sick leave incidence may occur in the last six months. The duration models support this view. As the incentives to reduce sick leave deteriorates in the last months before quit, a longer absence duration is expected.

On the other hand, while a selection regarding absence incidence can be disproved, no conclusion about selection problems regarding absence duration can be made. In the Weibull model and cloglog model, the contributions to the hazard of the two time-intervals are almost the same. In the Cox model, the last six months are insignificant. Therefore, those who are on sick leave in the last year might have a lower health status than others.

6. Conclusion

The aim of this thesis is to examine how economic incentives are related with sick leave behavior. Two important issues are addressed. First, the reaction of employers to absenteeism is analyzed. In particular, it is tested if sick leave affects pay rise. In addition, incidence and duration of sick leave spells and their relation to several economic incentives are examined. In this manner, moral hazard problems related to sick leave may be detected. Both analyzes revealed interesting results which partly reconfirm recent research and partly contribute with new evidence.

6.1 Sick leave and pay rise

Sick leave does affect pay rise. The higher the absence rate the lower is the estimated pay rise, if any. This result holds for total sick leave in general, but also if self-certified and physician-certified absence are considered separately. Regarding total sickness absence, even low rates in the the interval 1 to 3% seem to affect future earnings negatively. Compared to those with less than 1% total sick leave, a rate of 3 to 5% is estimated to reduce extra pay rise by around 1.4%. Absence rates above 5% are predicted to be relatively penalized by around 2%. Moreover, self-certified sick leave appears to affect additional pay rise somewhat stronger than physician-certified sick leave.

These results seem to be robust with respect to individual heterogeneity. Provided that such individual effects are constant over time, they seem not to bias the estimates on sick leave. Therefore, work motivation or other unobservable individual heterogeneity are unlikely to influence the relation between sick leave and pay rise. In addition, estimation is performed with several necessary control variables. Hence, the effect of sickness absence on additional pay rise holds under strict conditions. The analysis is however limited to only one group of companies.

Nevertheless, at least in the group of companies under study, pay rise is a disciplinary device. If employees are penalized for being on sick leave, the firm creates an incentive to be present at work. This argument is based on the assumption that employees actually know that such a disciplinary relation exist. For the firm, it has however not necessarily to be an explicit policy which is enforced enforced consciously. Despite the penalty, an employee may still find it reasonable to stay at home. The incentive to be present has to be weighted up against health status or other reasons for being absent. The theory of pay rise as a disciplinary device helps thus explaining why generous sickness insurance systems are not exploited to full extent. There is still costs associated with sick leave, even if income is fully replaced under absence.

Furthermore, the firm is usually unable to observe whether a sick leave spell is well-founded or not. It is not be in the firm's interest to penalize legitimate sick leave too hard and thus induce presenteeism. Physician-certified spells appear, of course, to be more serious and hence necessary. On the other hand, self-certified absence can be abused easily. This may explain why the latter is likely to be penalized harder.

The results regarding sick leave and pay rise are, at least for moderate absence rates, somewhat similar to two recent studies by Hansen (2000) and Markussen (2009). While these two studies employ register data to investigate whether wage changes could be a disciplinary device, this analysis examines the question directly at the firm level. The advantage of the latter is that measures of sick leave, including self-certified absence, and extra pay rise are highly accurate. Replicating the result at the firm level thus emphasizes that such a relation is highly reasonable, while the work by Hansen and Markussen suggests that the relation also holds in general.

6.2 Sick leave and moral hazard

Several of the results regarding incidence and duration of absence spells fit well to relation between sick leave and pay rise. In the models for incidence and duration, the effect of the wage level, tenure and the time before before quit are examined. Especially the results related to the time before an employee leaves the firm are found to be interesting, while the impacts of the two other variables of interest are more intricate to interpret.

6.2.1 Sick leave before quit

The sick leave system seems to be subject to moral hazard. This becomes evident when considering absence behavior in the months before an employee leaves the group of companies. Both the incidence and duration of absence spells are predicted to increase in the last months. First, regarding incidence, the probability of starting a new spell becomes significantly higher in the last six months. This increase stems solely from an increased inflow into self-certified spells. Since this kind of absence is easier to abuse than certified sick leave, it gives a strong indication of moral hazard. Furthermore, regarding absence duration, the results also indicate longer spells in the last twelve months. This supports the moral hazard interpretation.

In the logit models for incidence, there is no evidence that those who leave are sicker than others. A selection mechanism, which would bias the results for absence incidence, could be rejected. On the other hand, a selection bias can not be rejected in the models for duration. Moreover, it is also uncertain if the change in sick leave behavior in the last months holds for the whole population of employees. Some employees, however, have definitely a higher sick leave before leaving the group of companies.

Moral hazard, in form of higher sick leave, is expected to arise in the last months of work because an employee hardly can be penalized for a change in absence behavior. Several incentives to be present, e. g. pay rise and promotions, deteriorate. There is really no cost related to refused pay rise or promotion when an employee leaves the firm anyway. This result is somewhat analogous to the analysis of Ichino and Riphahn (2005), who postulate that employees are likely to change their absence behavior after probation.

6.2.2 Wage level and tenure

It is expected that the wage level has no direct effect on the incidence or duration. Since the replacement ratio in Norway is 100% from the first day of absence, no direct cost is linked to the wage level. Wage quantiles can, however, serve as proxies for different types of jobs. Following this interpretation, the negative relation between high wages and sick leave may be the result of a selection. First, low absence rates may give higher extra pay rise. Furtermore, having a low sick leave may be important for getting high paid jobs. Promotions and higher education migh be an additional selection mechanism. Although somewhat speculative, such a theory could explain the pattern revealed for the inflow into sick leave. On the other hand, no significant correlation between wage and absence duration is found.

Regarding tenure, it is hard to draw a clear-cut conclusion. Although significant effects are estimated on different tenure categories in almost all models, their interpretation remains a puzzle. Incidence and duration appear to increase when going from the first year of tenure to the next tenure categories. However, a convincing effect of probation or temporary positions on sick leave is not found. Incidence and duration decrease again after five years of tenure. Hence, while an effect related to job quitting appears to be present, sick leave behavior is unlikely to change in the beginning of an employees career.

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