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Teachers' Sickness Absence in Primary Schools: A Panel Data Multilevel Analysis*

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Abstract

This paper uses longitudinal employer–employee data and multilevel models to examine both observed and unobserved variation of the probability and length of certified and self-certified sickness absence for Norwegian primary school teachers. We argue that self-certified absences are particularly prone to moral hazard. We find that most of the observed teacher, school and municipality characteristics are significantly associated with the probability and the length of sickness absence. However, most of the unexplained variation is attributed to teacher factors rather than influenced by variation at the school or municipality levels. Teacher characteristics that may be associated with less attachment to the workplace increase the probability of self-certified absences. Moreover, the unexplained variation in schools and at municipality level is higher for self-certified than for certified sickness absence. There may be some scope for reducing self-certified absence by improving work conditions or changing administrative practices, but our main policy conclusion is that to reduce sickness absence, the main focus must be on individual health and the incentives to report sick.

Keywords: sickness absence, employer-employee data, multilevel analysis

JEL-codes: J21, J22, J28

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1. Introduction

There are substantial differences in the level of sickness absence between European countries, but the differences do not appear to be correlated with the health status of the respective countries' populations. Norway is a good example of this paradox. The rate of sickness absence has been increasing over the last 15 years[1] and is among the highest in Western Europe, with about twice as many sick days as the average of the former 15 EU countries (Eurostat, 2005). There are no signs of deteriorating health in the population during this period. On the contrary, the life expectancy in Norway is among the world's highest, and has increased particularly sharply over the last 20 years (http://www.ssb.no/befolkning/), and other objective and subjective measures of health have evolved positively (Waaler *et al*., 2003).

In the economic literature, the level of sickness absence tends to be explained by the degree of generosity of the social insurance system (e.g., Allen, 1981; Barmby *et al*., 1991; Johansson and Palme, 1996, 2005). This appears to be a fair description of the situation in Norway. Sickness insurance covers all workers, with a compensation ratio of 100% from day 1 up to a maximum of 1 year. With such generous sickness insurance, moral hazard obviously becomes an important issue. However, while standard insurance theory under such circumstances prescribes strict screening and gatekeeping to alleviate moral hazard, the Norwegian system is usually liberal. For the first 3 or 8 days (depending on the system ruling in the workplace in question) workers are allowed to report sick without any medical certification. For longer spells, a certificate from a medical doctor is required. There is evidence that Norwegian GP's are liberal gatekeepers (Carlsen and Norheim, 2001, 2005). The generosity in terms of entitlement, compensation rate and certification requirements imply that sickness absence should not be analysed purely as a health phenomenon. From an

[1] An exception being the year 2004, where the sickness absences dropped significantly during the first two quarters, after which they continued to grow.

economist's point of view, the phenomenon should rather be analysed as labour market behaviour with moral hazard as an additional dimension.

Because there is no form of control over self-certified absence (and the replacement rate remains 100%), one might expect that moral hazard is more of a problem for self-certified than for certified absences. Unfortunately, up to now, data have been available only for absences remunerated by The Social Insurance Administration, and these absences are certified.

In this paper, we explore new public employer–employee data that are unique in including self-certified as well as certified absences. The data is recorded for most primary and secondary school teachers in Norway. The data contains individual information on income, education, gender, age, municipality of residence and employment as well as other variables. The individual data are merged with their respective schools by unique identification codes. This makes it possible for us to create group data based on person registers (school fractions of males/females, age and education profile in the schools, etc.). Finally, the merged employer–employee data are merged with municipality data from The Regional Database administered by Norwegian Social Science Data Services (NSD), allowing us to control for urban/rural locality, local labour market and living conditions.

Individual (register) data on long-term sickness absence, sometimes with data on job characteristics, have been around for a while now. They have proven to have a high degree of heterogeneity as regards *individual characteristics* (gender, education, branch, etc.). Moreover, there exist some plant/firm-level data, allowing the researcher to test for the effects on sickness absence of the firms' economic performance, and *group effects* such as number employed, share of male workers, average education, etc. Such group effects (unfeasible with ungrouped individual data alone) are important when analysing the effects on sickness absence of organization of work, social norms at the workplace and other variables.

The issue is particularly important here because it may be the case that there is an unobservable effect common to all teachers within the same school and we need to control for dependence on unobservables within a school. In particular, if the within-cluster unobservables are correlated with regressors, the regression parameters are inconsistent and suitable alternative estimations are needed (Cameron and Trivedi, 2005). Hence, it is important to analyse multilevel data in an approach that embodies within group (e.g., within school) and between group relations within a single analysis. Furthermore, clustering imposes a correlation structure on the data, making conventional regression techniques inefficient (Rice and Jones, 1997). Therefore, a multilevel analytical approach is relevant for more efficient estimation as well. With *merged* employer–employee data it is possible for us to model individual and group effects *simultaneously*.

The ability to partition variance at different levels (e.g., at municipality, school and teacher levels) is a unique feature of multilevel regression analysis. By decomposing variances at different levels, one may be able to quantify, in particular, how much of the school differences in the probability or the length of sickness absence are explained by differences in teacher composition of the school or municipality and how much of these differences are explained by school characteristics or municipality-level attributes.

The ability to disentangle individual from school effects may have policy implications. In very general terms, if individual effects dominate, the focus should be on individual health and incentives that may influence the propensity to report sick. If, on the other hand, school effects dominate, the policy should be directed towards improving working conditions and employers' incentives.

The paper is organized as follows. In the next section, we give a brief description of the sickness insurance system in Norway. Data are presented in Section 3, while Section 4 reports the econometric methods and models. Estimation results are presented in Section 5. Finally, Section 6 offers some concluding remarks.

2. The Norwegian Sickness Insurance System

Sickness insurance is mandatory in Norway and covers all workers employed for more than 4 weeks. The compensation ratio is 100% from day 1 for a period no longer than 1 year. There is an upper compensation limit of approximately 50,000 EURO, but through negotiations between employers and employees this ceiling has been removed in the public sector and in most large firms and many small firms in the private sector.

A worker reporting sick will be financed by his/her employer from day 1 to day 16, after which the National Insurance Administration takes over from day 17 up to the maximum of 1 year. Workers sick for longer than a year may be transferred to rehabilitation and disability programmes after medical screening.

No medical certification is required for sickness spells lasting from 1 to 3 days. As of 2001, firms have been encouraged to join a publicly organized campaign called Including Working Life (*Inkluderende arbeidsliv*, IA), allowing self-certified sickness spells of up to 8 days. Workers are allowed to self-report sick up to four times per year. Spells lasting more than 3 or 8 days require a medical certificate; an even more detailed certificate is required after 8 weeks. However, it should be noted that Norwegian GPs are considered to be very liberal gatekeepers. Moral hazard, which is always a problem with this type of social insurance, is accordingly very much an issue.

3. The Data

Our main data source is a longitudinal personnel register administered by the Norwegian Association of Local and Regional Authorities (KS), which provides individual information on certified and self-certified sick leave for Norwegian primary and lower secondary school teachers in 2004–2006. For both self-certified and certified sick leave, absence days are recorded as the cumulative number of days per quarter. The register also contains teacher-specific information on yearly income, working hours (as a proportion of a full time position), type of position, tenure (number of years), age, gender and municipality of residence and employment.

In the data set, each teacher is connected to a school and a municipality by unique identification codes, making it possible to merge teacher-specific information with information on workplaces and municipalities. Data on workplace characteristics are taken from the Ministry of Education (Grunnskolens informasjonssystem, GSI). From this register, we have school-specific information on the number of employees, number of pupils per teacher and the proportion of pupils receiving special education. Information on working municipalities is taken from Statistics Norway (SSB) and includes number of inhabitants, population density and indexes on living conditions and unemployment. All dependent and independent variables used in the analysis are defined in Table 1.

Not all municipalities report information to the Norwegian Association of Local and Regional Authorities every year, and our data set is therefore not a sample of the total population of teachers, schools and municipalities. However, the sample is quite large and includes information on 53,753 teachers (from a total of 65,376) working in 2028 schools (from a total of 3160) located in 344 municipalities (from a total of 430). We have also excluded small schools (schools with less than 10 teachers) and teachers older than 67 years from the analysis.

<<<< Table 1 about here >>>>

Descriptive statistics and number of observations used in the analysis are presented in Table 1. We see that the typical Norwegian teacher is a 46-year-old woman with a bachelor's degree, working 87% of a full time position with around 20 years work experience. The average school in our sample has around 40 employees, around 11 pupils per teacher and around 14% of pupils receive some form of special education.

From Table 1, we further see that the average length of certified sick leave is quite high in this period, 15.5 days, while the average self-certified absence is around 2 days. Around 39% of teachers take certified sick leave each year; the corresponding figure for self-certified sick leave is almost 60%.

<<<< Tables 2 and 3 about here >>>>

As seen from Tables 2 and 3, there are large variations in the average length of sickness absence between schools and municipalities. For example, 25% of schools had average certified sickness absence of less than 8 days and average self-certified sickness absence of less than 1.3 days in 2005. Looking at the 25% of schools with the highest absence, we see that average certified sick leave is 16 days or more while average self-certified sick leave is 2 days or more. Variation in sickness absence between municipalities is also quite high, but less than the variation between schools.

4. Methods

Our econometric analysis anticipates that teachers' probability of sickness absence (SA) and the length of SA (certified by a GP or self-certified) are partly dependent on (i) the time of observation (because we have repeated measures of the same teacher, this is interpreted as observations that are nested "within a teacher"), (ii) teachers' personal attributes, (iii) school characteristics, and (iv) the administrative municipalities to which they belong. This hierarchical structure in teachers' likelihood and length of SA are modelled by separating the time (level 1), teacher (level 2), school (level 3) and municipality (level 4) sources of variation.[2]

Assuming that all four-level coefficients are fixed (i.e., the coefficient does not vary with higher-level regressors or with unobservables), except that the intercept varies randomly, we may write a four-level random intercept logit model for teachers' probability of SA (certified by a physician or self-certified) as a latent-response model (see Cameron and Trivedi, 2005; Rabe-Hesketh and Skrondal, 2005):[3]

$$S^{*}_{msit} = \beta X_{msit} + \gamma Y_{mst} + \delta Z_{mt} + \phi t + w_m + u_{ms} + e_{msi} + \varepsilon_{msit} \qquad (1)$$

where S_{msit} = 1 if S^{*}_{msit} > 0, and S_{msit} = 0 otherwise; and e_{msit} has a logistic distribution with variance $\pi^2/3$.

To identify the factors influencing teachers' length of SA, we consider a four-level random intercept linear regression model and estimate the length of SA conditional on having reported sick. To account for the right-skewed distribution of the length of SA, equation 2 employs the log transformation of S_{msit} :

$$\ln S_{msit} = \beta X_{msit} + \gamma Y_{ms} + \delta Z_m + \phi t + w_m + u_{ms} + e_{msi} + \varepsilon_{msit} \qquad (2)$$

In equations 1 and 2, S^{*}_{msit} and S_{msit} represent the probability and length of teachers' SA, respectively, which are related to a vector of teacher-level explanatory variables *X*, the school characteristics *Y*, residing municipality characteristics *Z*, and time of observation *t*.

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[2] Our use of this approach is also inspired by Antweiler (2001). By using Monte Carlo simulation, Antweiler notices a downward bias in the standard errors of regressors when using the conventional (non-nested) random effect estimator rather than the nested random effect estimator on a hierarchical panel.

[3] In more general multilevel models, with a randomly varying intercept, all coefficients may have fixed (non-randomly varying) as well as randomly varying coefficients (i.e., random coefficients model). For details, see Cameron and Trivedi (2005) and Snijders and Berkhof (2008). We have also tried to specify randomly varying coefficients models; however, none of these models converged.

In the above specifications, w_m is the random error term for the mth municipality, u_{ms} denotes the nested effect of sth school within the mth municipality, and e_{msi} indicates the nested effect of a teacher i working at the sth school within the mth municipality. ε_{msit} is the error term for ith teacher working at time t in s*th* school within the mth municipality. This model allows for an unequal number of individuals in each municipality/school as well as different numbers of observed time periods across teachers (Baltagi *et al*., 2001).

Each error term is assumed to be independently and identically distributed (iid) with mean zero and their respective variances. These disturbance terms are assumed to be independent of each other. These two assumptions focus only on the random part of the model (Raudenbush and Bryk, 2002), and having a large sample at our disposal (see Section 3). We are quite confident that the assumptions will not be violated.

There remains a debate in econometrics on the appropriateness of using random effects estimators as opposed to fixed effects. In this paper, because we desire to model the multilevel structure of the data, random effects emerge as the only option. As with the conventional (non-hierarchal) *random effect* model, a further assumption is required for our random intercept model,[4] that is, E $[\varepsilon_{msit} | X_{msit}] = 0$ (also called the orthogonality assumption), implying that Cov $(\varepsilon_{msit}, X_{msit}) = 0$.[5]

Mundlak (1978) demonstrates that the conventional random effects model can be adjusted to account for the correlation between unobserved heterogeneity and the explanatory variables. By assuming that the unobserved factors are correlated with the group means of the explanatory variables, Mundlak (1978) attempts to parameterize the individual effect of the random effect model and use the within-groups mean as the independent variables. In

[4] The conventional two-level (e.g., teacher and time) panel data *random effect* model is also known as the *random intercept* model (Cameron and Trivedi, 2005).

[5] The orthogonality assumption needs to be fulfilled for other levels as well, e.g., it is required that Cov $(e_{mst}, Y_{mst}) = 0$.

particular, Mundlak's approach involves modelling the correlation of unobserved heterogeneity (e.g., at teachers' level) with regressors in an auxiliary equation, such as $e_{msi} = \pi\overline{X}_{msi} + v_{msi}$. To handle the problem of unobserved heterogeneity, this paper uses a Mundlak-type specification, where we add the within-teachers' means of all dependent variables at teacher level (where most of the unobserved heterogeneity would be expected):[6]

$$S_{msit} = \beta X_{msit} + \pi\overline{X}_{msi} + \gamma Y_{mst} + \delta Z_{mt} + \phi t + w_m + u_{ms} + v_{msi} + \varepsilon_{msit} \qquad (3)$$

The error term from Mundlak's auxiliary equation (v_{msi}) is now included in the error term of the augmented equation 3 (i.e., v_{msi}), which is also assumed to be iid. Note that in this model, β represents the within-teacher effect and $\beta + \pi$ is the between-teacher effect.

Hausman (1978) proposes a general procedure for tests of model specification, which can be interpreted here as testing the equality between the within-group regression coefficients and the between-group coefficients (Baltagi, 2005). In other words, the orthogonality can be tested by testing the effects of these cluster means included as additional variables in the fixed part of the model, which is equivalent to testing the hypothesis that $H_0 : \pi = 0$ in equation 3 (Baltagi, 2005).[7] Even if statistically $\pi \neq 0$, given the correlation between the individual effects and the explanatory variables is partly captured in equation 3, Mundlak's (1978) approach suggests that the heterogeneity bias will be minimal. Moreover, with other advantages (e.g., allows for including the time invariant variables such as gender), Mundlak (1978) also notices that the fixed effects methods evaluate effects only for

[6] We also use the same approach for the school-level covariates; however, none of the cluster means of school-level coefficients are found to be significant.

[7] If there is a difference between the within-group and between-group regression coefficients, then unbiased estimates for the fixed within-group effects can be obtained also with random effects models, provided that the group means of the explanatory variables are included among the fixed-part variables (Skrondal and Rabe-Hesketh, 2004; Snijders and Berkhof, 2008).

observations in the sample, making no prediction for out-of-sample observations, and this makes the random effects estimator preferable (see Johnes, 2007).

To examine the variation explained by different levels, we estimate four sequential models. The four models differ in the covariates included, i.e., in the fixed part, the random components are the same. The first model is a null (empty) model with no predictor in the fixed part of the model (**Model 0**). This model presents a baseline for comparing the size of higher-level variations (e.g., school-level variations) in teachers' length of sickness absence in subsequent models. In the second model, we add all the teachers' characteristics and time dummies in the fixed part of the model and examine the effect of teacher-level predictors (both within and between) on the probability and length of sick leave (**Model 1**). **Model 2** is the same as Model 1, but adds school-level characteristics in the fixed part of the model. Controlling for teachers' characteristics, this model potentially examines the effect of school-level predictors on teachers' sickness absence (fixed part). In the random part of the model, the unexplained characteristics of the schools' effects on teachers' sickness absence is estimated before and after taking into account the effect of the school-level observable characteristics. Following this approach, we can examine how much unexplained variation is reduced. Finally, **Model 3** includes not only all teacher and school-level predictors but also adds municipality-level observable characteristics as the fixed effect. In the random part of the results, this model allow us to examine the extent to which municipal observable characteristics explain municipality-level differences in teachers' probability of sick leave and the length of sick leave (**Model 3**).

To illustrate how observed covariates at different levels explain teachers' sickness absence, we calculate McKelvey and Zavoina pseudo-R^2 for different models: $R^2 = \sigma_p^2 \big/ (\sigma_p^2 + \sigma_M^2 + \sigma_S^2 + \sigma_i^2 + \sigma_t^2)$.

The numerator of the ratio is the variability in the dependent variable that is predicted by the model ($\sigma_p{}^2$).[8] The denominator of the ratio is the total variability in the dependent variable. Thus, this ratio is the proportion of the total variability explained by the model (i.e., *pseudo-R^2*).

To determine the relevance of the school or municipality differences (unexplained variances) for understanding the teachers' differences in sickness absence behaviour, we calculate the intraclass correlation (ICC). The intraclass (cluster) correlation can be expressed as the proportion of teacher differences in the length of sick leave that is at the school or municipality level. For example, the proportion of the teachers' unexplained variance ($\sigma_M^2 + \sigma_S^2 + \sigma_i^2 + \sigma_t^2$) in sickness absence that is at the school level (σ_S^2) can be calculated by the general formula: $ICC = \sigma_S^2 / (\sigma_M^2 + \sigma_S^2 + \sigma_i^2 + \sigma_t^2)$. The closer the ICC is to 0%, the smaller the proportion of the total variance is at the school or the municipality level.

5. Results

In this section, we first present the findings of the fixed-part results for both certified and self-certified SA, and for the probability followed by the length of the SA. Analogously, the next subsection illustrates the findings of the random-part results for both the probability and length of certified and self-certified SA. No noteworthy differences between Models 1–3 (both statistical significance level and the magnitude of the coefficients) are observed in the fixed part of the models. Hence, in illustrating the fixed-part results, we emphasize the findings based on our final model (Model 3). Moreover, in interpreting the fixed-part results,

[8] For the random intercept logit model, the calculation is based on predicting a continuous latent variable underlying the observed dichotomous (0-1) outcomes in the data.

we focus on the between-teacher effects (i.e., $\beta + \pi$, in equation 3), but not within-teacher effects (i.e., β in equation 3).[9]

5.1 Fixed-part results

5.1.1 Probability of sickness absence

Teacher-level characteristics

As seen in Tables 4 and 5, most of the observed teacher attributes are significantly associated with the probability of certified and self-certified SA. We note that men are less likely to be absent, whether certified or self-certified. However, there are some important differences between certified and self-certified absences. The probability of having a self-certified absence decreases by age and experience, but for certified absences, it is the other way around.[10] We argued in the introduction that self-certified absences—where there is no control or monitoring apart from counting absence days—are more subject to moral hazard than those that are certified by a physician. Thus, one explanation of the observed differences could be that older teachers feel more 'responsible' and avoid very short absences where there is no control for the cause. If certified absences are more related to health, the effect of age (and experience) on certified absences could be a health effect.

Working hours have a negative effect on certified but a positive effect on self-certified absences. The latter result could be explained by exposure: teachers who have a less than full time position have less need to take a day off (for illness or other reasons). Even so, it may be the case that full time teachers actually are in better health, which may explain the negative

[9] In all models (see Tables 4–7), some of the coefficients of cluster means at teacher level are significant (i.e., $\pi \neq 0$); hence, these coefficients may suffer from heterogeneity bias. Nevertheless, as discussed earlier, Mundlak's (1978) approach allows us to minimize such heterogeneity bias in the estimations.

[10] Note that the within teacher *age effect* is positive (β); however, the between teacher *age effect* or *cohort effect* ($\beta + \pi$) is negative.

effect on certified absences. The negative effect of income on certified absences may be explained similarly, as income is closely related to working hours for this fairly homogeneous group of workers.

<<<< Tables 4 and 5 about here >>>>

The probability of self-certified leave decreases with education and position: teachers with a degree have less absence than assistant teachers, while headmasters and deputies have less absence than teachers in ordinary positions. Again, the explanation could be ‘responsibility’ (leaders), or better job satisfaction (bachelors/masters). Headmasters and deputies also have less certified absences than others. It is not obvious that leaders are in better health than others, but the ‘responsibility’ argument might be applied here too, as it will be an individual assessment whether to visit a physician for many conditions.

School-level characteristics

The number of pupils per teacher, and the proportion of pupils who receive special education may indicate more demanding working conditions. These factors increase both types of absence, as might be expected. It is less clear why larger schools (more employees) have less uncertified absences. However, after controlling for pupil per teacher and pupils with special demands, it could be the case that the work environment is better in larger than in smaller schools.

Municipal-level characteristics

We also find indications that sickness absence differs across municipalities. Teachers living in communities with less favourable living conditions, as indicated by the living conditions index, have a higher probability of absence. Moreover, the probability of absence is lower in less centralized areas. These findings may be explained as indicating that more stressful environments induce more absence. Alternatively, there may be a more general acceptance of absence in centralized municipalities.

5.1.2 Length of sickness absence

Turning to the length of certified leave, we find that most of the significant coefficients of individual-level variables have the same sign as for the probability of leave. However, headmasters and deputies have longer absences than other teachers. This may be consistent with the opposite sign for the probability of absence: leaders have fewer absences, but given that they are absent, they are sicker because the absences last longer. Of other results, we note that the living conditions index has the same sign as the absence probability. However, it is harder to explain that the proportion of pupils with special education and the local unemployment level affect the length of absences negatively. Finally, we remind the reader that the results with respect to length of absence are conditional on being absent in the first place; thus, they cannot be generalized to the population of teachers.

<<<< Tables 6 and 7 about here >>>>

5.2 Random-part results

5.2.1 Probability of sickness absence

To what extent are school- or municipality-level observed and unobserved characteristics important for teachers' probability of reporting sick? Tables 8 and 9 describe the random part of the results that gives us indications of this question. As seen in Table 8, the null model with no predictors (Model 0) shows a significant variation in the certified sickness absence between teachers ($\sigma_i^2 = 2.118$), between school ($\sigma_S^2 = 0.075$) and between municipalities ($\sigma_M^2 = 0.112$). After controlling for teachers' observable attributes (Model 1), a decrease in the variation between teachers ($\sigma_i^2 = 2.000$) and between schools ($\sigma_S^2 = 0.070$) is observed, but the variation is increased at the municipality level ($\sigma_M^2 = 0.163$). After controlling for the teachers' and schools' characteristics (Model 2), the variation between schools ($\sigma_S^2 = 0.067$) and municipalities ($\sigma_M^2 = 0.153$) are decreased slightly. Finally, after controlling for teachers', schools' and municipality observable attributes (Model 3), between-teacher and between-schools variation remained constant; however, between-municipality variation is reduced ($\sigma_M^2 = 0.128$).

<<<< Table 8 about here >>>>

Nevertheless, to quantify the extent of the role that school or municipality variations play in determining the teachers' certified sickness absence, ICC (cluster) statistics can be used. In the random part of our results (in the null model), as seen in the bottom part of Table 8, the ICC is 1.34% (Model 0) at the teacher level and 2.00% at the municipality level. After including teacher- and school-level predictors and municipality-level observable characteristics (Model 3), the ICC is decreased at the school level (1.21%) and increased at the municipality level (2.34%). This result suggests that variation in the teachers' likelihood of certified sickness absence is mainly affected by teachers' individual attributes (around 96%) rather than influenced by school-level variation or differences in their residence municipality characteristics.

<<<< Table 9 about here >>>>

We further examine the degree to which school- or municipality-level observed and unobserved attributes contribute to the teachers' probability of self-certified sickness absence. As seen in the lower part of Table 9, the overall variation in school or municipality level seems considerably higher for self-certified absence. In the null model, the ICC is 4.31% (Model 0) at the school level and 6.07% at the municipality level. As before, after including teacher-, school- and municipality-level observable characteristics (Model 3), the ICC is decreased slightly at both school (4.15%) and municipality (5.09%) levels. Note that for the probability of self-certified sickness absence, more than 10% variation is found at school and municipality level, which is three times higher than for the certified sickness absence.

5.2.2 Length of sickness absence

As with the probability of SA, we examine the extent that school- or municipality-level observed and unobserved characteristics are important for teachers' length of sickness spells.

<<<< Table 10 about here >>>>

As seen in Table 10, the null model with no covariates (Model 0) shows a significant variation in certified SA between teachers ($\sigma_i^2 = 0.399$), between school ($\sigma_S^2 = 0.013$) and between municipalities ($\sigma_M^2 =$ 0.025). After controlling for teachers' observable characteristics (Model 1), a decrease in the variation is observed at the teacher and school levels ($\sigma_i^2 =$ 0.364; $\sigma_S^2 = 0.012$), but is slightly increased at the municipality level ($\sigma_M^2 =$ 0.032). However, after controlling for teachers' and schools' attributes (Model 2), the variation remained constant at all three levels. Finally, after controlling for teacher, school and municipality observable attributes (Model 3), between-teacher and between-school variation remains constant, but between-municipality variation is slightly reduced ($\sigma_M^2 =$ 0.028).

Analogous to the *probability* of teachers' certified SA, ICC statistics have been calculated for the *length* of certified SA. In the random part of our results (in the null model), as seen in the lower part of Table 10, at teacher level the ICC is 0.82% (Model 0) and 1.52% at municipality level. After including teacher-, school- and municipality-level observables in Model 3, the ICC decreases at school level (0.72%), but increases slightly at municipality level (1.68%). As before, this finding suggests that variation in the teachers' length of certified SA is mainly affected by teachers' individual attributes (around 98%) rather than by school-level variation or differences in the municipality-level characteristics where they live.

<<<< Table 11 about here >>>>

We further illustrate the extent that school- or municipality-level observed and unobserved attributes contribute to the teachers' length of self-certified SA. As can be seen in the bottom part of Table 11, compared with the certified SA, the variation in school or municipality level seems rather higher for the length of self-certified SA, as earlier. In Model 0, the ICC is 2.17% at the teacher level and 2.35% at the municipality level. After including teacher-, school- and municipality-level observable characteristics (Model 3), the ICC decreases slightly both at the school level (1.84%) and municipality level (2.19%). Though comparatively small, for the length of self-certified SA, about 4% variation is found at the school and municipality level, which is twice as high as is observed for the certified SA.

6. Conclusion

The purpose of this paper has been to determine whether factors at the individual or at the school and municipality level are the most important sources of variation in sickness absence among Norwegian teachers. We also aimed to examine whether those factors may be attributed to the moral hazard inherent in a sick pay system with a low control level and no pecuniary costs for workers. A panel of more than 55,000 teachers was analysed for the period 2004–2006, using multilevel methods. Our results clearly show that the main source of variation is at the individual level. Furthermore, we find important differences between self-certified absences—presumably most suspect to moral hazard—and absences that are certified by a physician. Teachers who are younger and who have shorter experience are more prone to absence without certification. Headmasters and deputies have less self-certified absence than teachers in regular positions, and teachers with a degree have less absence than teachers without a degree. Even though we cannot rule out health differences between those groups, it is reasonable to interpret these results as indicating that teachers with a closer attachment to the workplace due to position and/or education act more ‘responsibly’ when confronted with the moral hazard in self-reporting. The fact that the probability of *certified* absences *increases* with age, normally associated with a higher risk of health problems, strengthens this interpretation.

It is also an important finding that while most of the unexplained variation is attributed to teacher factors, the variance at the school and municipality level is almost three times higher for self-certified than for certified absences (probability as well as length). This may be explained by different ‘absence cultures’ among employees, but also by differing work conditions: the probability of absence increases with pupils per teacher and with the proportion of pupils receiving special education.

Our main policy conclusion is that to reduce sickness absence, the main focus must be on individual health and the incentives to report sick, as most variation is found at the individual level. The scope for reducing absence by improving working conditions may seem smaller, more so for self-certified than for certified absences.

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Table 1: Variable definitions and descriptive statistics of the variables used in the analyses, by year

Teacher characteristics		2004	2005	2006
Sick days (certified)	Yearly number of GP certified sick days	15.294 (37.055)	15.178 (37.612)	16.070 (38.694)
Sick days (not certified)	Yearly number of self-certified sick days	1.970 (2.690)	2.203 (2.874)	2.194 (2.873)
Sick days (certified) > 0	Sick days (certified) greater than zero	0.390 (0.488)	0.385 (0.487)	0.389 (0.488)
Sick days (not certified) > 0	Sick days (not certified) greater than zero	0.572 (0.495)	0.597 (0.491)	0.592 (0.492)
Male	1 if the teacher is male, 0 otherwise	0.263 (0.440)	0.272 (0.445)	0.272 (0.445)
Age	Age of the teacher	45.313 (10.897)	45.738 (10.735)	46.116 (10.641)
Income/1000	Yearly income (in 1000 NoK)	329.254 (48.944)	339.887 (46.562)	351.735 (46.602)
Working hours	Percentage of a full time position	86.174 (20.883)	87.302 (20.197)	87.553 (19.973)
Seniority	Number of years since first employed	19.493 (10.718)	19.987 (10.649)	20.358 (10.583)
Position				
Assistant teacher	1 if teacher is assistant teacher, 0 otherwise	0.109 (0.311)	0.084 (0.278)	0.082 (0.274)
Teacher with bachelors degree	1 if teacher with a bachelors degree, 0 otherwise	0.776 (0.417)	0.808 (0.394)	0.814 (0.389)
Teacher with masters degree	1 if teacher with a masters degree, 0 otherwise	0.032 (0.175)	0.032 (0.175)	0.031 (0.175)
Assistant/deputy headmaster	1 if teacher is assistant/deputy headmaster, 0 otherwise	0.046 (0.210)	0.045 (0.207)	0.042 (0.201)
Headmaster	1 if teacher is headmaster, 0 otherwise	0.032 (0.190)	0.031 (0.173)	0.031 (0.173)
School characteristics				
Number of employees	Number of teachers (full time)	40.132 (19.478)	36.883 (18.512)	35.153 (17.380)
Pupils per teacher	Number of pupils per full time teacher	11.571 (1.628)	11.342 (1.598)	11.005 (1.551)
Proportion special education	The proportion of pupils receiving special education	0.131 (0.033)	0.137 (0.032)	0.143 (0.037)
Municipality characteristics				
Number of inhabitants	Number of inhabitants in employment municipality	62.337 (77.803)	55.740 (71.680)	49.271 (67.507)
Index living conditions	Employment municipalities ranged from 1 to 10, 1 most underprivileged	5.546 (1.750)	5.615 (1.658)	5.713 (1.621)
Index unemployment	Employment municipalities ranged from 1 to 10, 1 highest unemployment	5.789 (2.537)	5.856 (2.405)	5.908 (2.377)
Population density	Percentage of the population living in densely populated areas			
Rural area (low density)	Employment municipalities with low population density	0.137 (0.344)	0.127 (0.333)	0.137 (0.344)
Other urban (medium density)	Employment municipalities with medium population density	0.313 (0.464)	0.338 (0.473)	0.361 (0.480)
Urban (high density)	Employment municipalities with high population density	0.550 (0.498)	0.535 (0.499)	0.502 (0.500)
Number of observations		28,847	35,562	41,027
Number schools		1085	1445	1737
Number municipalities		184	242	301

Note: Means or proportions of variables, standard deviation of variables in the parentheses

Table 2: Average sick leave days, by schools

Years		2004			2005			2006	
Percentiles	25	50	75	25	50	75	25	50	75
Certified sick leave	7.85	11.78	16.54	7.53	11.65	16.60	7.91	12.56	18.16
Self-certified sick leave	1.17	1.58	2.07	1.31	1.80	2.41	1.31	1.81	2.40

Table 3: Average sick leave days, by municipalities

Years		2004			2005			2006	
Percentiles	25	50	75	25	50	75	25	50	75
Certified sick leave	13.02	15.35	17.71	12.55	14.84	17.32	13.62	16.07	18.26
Self-certified sick leave	1.69	1.89	2.23	1.81	2.33	2.55	1.88	2.26	2.49

Table 4: Fixed-part regression results for the probability of certified sick leave: Four-level random intercept logit models

Attribute	**Model 1** (teacher attributes)	**Model 2** (teacher + school attributes)	**Model 3** (teacher + school + municipality attributes)
Teacher characteristics			
Male	–0.698*** (0.024)	–0.691*** (0.024)	–0.691*** (0.024)
Age	0.447*** (0.040)	0.442*** (0.040)	0.431*** (0.040)
Mean age	–0.437*** (0.040)	–0.432*** (0.040)	–0.421*** (0.040)
Income/1000	–0.000 (0.000)	–0.000 (0.001)	–0.000 (0.001)
Mean income	–0.001 (0.000)	–0.001 (0.001)	–0.001 (0.001)
Working hours	–0.002* (0.001)	–0.002* (0.001)	–0.002* (0.001)
Mean working hours	–0.000 (0.001)	–0.000 (0.001)	–0.000 (0.001)
Experience	0.004 (0.020)	0.002 (0.020)	0.002 (0.020)
Mean experience	0.002 (0.020)	0.004 (0.021)	0.004 (0.021)
Position: base category: assistant teacher			
Teacher with bachelors degree	0.085 (0.057)	0.091 (0.057)	0.095 (0.057)
Teacher with masters degree	–0.007 (0.090)	–0.008 (0.091)	–0.010 (0.091)
Assistant/deputy headmaster	–0.180** (0.084)	–0.169** (0.085)	–0.166** (0.085)
Headmaster	–0.454*** (0.100)	–0.437*** (0.101)	–0.4317*** (0.101)
School characteristics			
Number of employees	-	0.002** (0.001)	0.002** (0.001)
Pupils per teachers	-	0.024*** (0.006)	0.018*** (0.006)
Proportion special education	-	0.408*** (0.123)	0.383*** (0.130)
Municipality characteristics			
Number inhabitants	-	-	0.001 (0.001)
Index living conditions	-	-	0.054*** (0.018)
Unemployment			–0.000 (0.014)
Rural areas	-	-	–0.134** (0.066)
Other urban areas	-	-	–0.305*** (0.070)
Year 2005	–0.369*** (0.036)	–0.362*** (0.036)	–0.351*** (0.035)
Year 2006	–0.696*** (0.061)	–0.677*** (0.061)	–0.657*** (0.060)
Constant	–0.229*** (0.119)	–0.667*** (0.145)	–0.761*** (0.171)
Pseudo-R^2	0.0076	0.0076	0.0077
Number of observations	105,244	105,244	105,244
Number teachers	55,137	55,137	55,137
Number schools	2028	2028	2028
Number municipalities	344	344	344

Note: Standard errors are in the parentheses. ‘*’, ‘**’ and ‘***’represents significance level at the 10%, 5% and 1% level respectively

Table 5: Fixed-part regression results for the probability of self-certified sick leave: Four-level logistic random intercept models

Attribute	**Model 1** (teacher attributes)	**Model 2** (teacher + school attributes)	**Model 3** (teacher + school + municipality attributes)
Individual characteristics			
Male	–0.361*** (0.023)	–0.355*** (0.023)	–0.355*** (0.023)
Age	0.328*** (0.040)	0.318*** (0.040)	0.310*** (0.040)
Mean age	–0.336*** (0.040)	–0.326*** (0.040)	–0.317*** (0.040)
Income/1000	–0.003*** (0.001)	–0.003*** (0.001)	–0.003*** (0.001)
Mean income	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
Working hours	0.020*** (0.001)	0.020*** (0.001)	0.020*** (0.001)
Mean working hours	–0.003*** (0.001)	–0.003*** (0.001)	–0.003*** (0.001)
Experience	0.007 (0.020)	0.009 (0.020)	0.009 (0.020)
Mean experience	–0.013 (0.0201)	–0.015 (0.020)	–0.015 (0.020)
Position: base category: assistant teacher			
Teacher with bachelors degree	–0.303*** (0.055)	–0.295*** (0.056)	–0.293*** (0.056)
Teacher with masters degree	–0.502*** (0.088)	–0.476*** (0.088)	–0.475*** (0.088)
Assistant/deputy headmaster	–0.928*** (0.083)	–0.922*** (0.083)	–0.922*** (0.083)
Headmaster	–1.625*** (0.098)	–1.608*** (0.098)	–1.605*** (0.098)
School characteristics			
Number of employees	-	–0.004*** (0.001)	–0.004*** (0.000)
Pupils per teacher	-	0.043*** (0.007)	0.038*** (0.007)
Proportion special education	-	0.452*** (0.151)	0.432*** (0.151)
Municipality characteristics			
Number inhabitants	-	-	0.002 (0.001)
Index living conditions	-	-	0.068** (0.028)
Unemployment			0.009 (0.019)
Rural areas	-	-	–0.380*** (0.097)
Other urban areas	-	-	–0.324*** (0.094)
Year 2005	–0.169*** (0.036)	–0.158*** (0.036)	–0.150*** (0.036)
Year 2006	–0.492*** (0.062)	–0.462*** (0.062)	–0.446*** (0.062)
Constant	–0.271** (0.120)	–0.982** (0.153)	–1.132** (0.198)
Pseudo-R^2	0.0080	0.0081	0.0082
Number of observations	105,436	105,436	105,436
Number teachers	55,154	55,154	55,154
Number schools	2028	2028	2028
Number municipalities	344	344	344

Note: Standard errors are in the parentheses. '**' and '***'represents significance level at the 5% and 1% level respectively

Table 6: Fixed-part linear regression results for the length of certified sick leave

Attribute	**Model 1** (teacher attributes)	**Model 2** (teacher + school attributes)	**Model 3** (teacher + school + municipality attributes)
Individual characteristics			
Male	–0.229*** (0.017)	–0.230*** (0.017)	–0.231*** (0.017)
Age	0.215*** (0.029)	0.213*** (0.001)	0.208*** (0.001)
Mean age	–0.209*** (0.030)	–0.207*** (0.030)	–0.202*** (0.030)
Income/1000	0.002** (0.001)	0.002** (0.000)	0.002*** (0.000)
Mean income	–0.001 (0.001)	–0.001 (0.000)	–0.001*** (0.000)
Working hours	–0.012*** (0.001)	–0.012*** (0.001)	–0.012*** (0.001)
Mean working hours	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Experience	0.023 (0.019)	0.023 (0.019)	0.022 (0.019)
Mean experience	–0.016 (0.019)	–0.015 (0.019)	–0.015 (0.019)
Position: base category: assistant teacher			
Teacher with bachelors degree	0.228*** (0.040)	0.227*** (0.039)	0.229*** (0.039)
Teacher with masters degree	0.146** (0.063)	0.141** (0.062	0.146** (0.062
Assistant/deputy headmaster	0.324*** (0.059)	0.323*** (0.058)	0.326*** (0.058)
Headmaster	0.305*** (0.071)	0.302*** (0.058)	0.306*** (0.058)
School characteristics			
Number of employees	-	0.000 (0.001)	–0.000 (0.001)
Pupils per teacher	-	–0.004 (0.003)	–0.003 (0.004)
Proportion special education	-	–0.139* (0.082)	–0.140* (0.082)
Municipality characteristics			
Number inhabitants	-	-	–0.000 (0.001)
Index living conditions	-	-	0.047*** (0.011)
Unemployment			–0.013* (0.008)
Rural areas	-	-	0.021 (0.038)
Other urban areas	-	-	–0.009 (0.023)
Year 2005	–0.226** (0.024)	–0.225** (0.024)	–0.220** (0.024)
Year 2006	–0.353*** (0.038)	–0.354*** (0.038)	–0.344*** (0.038)
Constant	2.952*** (0.080)	3.026*** (0.096)	2.826*** (0.109)
Pseudo-R^2	0.0422	0.0423	0.0448
Number of observations	40,905	40,905	40,812
Number teachers	29,703	29,703	29,703
Number schools	2020	2020	2020
Number municipalities	343	343	343

Note: Standard errors are in the parentheses. '*', '**' and '***'represents significance level at the 10%, 5% and 1% level respectively

Table 7: Fixed-part linear regression results for the length of self-certified sick leave

Attribute	**Model 1** (teacher attributes)	**Model 2** (teacher + school attributes)	**Model 3** (teacher + school + municipality attributes)
Individual characteristics			
Male	–0.002 (0.008)	–0.002 (0.008)	–0.001 (0.008)
Age	0.082*** (0.015)	0.081*** (0.015)	0.081*** (0.015)
Mean age	–0.081*** (0.015)	–0.081*** (0.015)	–0.080*** (0.015)
Income/1000	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Mean income	–0.001 (0.000)	–0.001 (0.000)	–0.001 (0.000)
Working hours	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Mean working hours	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Experience	–0.021** (0.009)	–0.022** (0.009)	–0.022** (0.009)
Mean experience	–0.020** (0.009)	–0.021** (0.009)	–0.022** (0.009)
Position: base category: assistant teacher			
Teacher with bachelors degree	–0.128*** (0.020)	–0.124*** (0.020)	–0.123*** (0.020)
Teacher with masters degree	–0.108*** (0.031)	–0.106*** (0.031)	–0.105*** (0.031)
Assistant/deputy headmaster	–0.225*** (0.030)	–0.221*** (0.030)	–0.221*** (0.030)
Headmaster	–0.302*** (0.036)	–0.291*** (0.036)	–0.290*** (0.036)
School characteristics			
Number of employees	-	0.002*** (0.000)	0.002*** (0.000)
Pupil per teacher	-	0.005*** (0.002)	0.004*** (0.002)
Proportion special education	-	0.026 (0.044)	0.019 (0.044)
Municipality characteristics			
Number inhabitants	-	-	0.000 (0.000)
Index living conditions	-	-	0.020*** (0.007)
Unemployment			0.002 (0.005)
Rural areas	-	-	–0.055*** (0.021)
Other urban areas	-	-	–0.046** (0.022)
Year 2005	0.011 (0.012)	0.016 (0.012)	0.016 (0.012)
Year 2006	–0.037* (0.020)	–0.028 (0.020)	–0.027 (0.020)
Constant	1.088*** (0.041)	0.956*** (0.049)	0.0748*** (0.058)
Pseudo-R^2	0.0118	0.0154	0.0200
Number of observations	61,982	61,872	61,872
Number teachers	40,471	40,471	40,471
Number schools	2011	2011	2011
Number municipalities	341	341	341

Note: Standard errors are in the parentheses. ‘**’ and ‘***’represents significance level at the 5% and 1% level respectively

Table 8: Random-part results for the models with the probability of certified sick leave

Levels	**Model 0** (null model)	**Model 1**	**Model 2**	**Model 3**
Between municipalities: variance (constant)	0.112 (0.016)	0.163 (0.016)	0.153 (0.015)	0.128 (0.013)
Between schools: variance (constant)	0.075 (0.010)	0.070 (0.009)	0.067 (0.009)	0.066 (0.009)
Between teachers: variance (constant)	2.118 (0.056)	2.000 (0.056)	1.991 (0.055)	1.992 (0.056)
Within teachers (between time): variance (constant)	3.290 (1.813)	3.290 (1.813)	3.290 (1.813)	3.290 (1.813)
Intercluster correlation (ICC) (between municipalities)	2.00%	2.95%	2.79%	2.34%
Intercluster correlation (ICC) (between schools)	1.34%	1.27%	1.21%	1.21%
Intercluster correlation (ICC) (between teachers)	37.86%	36.17%	36.20%	36.37%
Intercluster correlation (ICC) (within teachers)	58.80%	59.61%	59.81%	60.08%

Note: Standard errors are in the parentheses

Table 9: Random-part results for the models with the probability of self-certified sick leave

Levels	**Model 0** (null model)	**Model 1**	**Model 2**	**Model 3**
Between municipalities: variance (constant)	0.355 (0.042)	0.367 (0.038)	0.336 (0.036)	0.286 (0.037)
Between schools: variance (constant)	0.252 (0.018)	0.247 (0.018)	0.232 (0.017)	0.233 (0.017)
Between teachers: variance (constant)	1.952 (0.053)	1.804 (0.053)	1.807 (0.053)	1.808 (0.052)
Within teachers (between time): variance (constant)	3.290 (1.813)	3.290 (1.813)	3.290 (1.813)	3.290 (1.813)
Inter-cluster correlation (ICC) (between municipalities)	6.07%	6.43%	5.93%	5.09%
Inter-cluster correlation (ICC) (between schools)	4.31%	4.32%	4.10%	4.15%
Inter-cluster correlation (ICC) (between teachers)	33.37%	31.61%	31.90%	32.18%
Inter-cluster correlation (ICC) (within teachers)	56.25%	57.64%	58.07%	58.57%

Note: Standard errors are in the parentheses

Table 10: Random-part results for the models with the length of certified sick leave

Levels	**Model 0** (null model)	**Model 1**	**Model 2**	**Model 3**
Between municipalities: variance (constant)	0.025 (0.004)	0.032 (0.005)	0.032 (0.005)	0.028 (0.005)
Between schools: variance (constant)	0.013 (0.003)	0.012 (0.003)	0.012 (0.003)	0.012 (0.003)
Between teachers: variance (constant)	0.399 (0.014)	0.364 (0.014)	0.364 (0.014)	0.364 (0.014)
Within teachers (between time): variance (constant)	1.276 (0.014)	1.242 (0.014)	1.242 (0.014)	1.242 (0.014)
Inter-cluster correlation (ICC) (between municipalities)	1.52%	1.94%	1.97%	1.68%
Inter-cluster correlation (ICC) (between schools)	0.82%	0.70%	0.70%	0.72%
Inter-cluster correlation (ICC) (between teachers)	23.26%	22.03%	22.09%	22.14%
Inter-cluster correlation (ICC) (within teachers)	74.40%	75.33%	75.24%	75.46%

Note: Standard errors are in the parentheses

Table 11: Random-part results for the models with the length of self-certified sick leave

Levels	**Model 0** (null model)	**Model 1**	**Model 2**	**Model 3**
Between municipalities: variance (constant)	0.013 (0.002)	0.013 (0.002)	0.013 (0.002)	0.012 (0.002)
Between schools: variance (constant)	0.011 (0.001)	0.011 (0.001)	0.010 (0.001)	0.010 (0.001)
Between teachers: variance (constant)	0.135 (0.003)	0.132 (0.003)	0.131 (0.003)	0.131 (0.003)
Within teachers (between time): variance (constant)	0.392 (0.003)	0.389 (0.003)	0.389 (0.003)	0.389 (0.003)
Inter-cluster correlation (ICC) (between municipalities)	2.35%	2.42%	2.35%	2.19%
Inter-cluster correlation (ICC) (between schools)	2.17%	2.00%	2.02%	1.84%
Inter-cluster correlation (ICC) (between teachers)	24.59%	24.19%	24.12%	24.21%
Inter-cluster correlation (ICC) (within teachers)	70.89%	71.39%	71.51%	71.76%

Note: Standard errors are in the parentheses

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