Absenteeism predictors: least squares, rank regression, and model selection results

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Abstract. This paper examines the determinants of absenteeism, using OLS, rank-based regressions, and a model selection procedure. The results show that personal attributes are the most important determinants of long-term absences. For total working days lost the penalty factors are the most significant predictors. The results also show that absenteeism tends to be lower among firms with more part-time workers. Unionization, on the other hand, increases the total days lost due to absenteeism.

Les prédicteurs d'absentéisme: résultats à partir de la méthode des moindres carrés, de la régression de rangs, et de la procédure de sélection de modèle. Ce document examine les déterminants de l'absentéisme en utilisant la méthode des moindres carrés ordinaires, les régressions de rangs, et la procédure de sélection de modèle. Les résultats montrent que les caractéristiques personnelles sont les déterminants les plus importants des absences prolongées. Pour ce qui est du total des journées de travail perdues, les facteurs de pénalisation sont les prédicteurs les plus significatifs. Les résultats montrent aussi que l'absentéisme tend à être plus faible dans le groupe de firmes qui a le plus de travailleurs à temps partiel. La syndicalisation, d'autre part, accroît le nombre de journées de travail perdues par absentéisme.

I. INTRODUCTION

Evidence from several countries suggests that absenteeism is a serious economic problem. For example, Hedges (1977) found that the percentage-hours lost due to absenteeism in the United States is about 3.5 per cent, while during the same time period only one-third of 1 per cent of person-hours was lost due to work stoppage. In Canada estimates by Mikalachi and Gandz (1979) indicate that the total person-days lost through absenteeism is about eleven times more than the working days lost due to strike activity. More recent Canadian evidence (Akyeampong 1988)

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shows that in 1987 2.9 million employees were off work in an average work week. This translates into a reduction of the Canadian labour force potential by 11.71 per cent, or 53.4 million hours. Doherty (1979) reports similar results for the United Kingdom, where 300 million working days are lost annually because of certified incapacity for work in contrast to only about 8 million working days lost because of industrial disputes.

In spite of the magnitude of the financial costs associated with absenteeism, very few have done economic studies in this area.[1] Those who have done so include Allen (1981), Doherty (1979), Leigh (1983), and Winkler (1980). As noted by the latter, the lack of economic research on absenteeism may have been caused largely by the paucity of readily available data. It is also worth noting that none of these economic studies used Canadian data.

To date, Canadian studies on absenteeism have been undertaken mainly by business faculty. Some focused on the magnitude of the absenteeism problem (Mikalachi and Gandz 1979; Robertson 1979) while others have attempted to identify the factors that cause the problem. Baba (1990), for example, found that the number of children, comparative absence, job involvement, and stress have significant effects on absenteeism, and Hackett et al. (1989) identified ill health and tiredness as possible causes of absences among nurses. Ng (1989), on the other hand, estimated a significant relationship between sick-leave policies and absenteeism. At a more theoretical level, Nicholson and Johns (1985) examined the possible influence of absence culture and psychological contract on absenteeism.

The purpose of this paper is to propose an empirical model of absenteeism based upon a variant of the work-leisure model developed by Allen (1981) and to test the proposed model using Canadian firm-level data. The study contributes to existing economic research on absenteeism in a number of ways. First, our data cover an entire year in contrast to the two-week periods of Allen (1981) and Leigh (1983). Allen (1981, 86) recognizes that a too-short period of survey may contain high transitory components, which in turn may reduce the reliability of the results. Our results are thus expected to gain some reliability.[2]

Second, this study attempts to identify the causes of interfirm variation in absenteeism. With the exception of Ng (1989), previous Canadian empirical studies have focused on absence-inducing factors across individuals. Third, our study examines the absenteeism effect of several characteristics of the firm, which previous economic studies did not consider. These are the proportion of part-time workers, the frequency of overtime work, and whether the firm is non-profit. The rationale for including these characteristics is discussed later in the paper.

Fourth, in an attempt to distinguish between short-term and long-term absences, we seek to identify whether person-days lost per employee and the frequency of

1 Applied psychologists, however, have taken great interest in studying this problem, attempting to identify the interaction between absenteeism and various measures of job satisfaction. For an excellent review of this literature see McShane (1984).

2 Although Winkler (1980) used annual absenteeism data, the study was restricted to school teachers. Doherty (1979) also used annual data, but they were aggregated at the national level.

absences exceeding five days are affected by similar factors. A preferred alternative would have been to separate person-days lost due to short-term absences (less than five days in our case) from the person-days lost due to longer- term absences (defined as those exceeding five days). Such categorization was not feasible, however, since very few firms in our sample maintained this type of data.

Finally, in the area of statistical techniques, we use non-parametric regression together with the conventional ordinary least squares (OLS) regression. Since non-parametric regression is a rank-based method, its results are less vulnerable to extreme influences (which are more likely in small samples) and violations of the distributional assumptions regarding the error term in regression equations. To our knowledge, the application of non-parametric regression is virtually non-existent, except for the study by Ullah (1988).

II. THEORETICAL UNDERPINNINGS

Previous theoretical research in the area suggests that absenteeism can be linked to job satisfaction (Vroom 1964),[3] personal characteristics (Cooper and Payne 1965), health factors (Parkes 1983), absence culture (Nicholson and Johns 1985), and non-work or leisure activities (Allen 1981). In this paper our empirical specification is derived from the latter research, to which we add variables from the other conceptualizations of absenteeism.

To the extent that voluntary absenteeism can be viewed as a form of leisure,[4] the decision regarding whether to be absent from work can be analysed in terms of the conventional work-leisure model. This approach, first developed by Allen (1981), yields the following predictions:[5] (1) The effect of wages on absenteeism are a priori indeterminate because of the income and substitution effects. An increase in wages means both costlier absenteeism (less leisure and thus lower absenteeism) and greater ability to afford absenteeism (more income and thus higher absenteeism). However, if sick-leave pay is available, the substitution is no longer present. In this case the impact of wages will be unambiguously positive.

(2) Non-labour income and absenteeism are positively related, because the latter is perceived to be a normal good. (3) The relationship between scheduled working hours and absenteeism is positive, because with longer working hours, satisfaction derived from an additional unit of leisure time is higher. (4) An inverse relationship between the penalty for absenteeism and the level of absenteeism is anticipated. (5) A negative relationship between work-schedule flexibility and absenteeism is anticipated. When the work schedule is inflexible, it may be more difficult for workers to get time off for non-market activities. Since absenteeism is an alternative way of getting time off, lower work-schedule flexibility is therefore expected to increase absenteeism.

3 Recent reviews, however, have questioned the relationship between job satisfaction and absenteeism (Hackett and Guion 1985).

4 In the present context, leisure is defined to include all activities outside work, ranging from job search to recovery from an illness.

5 For a rigorous treatment of the model see Allen (1981).

From the above predictions, the general formulation for our empirical model can therefore be expressed as

$$\text{Absenteeism} = g(w, \textsc{tw}, P, F),^{6}$$

where W is wages, TW represents the number of working hours, P is the penalty for absenteeism, and F denotes the degree of work-schedule flexibility.[6]

To incorporate the work of other theoretical research in absenteeism, we expand our empirical equation to include job satisfaction and the personal characteristics of the workers. An inverse relationship between job satisfaction and absenteeism is expected, because of the tendency for individuals to avoid obligations they find dissatisfying (Nicholson and Johns 1985).

The effect of personal characteristics has been examined in a multitude of studies (Allen 1981; Leigh 1983; Winkler 1980), and in this paper we propose to examine three such characteristics, including sex, age, and education. From the literature on quits, it is hypothesized that females are more prone to quit because they have relatively weak attachments to their jobs (Viscusi 1980). Extending this argument to absenteeism, one would therefore expect females to have a higher level of absenteeism than their male co-workers. Further support for this hypothesis can be found in Leigh (1983), who found that females are more sensitive to absence-inducing events such as lack of sleep. Similarly, Youngblood (1984) showed that females are more likely to take time off for illnesses.

The age profile of employees may be viewed as a proxy for the health of the employees as well as for the working conditions in the organization (Leigh 1983). On one hand, firms with older employees are more likely to experience higher absenteeism because of health-related problems. On the other hand, it may be argued that older employees tend to enjoy more pleasant working conditions. Since the latter are inversely related to absenteeism (Farrel and Stamm 1988), older employees are less prone to absences. Because of these conflicting arguments, the relationship between absenteeism and age is indeterminate.

The last personal characteristic included in the analysis is the education level of the employees. In general, more educated employees are less likely to work in injury-prone jobs. Following the posited relationships between health factors and absenteeism (Parkes 1983); Hackett et al. 1989), it therefore follows that more educated employees are less absence prone. In addition, it may be argued that these employees have more autonomy at work and more involvement in their jobs. Since these work facets are associated with lower absenteeism rates (Baba 1990), one would anticipate further reduction in absenteeism among educated employees.

6 Non-labour is excluded from the estimating equation because the unit of observation of our sample is the firm instead of the individual worker.

III. THE OPERATIONAL MODEL

From the previous section we propose an estimating equation of the following form:

$$\text{Absenteeism} = a_0 + a_1\text{AVEWAGE} + a_2\text{OTDUM} + a_3\text{PTPROP} + a_4\text{UNPROP} + a_5\text{SWDUM} + a_6\text{SCOSTDUM} + a_7\text{LOFFPROP} + a_8\text{FEMDUM} + a_9\text{AGEPROP} + a_{10}\text{DEGPROP} + a_{11}\text{UMDUM} + a_{12}\text{PUBDUM}.^7$$

As discussed earlier, the expected sign for the wage variable (AVEWAGE) is ambiguous. However, if sick-leave pay is controlled for, then the anticipated sign for AVEWAGE is positive.[7]

The sign for the overtime variable (OTDUM) is expected to be positive. In organizations where overtime is common, employees face longer working hours (by definition) and less work-schedule flexibility. The income-leisure model would predict higher absenteeism rates for such firms. On the other hand, firms with more part-time employees (PTPROP) are expected to experience lower absenteeism levels for the following reasons. First, part-time workers have fewer scheduled working hours[8] and would therefore derive less satisfaction from an additional unit of leisure time obtained through absenteeism. Second, these workers have greater work-schedule flexibility[9] which therefore makes it unnecessary for them to resort to absenteeism to pursue non-market activities. Third, part-time workers have less job security and thus face a greater penalty for not showing up to work when scheduled.

The availability of shift work can be viewed as a proxy for work-schedule flexibility, since it allows workers to substitute between shifts to attend non-market activities. Thus, in firms where shift work is common (SWDUM), employees are less likely to resort to absenteeism to pursue non-work activities. These firms are therefore expected to have lower abesenteeism rates.

It is anticipated that the union variable (UNPROP) will be positively related to absenteeism. Union workers are generally better protected against disciplinary action than non-union workers. In other words, in a union environment sanctions for absenteeism have less serious consequences and are therefore less of a deterrent against abuses in absenteeism.[10] In addition, given the well-known inverse relationship between job satisfaction and unionization (Smith and Hopkins 1979; Gordon

7 The definitions, means, and standard deviations are presented in table 1.

8 Another possible proxy for the number of scheduled work hours is the standard number of working hours in a given day. In our sample we observe little variation across organizations in terms of the number of hours in a typical work shift. Hence, we do not use this proxy.

9 In the light of our discussion on overtime and part time as proxies for work-schedule flexibility, one would expect the correlation between the variables OT and PT to be negative. In our sample we observe the correlation coefficient to be -0.17. Positive correlation between OT and PT is possible, however, if organizations have both seasonal sales and a seasonal production schedule.

10 It may be argued that unions will have their own disciplinary measures for members who are prone to absenteeism in order to protect the image of the majority of workers who go to work regularly (Allen 1981, 81). Although lower absenteeism may result, such effects are not likely to dominate: if union-imposed penalties are greater, workers will have less incentive to become union members.

and Long 1981), it can be argued that job dissatisfaction among union workers is another reason why they are more absence prone than their non-union counterparts.

To measure further the extent of the sanctions for absenteeism, we introduce a sick-leave policy variable (SCOSTDUM) indicating loss of pay for those not showing up to work when scheduled. Obviously, where such a policy is in effect,[11] absenteeism will be lower than in firms where the penalty for absenteeism is negligible.

A lay-off variable (LOFFPROP) is included in the estimating equation for several reasons. Lay-offs can be viewed as a proxy measuring the penalty for absenteeism. During periods of high lay-offs, workers have (by definition) less job security. Now, to the extent that employers may use absenteeism as a criterion for deciding who are to be laid off, poor economic times are associated with a high penalty for absenteeism. During periods of lay-offs workers would therefore be less willing to take unscheduled time off from work (Doherty 1979; Hedges 1973). On the other hand, it may be argued that during these times workers are more dissatisfied with their jobs because of the uncertainty generated by the lay-offs. Consequently, they can become more absence prone (Hedges 1973). Furthermore, in anticipation of pending lay-offs, workers may use absenteeism to carry out their job search activities. Because of these conflicting explanations, the impact of lay-offs on absenteeism is therefore indeterminate.

The next three variables in our estimation equation are the personal variables representing, respectively, the sex (FEMDUM), age (AGEPROP), and education of the workers (DEGPROP). From the discussion in the theoretical section, we anticipate female workers to be more absence prone, educated workers less absence prone, and an indeterminate relationship between age and absenteeism.

Job satisfaction is controlled for through the UMDUM variable, and on the basis of studies that have focused on this issue (Vroom 1964) we postulate a negative coefficient for this factor. The last variable (PUBDUM) in the regression equation is included to capture possible absenteeism differentials between profit and non-profit organizations.[12] Since these two types of organizations vary with respect to numerous organizational characteristics, we do not hypothesize any a priori sign for the PUBDUM variable.

Robertson (1979) argues that it is desirable to distinguish between long-term and short-term absences because the latter are generally voluntary and controllable, while the former are usually involuntary. To shed some light over this distinction, we use two competing measures of absenteeism: (1) the number of person-days lost due to absenteeism per employee per year (TOTAL), and (2) the number of absences exceeding five consecutive working days per employee per year (5DAY).

11 This would include those firms with no paid sick-leave days, those with no payment for one-day absences, and those paying for sick-leave days on the basis of seniority.

12 The non-profit organizations in our sample include government departments, hospitals, and school boards. About one-third of our sample organizations belong to this category (see table 1).

IV. DATA COLLECTION AND DESCRIPTIVE STATISTICS

To generate the data for this study two questionnaires were developed.[13] The first questionnaire (A) was designed to obtain general information about the nature of the firm, the existing sick-leave policies and management's perception about the employee-employer relationship. The second questionnaire (B) was designed to obtain detailed statistics regarding wages and salaries paid, the personal characteristics of the employees, and the magnitude of absenteeism and quit rates over the last fiscal year.

After the questionnaires were developed, eighty organizations from Saskatoon, Saskatchewan, were randomly selected from the *Saskatoon Personnel Directory* and the *Saskatchewan Manufacturers' Guide.* These organizations were first contacted by letter requesting their participation in the survey, followed up by a telephone call to the personnel managers.[14] An additional thirty firms from the *Guide* and the *Directory* were later contacted, and, in total, sixty-three organizations indicated their willingness to participate in the survey. An interview arrangement was then made with each of these firms. All interviews were conducted using questionnaire A and at the end of each interview, the interviewee was given questionnaire B to fill out and return by mail at a later date.

Of the organizations interviewed, fifty-six returned the second (B) questionnaire. Nine organizations were excluded because of improper coding and another fourteen were excluded because of missing data on five-day absences. We were thus left with a sample size of thirty-three organizations. A descriptive overview of the sample organizations suggests that a very broad spectrum has been covered. The size ranges from eighteen to 2,719 employees, with an average of 471. Fourteen organizations were not unionized, and the unionized work force varies from 23 to almost 100 per cent among the remaining nineteen organizations. About two-thirds of the organizations were from the private sector.

Table 1 provides some descriptive statistics about the sample. In our sample a firm lost an average of 6.22 working days per employee per year. Of this figure, more than 11 per cent is due to longer-term absences.[15] The variability across organizations is quite high in terms of both standard deviation and range, indicating the need and the opportunity to find the impact of firms' characteristics on absenteeism.

Overtime and shift work seems to be widespread in our sample. Nearly 70 per cent of the firms reported overtime work to be quite common, and 67 per cent reported the same regarding shift work. When it comes to the part-time work force, a typical organization hired only 3 per cent of its employees on a part-time

13 These questionnaires are available upon request.

14 Two government organizations from Regina, Saskatchewan, learned about the survey and called us to express their interest in participating in the survey. They were subsequently added to the original list.

15 On average, an organization lost over 0.7 days (0.14 times five days) owing to long-term absences. This is 11 per cent (0.7 days / 6.22 days) of the average number of working days lost due to absenteeism per employee.

TABLE 1

Definitions, means, and standard deviations of absenteeism and the explanatory variables

Variable	Definitions	Mean	Standard deviation
TOTAL	No. of working days lost per employee per year	6.216	4.563
5DAY	No. of five-day absences per employee per year	0.138	0.097
AVEWAGE	Total wage payments per employee	22,330	7,705
OTDUM	= 1 if overtime is common	0.697	0.467
PTPROP	Per cent of part-time employees	11.880	18.420
UNPROP	Per cent of unionized employees	45.580	41.920
SCOSTDUM	= 1 if absenteeism is costly	0.182	0.392
LOFFPROP	Proportion of employees laid off	0.029	0.088
SWDUM	= 1 if shift work is common	0.667	0.479
FEMDUM	= 1 if <10 per cent females employed	0.152	0.364
AGEPROP	Proportion of employees over fifty	13.670	13.210
DEGPROP	Proportion of employees with university degree	22.670	23.250
UMDUM	= 1 if union-management relationship is perceived to be good	0.637	0.489
PUBDUM	= 1 if firm is non-profit	0.333	0.000

basis.[16] The standard deviation and the range of the lay-off proportion variable (LOFFPROP) show that in specific cases, lay-off might have been a major problem. In about one-fifth of our sample organizations an employee had to lose some pay for taking sick-leave. The employee-employer relationship, in general, seemed to be satisfactory as viewed by management.

Regarding the demographic characteristics, 15 per cent of organizations had less than 10 per cent female employees. An average organization had about 14 per cent older (fifty years or more) employees. The education level of employees seems to be quite irregular across our sample organizations. In a typical (median-wise) organization 15 per cent of the employees had a university degree. However, the evidence ranges from zero to 75 per cent of employees having a university degree.

Overall, our sample firms are unionized with satisfactory union-management relationships and have overtime and shift work but not part-time, lay-off, and pay loss for sick-leave as common practices. They tend to have a well educated labour force and are well-represented by females and older employees. This average picture, of course, is overshadowed (perhaps desirably so) by significant variability in absenteeism experience and the potential factors affecting absenteeism.

V. METHODOLOGY

To estimate the determinants of absenteeism, we have adopted the following estimation procedures: ordinary least squares (OLS), non-parametric or rank-based re-

16 The distribution of the part-time proposition (PTPROP) variable seems to be skewed to the right. For this reason we chose the median value to describe the typical firm.

gression, and model selection. The last two estimation procedures are employed because of the modest ($N = 33$) size of our sample. Because they are relatively unknown among non-econometricians, some descriptions of these procedures are provided below.

1. Rank-based regression

The ordinary least squares regression method produces coefficient estimates by minimizing the sum of squared residuals. The latter, in turn, can be expressed as a weighted sum of errors of the regression equation, with the weights depending upon the regressor *values*. These estimates can therefore be seriously affected by extreme sample observations in the regressand and/or regressor values. The problem of extreme influences is potentially serious in our case because of the modest size (thirty-three) of our sample. Also, the conventional t-tests and F-tests assume multivariate normality for the error vector in the regression equation. This is not necessarily a reasonable assumption in a small sample case, thus making conclusions based upon these tests suspect.[17] For these reasons, we employ a non-parametric regression method called rank-based regression.[18]

Rank-based regression minimizes a linear function of the residuals with weights depending upon the *ranks* of the residuals. Because this technique is rank based as opposed to value based, it is relatively insensitive to extreme data points. In other words, coefficient estimates generated from this technique are less influenced by extreme values in the sample.

To generate the estimates from this procedure, we use the rank regression facility of the statistical software MINITAB. Several points need to be discussed here. First, since the ranks are invariant to a constant shift, there is no natural interpretation of the estimated intercept term in the regression equation. Depending on whether or not the distribution of the error term is assumed to be symmetric, the estimate of the intercept term will differ. We use the default assumption in MINITAB; viz., the error distribution is symmetric.[19]

Second, because rank regression does not deal with squared variations and the estimated regression equation is not designed to pass through the point of sample means (for the regressand and regressors), it does not produce statistics such as R^2. Third, in rank regression all hypothesis testing is done in the form of testing restrictions. That is, the significance of an individual regressor is evaluated by testing the restriction of setting its coefficient to zero. Of the two alternatives available in MINITAB to test restrictions we chose the default, which is based upon the reduction in dispersion due to fitting the full model instead of the reduced model specified by the null hypothesis of restriction.[20]

17 Both the t- and F-distributions are parameterized by a modest number of parameters. This is why these tests are known as parametric tests.

18 For an extensive discussion on the rank-based regression method see Hettmansperger (1984).

19 Thus, our intercept estimate is the median of the Walsh averages of residuals. Given a random sample $x_1, x_2, \ldots x_n$, the $n(n+1)/2$ Walsh averages are defined by $(x_i + x_j)/2$, where i is less than or equal to j.

20 The test has a limiting F-distribution and the MINITAB default calculates the F-statistics as follows:

2. Model-selection procedure

Because the number of predictors in our estimating equation is large relative to the sample size, our results may suffer from the potential problems of lower precision and reduced economically meaningful explained variations (Judge et al. 1985; Kennedy 1985). It may be desirable, therefore, to use a subset of predictors instead of the full set to explain variations in absenteeism. Given that there are twelve predictors, we are thus faced with a total of (two^{12})4,096 possible sets of predictors. The issue then is to determine which of these subsets best predicts absenteeism. This is essentially the widely researched econometric problem of model selection.

Some of the commonly used procedures in model selection include forward selection, backward elimination, and stepwise regression. However, because these methods tend to select sets of predictors that are relatively uncorrelated, they may lead to biased coefficient estimates (Kennedy 1985). Furthermore, these methods do not explicitly consider the losses associated with choosing an incorrect model. For these reasons, we chose two alternative selection rules: the Akaike Information Criterion (AIC) and the Schwartz Criterion (SC). Both are based upon specific loss functions couched in terms of maximum likelihoods, and both penalize models (or subsets) for too many predictors and/or distance from the true model (Judge et al. 1985; Amemiya 1980).

To generate the best subset of predictors based on the above criteria, our model-selection procedure involves the following steps. First, for a given set of K_1 predictors we maximize the likelihood of function (in our case minimize error sum of squares) and calculate the log of maximum likelihood. Second, the AIC and the SC statistics are calculated. Third, steps 1 and 2 are repeated for all possible sets of K_1 predictors. Fourth, we choose the set of K_1 predictors with the minimum value for the statistics in question. Fifth, steps 1 through 4 are repeated for all possible values of K_1 (in our case 1 to 12). Sixth, among all sets of predictors derived from step 5 (in our case twelve), we choose the one with the minimum statistics values as the final model.

VI. EMPIRICAL RESULTS

1. OLS Estimates

The OLS regression results for nine different specifications are presented in table 2. First, we discuss the marginal influences of the individual factors in equations (1) through (3), followed by the group influences in equations (4) through (9). The purpose of estimating equations (1) and (2) is to examine whether the estimated coefficients are affected by the addition of the sick-leave variable. Comparing equations (1) and (2), we do not find the marginal influences of wages and other explanatory variables to be affected by the inclusion of the sick-leave policy variable, except for the drop (but not loss) in significance for the part-time (PTPROP) and

$((D_1 - D_2)J)$ (TAU/2), where D_1 is the dispersion of the reduced model, D_2 is the dispersion of the full model, J is the number of restrictions, and TAU is the scale estimate based on the length of the one-sample Hodges-Lehman 90 per cent confidence interval for location applied to the uncentred residuals of the full model.

unionization (UNPROP) variables. Our result therefore does not support the notion that with paid sick-leave the income effect will dominate the substitution effect, so that a wage increase will unambiguously lead to higher absenteeism. This finding is consistent with that of Allen (1981).

The estimates of equation (2) imply that wage (AVEWAGE), part-time (PTPROP), unionization (UNPROP) and employee-employer relationship (UMDUM) seem to matter for total working days lost. The estimated coefficient of AVEWAGE implies a wage elasticity of working days lost per employee close to unity. Given that the average worker takes about 6.22 days off per year, in order to reduce absenteeism per employee by one day the employer will have to increase annual wages by about 16 per cent, which, evaluated at the mean value of the sample, amounts to roughly \$3,600.

The elasticity of working days lost with respect to part time is about 0.2. This means if the average organization increases the percentage of part-time employees from 11.88 per cent to 23.76 per cent, it would be able to reduce the average absenteeism (working days lost per employee) by 1.25 days from a level of 6.22 days. Whether increasing the part-time proportion of employees is a viable strategy for controlling absenteeism, however, would depend upon the potential costs of doing so.

The elasticity of working days lost with respect to unionization is about 0.38, which translates into an average absenteeism rising to 6.45 days from 6.22 days for a 10 per cent increase in the degree of unionization. The elasticity of the employee-employer relationship variable, evaluated at the point of means, is estimated at 0.47.

Turning to the estimates for long-term absences (equation (3)), we find that two previously significant variables, representing wages and unionization, drop in significance. On the other hand, education attains significance. The other two personal attributes, namely sex and age, do not seem to matter, thus corroborating the findings of Allen (1981).

Overall, the explanatory power of our estimated equations seem reasonable, given that our regression is cross sectional. All the adjusted R^2s for equations (1) through (3) are greater than 40 per cent, and all these regressions are significant at the 1 per cent level. The estimations also appear to be clean in the sense that we were not able to detect any significant heteroscedasticity or multicollinearity problems.

Equations (4) through (6) are restricted versions of equation (2), and equations (7) through (9) are restricted versions of equation (3). The lists of regressors included in these restricted versions correspond to some broad groups of factors cited previously in the literature, namely, work schedule flexibility (equations (4) and (7), penalty for absenteeism (equations (5) and (8)), and personal attributes or demographic profile of employees (equations (6) and (9)). Our purpose in estimating the group equations is threefold: (a) to see if there is any change in the sign and statistical significance of the slope coefficients; (b) to have a general impression about the explanatory power (and importance) of the groups of factors; and (c) to see if the explanatory power (and importance) of groups change once we consider the longer-term absences.

TABLE 2

Ordinary least squares regression of the measures of absenteeism on the factors under consideration (standard error in parentheses)

Equation: Dependent variable:	1 TOTAL	2 TOTAL	3 5DAY	4 TOTAL	5 TOTAL	6 TOTAL	7 5DAY	8 5DAY	9 5DAY
Regressors	Coefficients (*t*-statistics)***								
CONSTANT	11.375**	12.450**	0.302**	4.038**	4.128**	5.744**	0.119**	0.094**	0.129**
	(2.83)	(2.79)	(0.06)	(1.65)	(1.20)	(1.80)	(0.04)	(0.03)	(0.03)
AVEWAGE	$-2 \times 10^{-4*}$	$-3 \times 10^{-4*}$	-3×10^{-6}	–	–	–	–	–	–
	(0.1×10^{-3})	(0.1×10^{-3})	(0.2×10^{-5})	–	–	–	–	–	–
OTDUM	0.151	0.797	−0.024	0.196	–	–	−0.019	–	–
	(1.41)	(1.41)	(0.03)	(1.68)	–	–	(0.04)	–	–
PTPROP	−0.122**	−0.109*	−0.002*	−0.060	–	–	−0.001	–	–
	(0.04)	(0.04)	(0.9×10^{-3})	(0.04)	–	–	(0.9×10^{-3})	–	–
UNPROP	0.064**	0.051*	3×10^{-4}	–	0.050*	–	–	$9 \times 10^{-4*}$	–
	(0.02)	(0.02)	(0.5×10^{-3})	–	(0.02)	–	–	(0.4×10^{-3})	–
SCOSTDUM	–	−3.543	−0.075	–	−1.160	–	–	0.003	–
	–	(2.14)	(0.05)	–	(1.95)	–	–	(0.04)	–
LOFFPROP	4.588	10.543	0.247	–	1.216	–	–	0.063	–
	(7.80)	(8.31)	(0.19)	–	(8.64)	–	–	(0.19)	–
SWDUM	2.999	3.813	0.109	4.134*	–	–	0.070	–	–
	(1.85)	(1.84)	(0.04)	(1.62)	–	–	(0.04)	–	–
FEMDUM	1.828	0.758	−0.002	–	–	0.365	–	–	−0.007
	(1.75)	(1.80)	(0.04)	–	–	(2.31)	–	–	(0.04)
AGEPROP	−0.078	−0.061	0.003	–	–	0.090	–	–	0.003
	(0.09)	(0.08)	(0.2×10^{-2})	–	–	(0.10)	–	–	(0.2×10^{-2})

TABLE 2 (*concluded*)

Equation: Dependent variable:	1 TOTAL	2 TOTAL	3 5DAY	4 TOTAL	5 TOTAL	6 TOTAL	7 5DAY	8 5DAY	9 5DAY
Regressors	Coefficients (t-statistics)***								
DEGPROP	−0.002	−0.015	−0.002**	–	–	−0.036	–	–	−0.002*
	(0.03)	(0.03)	(0.8×10^{-3})	–	–	(0.04)	–	–	(0.7×10^{-3})
UMDUM	−3.999*	−3.214*	−0.077*	–	–	–	–	–	–
	(1.48)	(1.50)	(0.03)	–	–	–	–	–	–
PUBDUM	−0.713	−1.701	−0.002	–	–	–	–	–	–
	(1.51)	(1.57)	(0.04)	–	–	–	–	–	–
R^2 (per cent)	66.5	70.5	66.6	22.9	23.7	7.9	14.3	16.2	29.6
Adjusted R^2 (per cent)	49.0	52.9	46.5	14.9	15.9	0.0	5.4	7.5	22.3
F-statistic	3.79	3.99	3.32	2.87	3.01	0.83	1.61	1.86	4.06
Degrees of freedom	11,21	12,20	12,20	3,29	3,29	3,29	3,29	3,29	3,29
P-value (per cent)	0.4**	0.3**	0.9**	5.4	4.6*	48.8	20.9	15.8	1.6**

* P-value is less than or equal to 5 per cent.
** P-value is less than or equal to 1 per cent.

TABLE 3

Non-parametric regression of the measures of absenteeism on the factors under consideration

Equation: Dependent variable:	(1) TOTAL	(2) TOTAL	(3) 5DAY
Regressors			
CONSTANT	9.752	10.951	0.334
	(2.50)	(3.08)	(0.07)
AVEWAGE	-1.6×10^{-4}	-2×10^{-4}	-3.9×10^{-6}
	(0.9×10^{-4})	(0.1×10^{-3})	(2.4×10^{-6})
OTDUM	0.024	0.559	−0.020
	(1.25)	(1.55)	(0.03)
PTPROP	−0.109**	−0.099*	−0.002*
	(0.04)	(0.04)	(0.9×10^{-3})
UNPROP	−0.058**	−0.049*	2×10^{-4}
	(0.02)	(0.02)	(0.5×10^{-3})
SCOSTDUM	–	−2.513	−0.013
		(2.36)	(0.05)
LOFFPROP	4.588	8.558	0.219
	(6.91)	(9.16)	(0.20)
SWDUM	2.563	3.426	0.013
	(1.64)	(2.03)	(0.04)
FEMDUM	1.399	0.699	−0.013
	(1.55)	(1.98)	(0.04)
AGEPROP	−0.055	−0.039	0.003
	(0.08)	(0.09)	(0.2×10^{-2})
UMDUM	−3.641*	−2.882	−0.083*
	(1.31)	(1.65)	(0.04)
DEGPROP	−0.004	−0.009	0.003**
	(0.03)	(0.04)	(0.8×10^{-3})
PUBDUM	−0.258	−1.365	−0.002
	(1.34)	(1.73)	(0.04)

* *P*-value is less than or equal to 5 per cent.
** *P*-value is less than or equal to 1 per cent.

As indicated by the estimates of equations (4) through (6), only the penalty group has a significant influence on total working days lost. Work-schedule flexibility and the personal attributes of the employees do not matter. Moving from TOTAL to 5DAY, the penalty group loses its explanatory power, while the personal attributes attain statistical significance.

In general, the directions of the influences are quite stable. However, since the factors gain some significance when we consider the groups as opposed to the full set of factors, this suggests a weak omitted variable effect in equations (4) through (9). Because of this potential problem we proceed to test the significance of the groups via testing restrictions on the respective sets of coefficients in equations (2) and (3). For example, to determine whether penalty significantly affects absenteeism, we conduct an *F*-test of restrictions that all the coefficients of the variables UNPROP, SWDUM, and LOFFPROP in equation (2) are equal to zero. Notice that since

TABLE 4

Parametric and nonparametric tests of the significance of groups of factors affecting absenteeism

A. F-test based upon restricted least squares regression			
Name of the groups of factors whose coefficients are restricted to zero	Work schedule	Penalty	Personal attributes of employees
Factors	OTDUM PTPROP SWDUM	UNPROP SCOSTDUM LOFFPROP	FEMDUM AGEPROP DEGPROP
	F-statistic $F_{3,20}$	$F_{3,20}$	$F_{3,20}$
Measures of absenteeism			
Equation (2): TOTAL	3.97*	5.79**	0.30
Equation (3): 5DAY	2.08	1.98	3.82*
B. F-test based upon restricted non-parametric regression			
Name of the groups of factors whose coefficients are restricted to zero	Work schedule	Penalty	Personal attributes of employees
Factors	OTDUM PTPROP SWDUM	UNPROP SCOSTDUM LOFFPROP	FEMDUM AGEPROP DEGPROP
	F-statistic $F_{3,20}$	$F_{3,20}$	$F_{3,20}$
Measures of absenteeism			
Equation (2): TOTAL	3.01	4.81*	0.13
Equation (3): 5DAY	2.55	2.54	4.79*
Critical value $F_{3,20}$ (5%) = 3.0984	Critical value $F_{3,20}$ (1%) = 4.9382		

* *P*-value is less than or equal to 5 per cent.
** *P*-value is less than or equal to 1 per cent.

this test rests upon a regression involving the full set of factors, misspecification is no longer an issue.[21]

The results are presented in panel A of table 4. The subgroups of work-schedule flexibility and penalty now come up with a relatively stronger showing and are significant in the case of total working days lost. They lose their significance in explaining longer-term absences, however, while the personal attributes group becomes statistically significant. These results are therefore consistent with the basic findings of the group equations of table 2.

2. *Non-parametric estimates*

We re-estimated equations (1), (2), and (3) of table 2 using rank-based regressions,

21 There is marginal gain in including the sick-leave policy variable as the adjusted R^2 moves from 49 per cent to 53 per cent.

and the results are presented in table 3. Overall, the results are comparable to the least square estimates. The estimated signs of the rank-based coefficients are similar to those of the OLS results, and except for the wage variable, the statistical significance of the variables is also similar. The regression results suggest that firms with more part-time employees and a good employer-employee relationship tend to experience lower absenteeism. Unionization has a positive impact on total person-days lost but no effect on the frequency of long-term absences. The education level of the workers, on the other hand, reduces the frequency of long-term absences.

The results of the group tests are presented in panel B of table 4. The main change from the OLS-based test of restriction results is the loss of significance of work-schedule flexibility in determining total working days lost. The significance of penalty in determining working days lost and of personal attributes in affecting long-term absences, however, are consistent with the OLS estimates.

3. Model-selection results

With regard to the model-seletion procedure results, we estimated 4,096 equations for each dependent variable and calculated the corresponding AIC and SC statistics values. Although for a given number of K_1 predictors both criteria yield the same selection, the global choice of SC includes one less predictor than that of AIC. Except for the extra predictor, the global choices of the two criteria give us the same set of predictors.[22]

The OLS results based on the SC criterion are presented in table 5.[23] For TOTAL the best model is a five-predictor model consisting of the wage, part-time, union, shift work, and employee-employer relationship variables. For 5DAY, the best model is one with six predictors including the part-time, costly sick-leave, lay-off, age, university degree, and employee-employer relationship variables.

The results of table 5 are quite consistent with the OLS estimates of the full set of factors (equations (2) and (3), table 2). With regard to TOTAL, the selection procedure chooses five predictors of which four are found to be statistically significant in the full-specification estimation. In a sense, then, the latter has quite accurately identified those factors that matter the most. Also, notice that neither result found any significant relationship between personal attributes and total absenteeism. Turning to 5DAY, the reduced model produces slightly more significant variables than the full model, but the more important point here is that one of the two variables gaining statistical significance is a personal attribute variable (AGEPROP). This in effect reinforces the main result of the full-specification model, namely, that for long-term absences, the personal attributes matter the most. Thus, in spite of our modest sample size and large number of predictors, the OLS results of the full model are quite stable.

22 For TOTAL the extra AIC predictor is SCOSTDUM, while for 5DAY it is AVEWAGE. Neither variable, however, is significant in the corresponding estimated equations.

23 The results of the AIC criterion are very similar to those of the SC criterion. It is for this reason that we have chosen to discuss only the results of the SC criterion.

TABLE 5

OLS results: factors chosen according to the Schwartz Criterion of model selection

	TOTAL	5DAY
CONSTANT	10.760**	0.0225**
	(2.078)	(0.045)
AVEWAGE	-0.221×10^{-3}*	–
	(0.8×10^{-4})	
PTPROP	−0.122**	-0.2×10^{-2}*
	(0.03)	(0.7×10^{-3})
UNPROP	0.61×10^{-1}**	–
	(0.02)	
SWDUM	2.37	–
	(1.34)	
UMDUM	−3.94**	-0.8×10^{-1}**
	(1.18)	(0.03)
SCOSTDUM	–	-0.76×10^{-1}*
		(0.03)
LOFFPROP	–	0.298
		(0.03)
AGEPROP	–	0.4×10^{-2}*
		(0.2×10^{-2})
DEGPROP	–	-0.3×10^{-2}**
		(0.6×10^{-3})
Adjusted R^2	0.56	0.51
F-statistic	9.11	6.5
Degrees of freedom	5,27	6,26
P-value (per cent)	0.0**	0.0**

* P-value is less than or equal to 5 per cent.
** P-value is less than or equal to 1 per cent.

VII. CONCLUSION

The purpose of this paper has been to identify factors that affect absenteeism across a sample of thirty-three Canadian firms. Owing to the modest size of our sample, the OLS regression procedure may not be appropriate, because the resulting estimates can be quite sensitive to large outlier values. As a check against the stability of our OLS results, we introduced estimates from rank-based regression and model-selection procedures. These two techniques are less vulnerable to extreme values and are therefore useful in small sample studies. To the best of our knowledge, there has been to date no empirical study in the social sciences literature that has used rank-based regression.

The results of the three estimation procedures are quite comparable, which therefore suggests that at least for our sample the outlier problems were not serious. In other words, our OLS estimates are quite stable in spite of our modest sample size. For this reason, the remainder of this paper will be based upon the OLS estimates.

Both counting the number of statistically significant variables and a comparison of the R-squared values indicate that our model explains total absent days better than long-term absences. In a sense, this is not a totally unexpected result, since long-term absences are usually considered to be beyond the short-term control of both the firm and the workers (Robertson 1979). This type of absenteeism can therefore be perceived to be the result of ill health and/or job-related injuries. These two factors have not been captured in the estimating equation, thus possibly explaining the relatively poor showing of the 5DAY results.

Turning to the individual variables, the results suggest that firms with more part-time employees and those with a satisfactory employee-employer relationship tend to have less absence-prone employees. It is well known that, given a choice, firms would prefer to hire part-time rather than full-time employees, and the usual explanation is that such a strategy would provide the firms with greater flexibility in dealing with a changing economic environment (Barkin 1987). Our results provide an additional explanation for this choice, namely, that the employment of part-time workers can be associated with lower absenteeism and related costs.

The regression results also indicate that high-wage firms and non-union firms experience fewer days lost due to absenteeism, while firms with more degree holders tend to have fewer five-day absences. The estimated inverse relationship between wages and absenteeism suggests that the substitution effect of a wage increase dominates the income effect. Existing evidence on this particular issue is inconclusive. Allen (1987) found a similar pattern, Winkler (1980) came up with the opposite result, and Doherty (1979) failed to find any statistical significance between absenteeism and income. Further research is clearly warranted here before we can unambiguously determine the direction of causation.

Unionization is found to increase total absent days but has no influence on long-term absences. This finding is consistent with the notion that the latter is uncontrollable and is not subject to abuses by the workers. Thus, although unions can shield the workers from sanctions against absenteeism, this fact would not induce the workers to take more five-day absences; such protection, however, does encourage the workers to take more short-term absences.

The results of the group tests indicate that total person-days lost and long-term absences are influenced by different factors. The penalty group appears to be the most significant predictor of total person-days lost, whereas long-term absences are affected primarily by the personal attributes of the employees. This finding provides further support for the view that at least in the short run there is not much that firms can do to reduce long-term absences. Increasing the penalty against absenteeism, however, would have an impact on short-term absences. It therefore follows that before any attempt is made to reduce absenteeism, firms must keep track of the type of absenteeism they are faced with.

It should be pointed out that the above results are subject to a number of limitations. First, while every possible attempt was made to generate a random sample, there is no guarantee that this is the case. For example, those firms that chose to participate may have done so only because they consider absenteeism an important problem. A sample selection bias may thus be present in our study, given that only 30 per cent of firms contacted participated in the survey.

TABLE 6

Two-stage least square estimates of TOTAL

	Specification 1[a]	Specification 2[b]	Specification 3[c]
CONSTANT	3.86	−48.69	10.03
	(8.88)	(744.35)	(8.58)
AVEWAGE	0.60×10^{-4}	0.25×10^{-2}	-0.25×10^{-3}
	(0.3×10^{-3})	(0.03)	(0.3×10^{-3})
PTPROP	-0.62×10^{-1}	0.41	−0.12
	(0.08)	(6.70)	(0.08)
UNPROP	0.50×10^{-1}	0.39×10^{-2}	0.56×10^{-1}
	(0.03)	(0.59)	(0.03)
SWDUM	1.78	−4.93	2.64
	(1.66)	(100.82)	(1.42)
UMDUM	−2.74	−2.74	−2.77
	(5.53)	(26.11)	(4.55)

a In specification 1, the exogeneous variables are PTPROP, UNPROP, SWDUM, OTDUM, and SCOSTDUM.
b Specification 2 is similar to specification 1, except that SCOSTDUM is replaced by FEMDUM.
c Specification 3 is similar to specification 2, except that FEMDUM is replaced by DEGPROP.

A second problem is that the data are generated on the basis of responses reflecting the viewpoint of the employer. Thus, while the latter may perceive the employee-employer relationship to be good, the employees may think otherwise. The estimated results with respect to our variable UMDUM should therefore be interpreted with care. A related problem is that the absenteeism data are based upon self-reports by the firms. It is therefore quite possible that the data collected are personal estimates of absenteeism instead of actual attendance records, especially regarding long-term absences.

Finally, it should be noted that the potential reverse causality problem may exist in the specified regression equations. For example, while wages should affect absenteeism, it is also possible that absenteeism may adversely affect wages. Similarly, management's perception about the employee-employer relationship may also be affected by the level of absenteeism in the firm. The coefficient estimates for AVEWAGE and UMDUM are therefore subject to potential reverse causality biases. Like that of Allen (1981), our attempt to resolve the potential problem between wages and absenteeism using the two-stage least squares procedure (2SLS) did not prove very successful. In table 6, we report some of the 2SLS estimates of the Schwartz Criterion five-predictor model (table 5) for TOTAL. In specification 1, the set of exogeneous variables includes PTPROP, UNPROP, SWDUM, OTDUM, and SCOSTDUM. In specification 2, SCOSTDUM is replaced by FEMDUM, and in specification 3, FEMDUM is replaced by DEGPROP. As can be seen, the magnitude and significance of the coefficient estimates for TOTAL are sensitive to the set of exogeneous variables used in estimating the 2SLS equation. This sensitivity in the results suggests a potential misspecification problem in the estimating equation for TOTAL, and for this reason the empirical results presented in this study should be treated with caution.

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