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Job satisfaction and employee turnover: A firm-level perspective

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Abstract

In this article I study how companies can use their personnel data and information from job satisfaction surveys to predict employee quits. An important issue discussed at length in the article is how employers can ensure the anonymity of employees in surveys used for management and human resources (HR) analytics. I argue that a simple mechanism whereby the company delegates the implementation of job satisfaction surveys to an external consulting company can be optimal. In the subsequent empirical analysis, I use a unique combination of firm-level data (personnel records) and information from job satisfaction surveys to assess the benefits for companies using data in their decision-making. Moreover, I aim to show how companies can move from a descriptive to a predictive approach.

Keywords

Job satisfaction, Personnel records, quits, retention, survey data

Introduction

When an employee quits, it imposes costs on the organization (Cascio, 2000; Wasmuth and Davis, 1983). The employee has to be replaced and the new employee trained. The quit may also cause significant and costly disruptions to the production process. Hence, irrespective of what is causing the quit,[1] there are clear incentives for the firm to prevent quits, or at least to be able to predict when and where quits can be expected. In this article I evaluate how companies can make use of available data sources (personnel records), and how they can complement these traditional data sources with survey data (such as job satisfaction surveys) to predict employee quits. As such, this study resonates well with the recent human resources (HR) analytics literature as it provides a detailed exam-

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ple of how a company can use data to predict the future within the domain of HR (Fitz-enz, 2010).

In the literature, there have been numerous papers establishing how demographic and firm characteristics influence employee turnover propensities.[2] Researchers have also stressed the close link between employee job satisfaction and firms' ability to retain employees. For example, Clark (2001) uses data from the British Household Panel Survey (BHPS) to show that satisfaction with total pay, job security, ability to work on own initiative, the actual work itself and hours of work leads to fewer quits. The paradox is, however, that while information on job satisfaction at the individual level is available in supplements to representative data sets, such as the BHPS, the National Longitudinal Survey of Youth (NLSY) or the German Socio-Economic Panel (GSOEP), it is not available to decision-makers in companies. Hence, managers cannot use this information to predict quits.

The main reason job satisfaction data (or, more generally, survey data) at *the individual level* are unavailable to managers is that employees are likely to respond strategically if the answers will be used at the individual level. For example, if employees are asked to evaluate their immediate manager, and the answers will be made available to the manager, it is most unlikely that the employees will rate their managers' performances poorly. Argyris (1994) discusses this mechanism in detail and states that a common response to risks and threats is self-protection, which implies a defensive strategy. Hence, our representative data sets allow us to establish the effects of job satisfaction on employee retention, but decision-makers in companies are generally unable to use job satisfaction scores at the individual level in their management of firms.

Nevertheless, many companies conduct employee surveys, and although they are used for multiple purposes, their relevance for predicting employee turnover is apparent. However, the overarching issue which companies have to deal with when conducting such surveys is to be able to elicit useful information, that is ensure that employees tell the truth. If employees answer randomly or strategically in such surveys, the company may at best end up with pages or megabytes of 'noisy information'. Therefore, employers will have to apply a particular mechanism that allows employees to give straight answers, while at the same time preserving their anonymity. One way to do this is simply to have an external consulting company conduct the job satisfaction survey. The consulting company will then provide the firm with information about the job satisfaction scores in an aggregated form, for example the average job satisfaction scores in departments. This approach preserves the employees' anonymity, and managers/employers will never see the original data based on individual answers. Managers can then make decisions based on these average job satisfaction scores, which are valuable, but clearly the average scores are less attractive than the individual scores.

In the first part of this article I provide a detailed discussion of and motivation for the mechanism applied by many firms when they have an interest in obtaining information conveyed in job satisfaction surveys, that is, they delegate the implementation of the survey to an external consulting bureau. A natural starting point is to think about the employment situation in the context of a prisoner's dilemma.[3] The employer and the employees have a common interest in successful implementation of the job satisfaction survey because it contains useful information for managers that will allow them to improve, for instance, their ability to predict quits, and it gives the employees a unique opportunity to provide feedback to managers which in turn may result in better management. The built-in tension resulting from the employees' potential interest in strategic manipulation of answers and the employer's interest in obtaining information about employees at the individual level and not just information in the form of department level averages implies that cooperation regarding implementation of the survey fails in a one-shot game. The only Nash equilibrium is the one where employees bias their answers and firms use the information at the individual level.

Moving slightly away from the simple prisoner's dilemma will allow for cooperation. For instance, in an infinitely repeated game, a simple grim trigger strategy can turn cooperation into a subgame perfect Nash equilibrium. In other words, if the relationship between employers and employees is long-term, an equilibrium outcome can be that employees tell the truth in the survey, and the firm only uses these answers in an anonymized way. This is because the long-term gains from cooperating with respect to the implementation of the survey will exceed the short-term gains from not doing so.

An alternative is to recognize that by delegating the implementation of the job satisfaction survey to an external consulting company, the firm commits itself to maintaining the employees' anonymity. It turns out that this in fact may be a good strategy for the firm. If the workforce is heterogeneous in the sense that a proportion of the employees are 'truth-tellers', that is they will always answer truthfully in survey questions while others may still have an interest in manipulating their answers, the firm (and the employees) will derive utility from implementing the survey.

In the empirical part of the paper, I use detailed firm-level data from a large Scandinavian service provider (2004–2010). The personnel records from the company are complemented with information from employee job satisfaction surveys. As a unique feature, I was able to obtain the individual-level survey data (and thus department-level averages). Hence, in the empirical analysis I aim to shed light on how valuable job satisfaction surveys are for companies and managers. Most importantly, I compare the relative value of having survey information at the individual as opposed to the department level, where the latter typically is the type of information available to companies and managers.

The empirical results show that the job satisfaction survey contains valuable information useful for predicting employee quits. Using only information from personnel records, 92.59% of employees can be correctly classified as either 'quitters' or 'stayers', and the probability to predict quits correctly, given the classification, is 34.29%. When personnel records are complemented with survey information at the department level, the ability to correctly classify the employees is 92.51%, and the ability to predict quits correctly, given the classification, is somewhat higher than before, namely 35.14%. However, when the survey information is used at the individual level, the ability to correctly classify employees is 92.61%, but the ability to correctly predict quits, given the classification, rises to 39.26%. Hence, the ability to correctly classify employees as quitters or stayers is insensitive to whether or not survey data are used, but the identification of quitters, given the classification, improves significantly once information from employee surveys is included in the analysis. This improved ability to predict quits will in turn allow companies to carry out better succession and recruitment planning, and in some cases it may even imply that quits can be prevented.

The remainder of the article is organized as follows: in the following section, a theoretical motivation for why some companies choose to delegate the implementation of job satisfaction surveys to external consulting companies is provided. In the subsequent section, the firm, the personnel records, and the data from the job satisfaction surveys are presented, followed by a presentation of the empirical results. The penultimate section provides a discussion of the results and the final section concludes with the findings.

Theory

In this section, I discuss how the delegation mechanism, namely the company's decision to have an external consulting company conduct the employee job satisfaction survey, can be optimal for the firm, and I derive the pay-offs for the company and the employees.

Conducting an employee survey is costly and time-consuming for both the company and the employees. However, if the company can elicit information about the employees' perception of their work situation and the employees in return receive better working conditions such as better management, there are benefits to both parties from engaging in the survey. Unfortunately, cooperation regarding the implementation of a survey is not a trivial equilibrium outcome, as will become clear in the following. In fact, the only achievable outcome in a 'simple' one-shot game is 'non-cooperation', where the survey is implemented but the information conveyed in the survey is of no value. It turns out, however, that if the firm commits to 'delegation' (i.e. it engages an outside consulting company to conduct the survey), it is possible to elicit important and useful information about the employees' perceived job satisfaction – information which in turn can be used to improve the company's ability to predict employee turnover or as input into other management decisions. While this value to the firm may be reduced somewhat if some employees adopt strategic behaviour in the way they answer the survey, it may not eliminate all benefits.

In order to formally analyse this employment situation, consider the following situation:[4] employees have a choice between telling the truth about their job satisfaction in an employee survey and strategically manipulating their answers. The employer has the choice between using the information from the employee survey at an aggregate level, which preserves the employees' anonymity, and using the information at an individual level, which violates the employees' anonymity.

Let us assume that the pay-off for employees from 'truth-telling' is 3 when the employer uses the data from the survey at an aggregate level that preserves their anonymity. The employees are better off if they manipulate the feedback they give to the employer, that is if they lie, and the employer uses the data at the aggregate level. In this case, the employees can manipulate the employer into improving the working conditions, which results in a pay-off of 4. There is also the option that the employer will use the survey answers at the individual level. If this happens and the employees have told the truth, it may have negative consequences. For instance, if the employees have revealed that they are dissatisfied with their immediate management or that they disagree with the way senior management is running the firm, it could prove harmful to the employees' future in the company. This situation would yield a pay-off of −3. If, however, the answers provided by the employees are biased and they are used at the

		Company	
		Applies survey information at an aggregate level (AL)	Applies survey information at the level of the employees (EL)
Employees	Truth-telling (TT)	3 , 3	− 3 , 4
	Strategic manipulation (SM)	4 , −3	− 2 , − 2

Figure 1. The simple prisoner's dilemma.

individual level, they introduce a lot of noise in the managerial decision-making which, combined with the cost of answering the survey, yields a pay-off of −2.

From the company's perspective, it is valuable when the employees tell the truth in the survey because it allows for better decision-making. When this information is applied at an aggregate level, the pay-off for the firm is 3. If the firm uses the information from the survey at the individual level, it is able to make even better decisions and the resulting pay-off is 4. In contrast, in the very unfortunate situation that the employees strategically manipulate their answers in the survey and the firm uses the information at an aggregate level, the firm would be basing its decisions on false information, and the consequence is a firm pay-off of −3. One example could be that the firm is tricked into spending resources on initiatives that improve the working environment when it is not necessary. Finally, manipulated survey information used at the level of the individual employee yields a pay-off of −2 for the firm.

The pay-offs for the employees and the company are summarized in Figure 1, where the (X,.) reflects the employees' pay-off and the (X,.) the employer's pay-off. This is a standard prisoner's dilemma situation with a unique Nash equilibrium at {SM, EL} resulting in pay-offs of {−2, −2}. In other words, the whole idea of collecting survey information about the employees' job situation is worthless.

Instead of modelling the situation as a one-shot game, it can be more appropriate to think of it as an infinitely repeated game – at least from the company's perspective (the individual employee may have a more short-sighted perspective). In other words, the company has a clear interest in being able to conduct job satisfaction surveys that elicit truthful information about the employees' job satisfaction over the longer term. This is because the company derives some utility from the surveys, even if the survey data are only applicable in an aggregate form that preserves the anonymity of the employees. In the repeated game, a simple grim trigger strategy can be used to implement cooperation in equilibrium. More specifically, cooperation {TT, AL} is a subgame perfect Nash equilibrium (if the discount factor is not too low) when (1) the parties cooperate in the first period and any period t thereafter; (2) the opponent has cooperated in all periods up to period t; and (3) the parties defect in every period following a period during which the opponent defected.

It becomes clear from the aforementioned arguments that a better outcome is achieved if the company and the employees can agree to implement the survey in a way that elicits truthful answers from employees and preserves their anonymity. Repeated interactions are one argument that makes such cooperation possible. While this may work, the set-up is continually challenged by the fact that the parties always have the possibility to defect, and that employees' attitudes may be somewhat short-sighted. For this reason, a second option is often chosen by firms: they have an external consulting company conduct the survey. In turn, the company receives information from the survey in the form of averages and standard deviations at the department level, which preserves the anonymity of the employees. The issue with this strategy is that when applied to our original set-up, where employees have an interest in manipulating the answers they give in the survey, the outcome would be (SM, AL) which yields a pay-off of −3 for the firm.

Nevertheless, the reason why commitment to anonymity (AL) may be optimal for firms is that this initial set-up may be too simplistic and may not resemble the actual working environment in companies. For example, it is easy to imagine that some (if not most) employees will tell the truth when they are asked about their working conditions. This situation is depicted in Figure 2. The company delegates the implementation of the survey to the consulting company. The two employees can then choose whether to tell the truth or manipulate their answers. One employee derives utility from manipulation (Employee 2), the other one does not (Employee 1), which I represent by a pay-off of $-\infty$. The three pay-offs are ordered as follows: (Company, Employee 1, Employee 2).

If the company delegates and employees tell the truth, pay-offs are (3,3,3). If the company delegates, Employee 1 tells the truth, but Employee 2 manipulates, then pay-offs are (2,2,3). In other words, the company benefits from the truthful answers, but as only half of the employees tell the truth, the benefits are lower than in a situation where both employees tell the truth. Similarly, Employee 1 derives utility from the truthful answers and the resulting better management and the pay-off is 2. Employee 2 derives utility from the manipulation, but the manipulation does not have full impact as it is contaminated by the true answers of Employee 1, which then results in a pay-off of 3. The pay-offs for the cases where Employee 1 manipulates answers in the survey are modelled in a similar way, but these are not relevant. Finally, because the company plays a passive role in the solution to this game due to its pre-commitment to delegation, the game can be reduced, which is illustrated in the lower part of Figure 2. From this it becomes clear that Employee 2 is indifferent regarding truth-telling and strategic manipulation, and in both cases Employee 1 and the company derive positive utility from the game. Hence, it pays off for all players to engage in the survey activity.[5]

The above analysis provides motivation for why companies and employees engage in survey activity. In the empirical analysis conducted in the following, I aim to shed some light on how valuable the survey information is for the company by conducting a quit analysis. This is done through an assessment of how well the company can predict quits when applying its conventional data resources (personnel records), and how well the company can predict quits when the personnel records are complemented by information

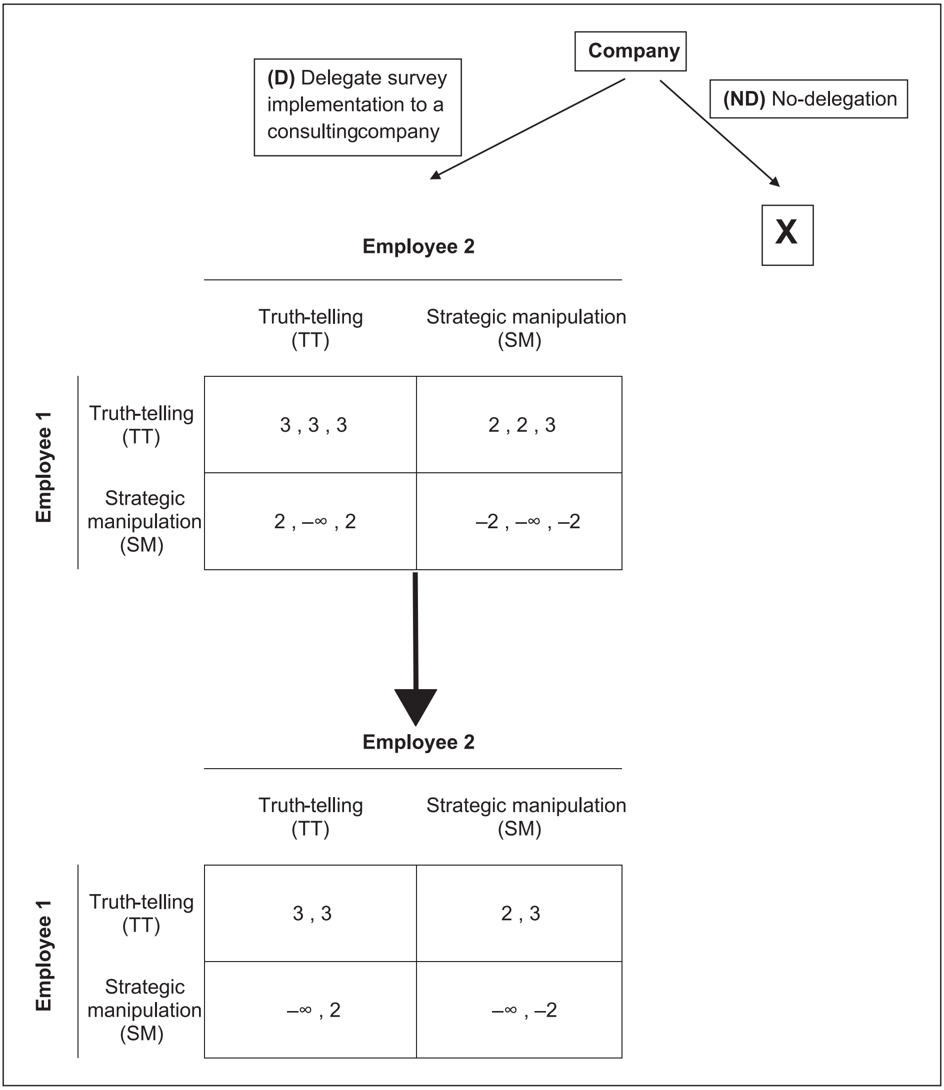

Figure 2. The prisoner's dilemma with delegation and two employee types.

from job satisfaction surveys. I will also shed light on how 'costly' it is for the company to use the survey information in an aggregate form that preserves the anonymity of the employees as opposed to using the information at the level of the individual employee.

The company and data

The company operates in the service sector, and the employees in this firm are predominantly white-collar workers. The firm is organized with headquarters and an extensive branch network, the latter involving close customer contact. The firm is a market leader in the domestic market and has some activities abroad. In this study, I use information about domestic employees. This involves 17,847 unique individuals and 89,077 person-year observations during the period 2004–2010.

The data stem from two sources. The first source is the firm's personnel records. These records contain information about wages, tenure with the firm, and demographic variables such as age and gender. The records also contain information about the employees' job level and department. The second source is an employee survey. The survey is structured around the Nordic Employee Index Model (Eskildsen et al., 2004) and is conducted every year. The survey includes 39 questions covering the following domains: overall satisfaction, loyalty, motivation, salary and benefits, corporate leadership, immediate manager, cooperation, conditions at work, career development and image. Table 6 in the Appendix shows the survey questions.

I restrict the sample by deleting the 2% of employees who are dismissed, as the company has no difficulty in explaining an exit of this type. This results in a sample of 87,237 observations. In regressions, I use a subsample where the first (2004) and the last year (2010) have been dropped. The last year is dropped because it is used to construct the quit variable, that is to assess whether employees working for the company in January in year t also work for the company in January in year t+1. The first year is dropped as the survey is conducted during the period from late September to early October, meaning that I match survey information from year t–1 to the personnel records from January year t when explaining quits between January year t and January year t+1. This results in a 'regression sample' of 62,845 observations. I also use a 'restricted sample', which consists of the subset of employees with full information, that is those who have full information on all personnel variables and who have provided answers to all relevant survey questions. This restricted sample contains 43,637 observations.

I provide descriptive statistics for the three samples in Table 1. In the full sample, the average age is 43.87 years, tenure with the firm is 18.26 years, and 53% of the employees are women. Furthermore, 11% of the employees serve as supervisors, and the employees are organized so that 52% work in the branches, 37% in central staff positions, 6% in market functions, and the remaining employees work in 'other' functions. When comparing this sample to the 'regression sample', there are no discernible differences. In a comparison with the 'restricted sample', which contains information on individuals who have answered all survey questions, it becomes clear that these employees are slightly older than those in the two other samples, they have a longer tenure with the firm, and are more likely to be branch workers.

The personnel records also contain information about the employees' job level and compensation. There are 11 job levels (detailed descriptions are not shown), and in the regressions these will be controlled for through a full set of job-level dummies. I will also follow Card et al. (2012), who show that relative wages are important for job satisfaction, and control for the residuals from a log wage regression in the quit models presented below. In the log wage regression (not shown), I control for the job level, a polynomial of degree 4 in age, a quadratic in tenure, dummies for gender and supervisor together with fixed effects for year and department.

When using survey data, it is important that the anonymity of the employees is preserved. Clearly, by delegating the survey implementation to an external consulting

Table 1. Descriptive statistics (Mean and standard. deviation).

	Full sample	Regression sample	Restricted sample
Quit rate	–	0.084	0.073
Age	43.87	43.83	45.14
	(10.49)	(10.56)	(9.94)
Tenure with the firm	18.26	18.12	20.49
	(13.22)	(13.35)	(12.56)
Women	0.53	0.53	0.51
Supervisor dummy	0.11	0.11	0.14
Employee distribution (%)			
Branches	0.52	0.52	0.57
Central staff	0.37	0.37	0.32
Market functions	0.06	0.06	0.06
Other	0.05	0.05	0.05
Unique individuals	17,649	16,464	13,192
Person-year observations	87,237	62,845	43,637

The full sample is based on the years 2004–2010, the regression sample on the years 2005–2009, and the restricted sample on the years 2005–2009.

company the firm commits strongly to maintaining the employees' anonymity, but this raises a new issue. The company will receive information from the consulting company which reflects the averages and standard deviations of the job satisfaction scores at the department level. However, in some of the smallest departments there is almost no difference (if any) between the averages (and standard deviations) and the employees' individual answers. Hence, for the company to respect the anonymity of the employees, the delegation has to be supplemented with the additional policy that the company only receives survey information from departments of a particular size. In the present context, the firm only receives feedback (averages and standard deviations) from the survey for departments with 10 or more employees.

The fact that the issue with small departments is a real concern becomes clear when studying the data. Over the sample period, as many as 1014 unique departments are observed. The largest of these departments consists of 373 employees and the smallest consists of just one person. The average department size is 16.46 (SD of 24.21), and 17% of the employees work in departments with fewer than 10 employees. Hence, the organizational structure implies that the company at best receives feedback from the survey for 83% of its employees.[6]

Estimation results

In this section, I present the results from three types of quit models. The first model is based on the company's personnel records. This type of model can be estimated by the company (or any company) and serves as a benchmark model. The second type of model is based on the personnel records and the information in the employee surveys used at the level of the individual employee. This model cannot be estimated by companies unless they violate the anonymity of the employees. The third type of model is based on the personnel records and survey information used at the department level. This model can be estimated by companies conducting employee surveys.

The *main purpose* of estimating the three types of model is to assess how well the different information packages can be used to predict employee quits. Hence, the models are constructed with the purpose of maximizing their predictive power. A *second-order purpose* is to identify the relations between particular variables available in the personnel records and the employee surveys and employee quits.

The estimation results of the first model, which is based on the information available in the firm's personnel records, are presented in the first column of Table 2. The results show that demographic variables such as age and gender are significant predictors for a quit. While it is easily seen that women are less likely to quit (a result also found by Sicherman, 1996), the interpretation of the age effect is more involved as the effect is captured by a fourth-degree polynomial. For this reason, the age effect is illustrated in Figure 3, which shows the predicted quit probabilities for the 'average' employee when the age variable takes on values in the 20–60 range.[7] From the quit-age profile it is clear that the youngest employees and employees in their mid-thirties have relatively high quit probabilities, whereas employees in their late twenties and those approaching 50 years are unlikely to quit. It is also apparent from the figure that individuals aged 60 years are very likely to quit as they start entering pension programmes. This trend continues for individuals above the age of 60.

Tenure is found to have a convex influence on the quit probability where quit probabilities are much higher for low-tenured employees, which is a common finding in the literature (Farber, 1999). It is also established that there is some variation in quit probabilities across departments. Employees working in the branches have lower quit rates than the reference group 'other', and employees in central staff positions are relatively more likely to quit. Employees in market functions have the same quit propensities as the reference group. Finally, in line with Card et al. (2012), it is established that employees with relatively higher wages (residuals) are less likely to quit.

The second model presented in Table 2 is based on the information conveyed in the personnel records and individual-level job satisfaction scores from the employee survey. The presented model is tested down from a 'full' model consisting of the variables from Model 1, a university dummy (see note in Table 2) and the 39 variables from the employee surveys. The variables from the personnel records are maintained throughout, but the survey variables are tested down.[8] The final model (presented in Table 2) includes only statistically significant survey variables. The significant survey variables are as follows:

1. I would like to be working in the company in two years' time
2. I would recommend others to seek employment with the company
3. My salary (including allowances and bonuses) compared with what I could get in a similar position elsewhere
4. My general benefits (holidays, pension and other benefits) compared with what I could get in a similar position elsewhere
5. I feel good about the workload in my job
6. The attention given to my professional and personal development
7. The company has a good image

Table 2. Logit estimates of employee quit behaviour.

	Model 1	Model 2
	Personnel records	Personnel records and employee survey information (individual level)
Personnel records:		
Wage residuals[1]	−0.491***	−0.604***
	(0.100)	(0.144)
Age	−1.574***	−0.486
	(0.273)	(0.453)
Age^2/100	6.824***	3.107*
	(1.010)	(1.622)
Age^3/1000	−1.277***	−0.729***
	(0.161)	(0.251)
Age^4/10000	0.087***	0.058***
	(0.009)	(0.014)
Tenure	−0.088***	−0.098***
	(0.004)	(0.006)
Tenure^2	0.002***	0.002***
	(0.000)	(0.000)
Woman	−0.171***	−0.215***
	(0.034)	(0.045)
Education: University[2]		−0.098**
		(0.046)
Supervisor	−0.053	0.027
	(0.063)	(0.074)
Branches	−0.188***	−0.331***
	(0.034)	(0.046)
Central staff	0.134**	0.023
	(0.065)	(0.087)
Market functions	0.051	0.010
	(0.066)	(0.082)
Employee survey: individual answers (scale 1 (low)–10 (high))		
I would like to be working in the company in two years' time		−0.135***
		(0.014)
I would recommend others to seek employment with the company		0.044**
		(0.017)
I always look forward to going to work		−0.039**
		(0.017)
My salary (including allowances and bonuses) compared with what I could get in a similar position elsewhere		−0.060***
		(0.013)
My general benefits (holidays, pension and other benefits) compared with what I could get in a similar position elsewhere		0.040**
		(0.017)

(Continued)

Table 2. (Continued)

	Model 1	Model 2
	Personnel records	Personnel records and employee survey information (individual level)
I feel good about the workload in my job		−0.032** (0.013)
The attention given to my professional and personal development		−0.033** (0.014)
The company has a good image		0.059*** (0.018)
Dummies for job level	YES	YES
Year dummies	YES	YES
Observations	62,845	43,637

[1]The wage residuals used stem from a log wage regression controlling for the job level, a polynomial of degree 4 in age, a quadratic in tenure, dummies for gender and supervisor together with fixed effects for year and department.
[2]Information on education is not available in the personnel records, and for that reason it is obtained from the survey. The answer to the education question can take one of seven different values, but the data reveal that the employees have problems identifying the right category, and their answers vary significantly across years. Based on the survey information, I construct one dummy called 'university degree' comprising employees with college or graduate degrees. The university category accounts for 26% of the individuals, but it is likely to be subject to significant measurement error.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

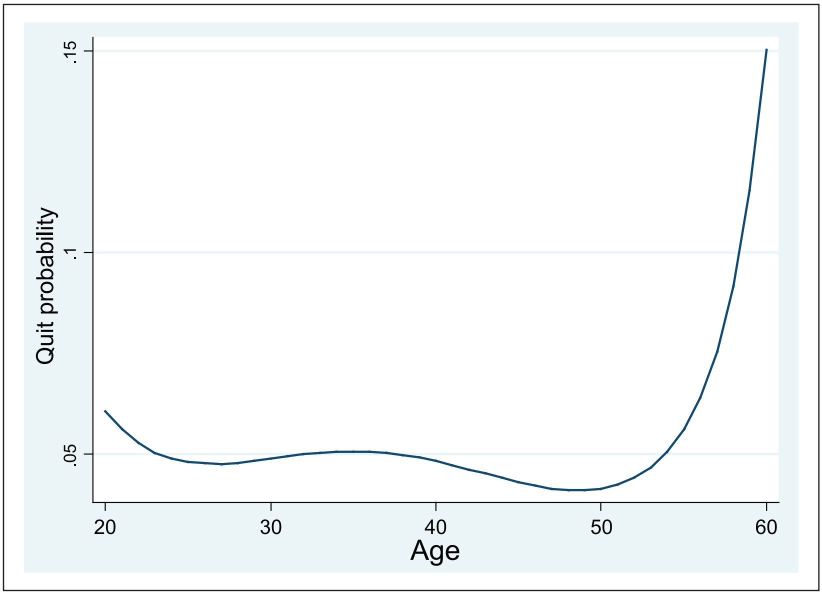

Figure 3. The quit–age profile.

When comparing these variables with the study by Clark (2001), it becomes clear that the identified drivers for quits touch upon the same dimensions, but they are not perfectly overlapping. Common ground is found in satisfaction with pay, workload and work content. In addition to the findings in Clark's (2001) study, I identify the intention (not) to quit, career development and company image as important factors in quitting decisions.

The effects of the personnel record variables are qualitatively similar when the survey variables are included. The main changes are that the age profile is somewhat altered and that the employees working in central staff positions are now determined to have quit probabilities similar to the reference group; before, they had higher quit propensities.

The effects of the survey variables are also important in their own right. Many of the survey variables have an expected negative effect on the quit probability. For instance, when employees give the question 'My salary (including allowances and bonuses) compared to what I could get in a similar position elsewhere' a high score, they are less likely to quit. Furthermore, when people feel good about their workload, when they look forward to going to work, and when they feel that attention is given to their professional development, they are more likely to stay. Finally, those employees giving the question 'I would like to be working in the company in two years' time' high scores have relatively low quit propensities.

More puzzling is that employees who give high scores when asked if they would recommend others to seek employment in the company and those with high scores on how they perceive the company's image are significantly more likely to leave the firm. These results suggest that the firm's external branding, which is a device normally used to attract employees, has an unintended negative retention effect, but other interpretations may also apply. Another result which is puzzling is that employees rating their general benefits (holidays, pension and other benefits) relatively high compared with what they could receive in a similar position elsewhere are more likely to leave. The most plausible explanation for this result is that these benefits are little valued by employees.

The third set of models builds on the information in the personnel records in combination with the information in the employee surveys used at the department level. The first model of this type is presented in Table 3 (Model 3). This model controls for the personnel records used previously and department-level averages for the survey variables. Model 4 is similar to Model 3, except that it contains both the averages and standard deviations for the survey variables at the department level. Model 5 is identical to Model 4, apart from being estimated on the subsample of departments that have 10 or more employees.

The results in Table 3 show that the effect of the personnel record variables is very stable across the three models (Models 3–5), and they mirror the results found in Models 1 and 2. What is much less stable is the set of survey variables ending up in the final specifications for each of the three models (see detailed results in Table 7 in the Appendix). In Model 3, the following survey questions remain after the model has been tested down:

1. I would like to be working in the company in two years' time
2. My general benefits (holidays, pension and other benefits) compared with what I could get in a similar position elsewhere
3. I rarely look for other jobs outside the company
4. The company is an organization characterized by sincerity
5. I feel that I would have many alternative job opportunities if I were to leave the company

6. My job security
7. The professional cooperation with my colleagues
8. My opportunities for professional and personal development

Table 3. Logit estimates of employee quit behaviour as modelled by the firm.

	Model 3	Model 4	Model 5
	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
	Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
Personnel records			
Wage residuals	−0.583***	−0.658***	−0.742***
	(0.101)	(0.104)	(0.112)
Age	−1.600***	−1.606***	−1.794***
	(0.275)	(0.276)	(0.299)
Age^2	6.918***	6.955***	7.636***
	(1.016)	(1.023)	(1.106)
Age^3	−1.291***	−1.298***	−1.406***
	(0.162)	(0.163)	(0.176)
Age^4	0.088***	0.088***	0.094***
	(0.009)	(0.009)	(0.010)
Tenure	−0.086***	−0.087***	−0.086***
	(0.004)	(0.005)	(0.005)
Tenure^2	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Woman	−0.162***	−0.166***	−0.158***
	(0.034)	(0.034)	(0.037)
Education: university	−0.080**	−0.091**	−0.093**
	(0.037)	(0.037)	(0.040)
Supervisor	0.006	0.005	−0.010
	(0.064)	(0.064)	(0.074)
Branches	−0.223***	−0.193***	−0.240***
	(0.040)	(0.040)	(0.046)
Central staff	0.004	0.053	0.009
	(0.069)	(0.069)	(0.073)
Market functions	0.029	0.113	0.068
	(0.069)	(0.069)	(0.076)
Averages for departments	YES	YES	YES
Std. dev. for departments	NO	YES	YES
Dummies for job level	YES	YES	YES
Year dummies	YES	YES	YES
Observations	62,663	62,083	52,015

*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

When compared with Model 2, only the first question (the intention to work in the company in two years' time) and the second question (general benefits) are present in both models. When comparing across Models 3–5, only four of the mean variables are present in all three models. A similar finding pertains to the standard deviations, where only five can be found in both Model 4 and Model 5. Naturally, part of the explanation is that the survey questions are constructed to produce highly correlated answers within each of the domains: overall satisfaction, loyalty, motivation, salary and benefits, corporate leadership, immediate manager, cooperation, conditions at work, career development and image (see additional discussion in Note 8). However, the lack of consistency between Model 2 and Models 3–5 questions whether the models using the department averages can be used to learn about individual quit behaviour. Nevertheless, Models 3–5 turn out to be important because they have higher predictive powers than baseline Model 1 – an issue which will be discussed explicitly in the next section.

Discussion

The empirical results presented in the previous section established the relationship between personnel and survey data, and quit probabilities. In this section, I will establish how well companies can predict employee turnover using the various models building on personnel and survey data, and I will shed light on how these different data types benefit the company.

Predictive performance

One way of evaluating the predictive performance of the models is to determine how well they predict quitters and stayers. We are interested in three performance measures: 'correctly classified', 'positive predictive value' and 'negative predictive value'.[9] Employees can be classified as either 'quitters' or 'stayers. In practice, this is done by choosing a threshold, for instance 0.5, and then classifying employees with predicted quit probability below 0.5 as 'stayers' and the remaining employees as 'quitters'. If an employee is classified as a 'stayer' and the employee actually stays with the company, then the person is correctly classified, and similarly for 'quitters'. The model's positive predictive value reflects the proportion of employees who actually quit, given they are classified as a 'quitter'. Similarly for the model's negative predictive value, which reflects the proportion of employees who actually stay, given they are classified as 'stayers'.

The performance measures for the five estimated models from the previous section are presented in the first three rows of Table 4. The first model building on personnel records correctly classifies 91.51% of the individuals when the threshold is set to 0.5. The model also correctly predicts quits for 29.13 of the employees classified as 'quitters', and it correctly predicts non-quits for 91.71% of the employees classified as 'stayers'. The results for the second model (column 2), which complements the information in the personnel records with detailed information from the job satisfaction survey, are superior to those we have observed for Model 1. The proportion of correctly classified individuals is 92.61 and the positive predictive value is as high as 39.26%. That is, among the individuals classified as 'quitters', 39.26% actually quit the job. The negative predictive value is 92.81%.

Table 4. Evaluation of model predictions and coverage.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Personnel records	Personnel records and employee survey information (individual level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
			Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
Correctly classified	91.51	92.61	91.50	91.50	91.40
Positive predictive value	29.13	39.26	28.90	27.83	28.49
Negative predictive value	91.71	92.81	91.72	91.72	91.62
Coverage (people)	62,845	43,637	62,663	62,083	52,015
Coverage (%)	100	69.4	99.7	98.8	82.8

While Model 2 is clearly superior in a comparison with Models 1, 3, 4 and 5, the ranking of Models 1, 3, 4 and 5 is more mixed. One reason is the variation in coverage. Model 1 covers 100% per cent of the employees, and Models 3 and 4, which complement the personnel records with means and standard deviations at the department level from the job satisfaction survey, have coverages of 99.7% and 98.8% respectively. Even in Model 5, in which the smallest departments are excluded, coverage remains at a level of 82.8%. This is to be compared with a coverage of only 69.4% in Model 2 where the personnel records are complemented by the detailed survey information at the individual level. Hence, for practical matters, it is noteworthy that – except for Model 1 – the models do not provide predictions on quit propensities for all employees.

Because the coverage varies across models, it is difficult to compare their actual predictive performance based on the results in Table 4 as different sets of individuals are studied in the various models. For this reason, I provide additional analysis of the models' predictive powers using the individuals for whom full information is available,[10] that is to say, those individuals who have no missing values in the personnel records and who provide answers to all questions in the survey. In other words, I base the analysis on the 43,637 observations used to estimate Model 2. Note that Model 5 still excludes the smallest departments and is thus based on only 32,814 observations.

The results based on the 0.5 threshold are presented in the upper part of Table 5. The models perform equally well when it comes to the proportion of employees with a correct classification (proportions varying between 92.51 and 92.61). Similarly, when it comes to the negative predictive value, there is little variation (ranging from 92.70 to 92.81). The real difference between the models is in their ability to predict quitters. The models with information from the job satisfaction surveys (Models 2–4)[11] classify more individuals as 'quitters' and have higher positive predictive values than Model 1, which is based only on the personnel records. From these results it is clear that job satisfaction surveys are valuable.

One caveat of using a threshold of 0.5 is that few employees are classified as 'quitters'. An alternative is to use the average quit probability of 0.08 as threshold. This clearly produces a different classification as can be seen in the lower part of Table 5. Using this alternative threshold, as many as 28% of the individuals are classified as 'quitters'. This, however, is a result of more individuals being misclassified, and the proportion of correctly classified individuals is observed to drop to a level of around 72% across the five models. A drop in the positive predictive value is also apparent. The one dimension on which the models are improving is in their ability to predict stayers, and the negative predicted value comes close to 96% in all models.

Hence, the choice of threshold clearly influences the information conveyed in the analysis, and the practitioner must decide whether the focus should be on correctly predicting stayers or quitters. If the focus is on quitters, then a high threshold is preferred as it classifies few as quitters, but the likelihood that those individuals would actually quit is fairly high. In contrast, if the focus is on identifying stayers, then a low threshold is preferred, since it categorizes relatively few as stayers and these have a remarkably high probability (close to 96%) of staying.

Table 5. Evaluation of model predictions.

		Model 1	Model 2	Model 3	Model 4	Model 5
		Personnel records	Personnel records and employee survey information (individual level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
				Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
Threshold: 0.5	Employees classified as quitters	140	163	148	151	112
	Correctly classified	92.59	92.61	92.59	92.58	92.51
	Positive predictive value	34.29	39.26	35.14	35.76	37.50
	Negative predictive value	92.77	92.81	92.78	92.78	92.70
Threshold: average quit probability (0.08)	Employees classified as 'quitters'	12,764	12,356	12,500	12,383	9,807
	Correctly classified	72.02	73.02	72.60	72.75	71.74
	Positive predictive value	14.75	15.27	14.94	15.13	15.11
	Negative predictive value	95.76	95.83	95.76	95.81	95.88

The 43,637 observations available to estimation of Model 2 are used in Models 1–4. Only 32,814 observations are used in Model 5.

Cost performance

While the above analysis summarizes the models' predictive powers, they do not directly provide information on the monetary benefits of better predictions. However, it turns out to be a difficult exercise to produce a metric for how much turnover costs are reduced when a firm improves its ability to predict employee quits. The reason is that such benefits can result both from more accurate expectations about actual employee turnover and from directly preventing employee turnover. In the first case, the firm can reduce the costs that result from disruptions of the production process when employees leave (not so) unexpectedly. The firm can also improve its succession planning and recruitment strategies. In the second case, turnover is prevented. The literature does contain estimates of the costs of turnover (costs that are saved if an unintended quit is prevented), but the costs vary significantly across employees. Wasmuth and Davis (1983) produce an extensive list of all the cost drivers for employee turnover. In turn, they argue that the costs of turnover for employees in the hospitality industry ranges from US$500 to US$5000, with an average of US$2300 (most likely in 1983 prices). This conclusion is the result of a careful assessment of both direct and indirect costs associated with employee turnover. Hence, even in the relatively standard employment situation of hospitality employees, turnover costs vary substantially across employees. From conversations with the firm that I study in this article it becomes clear that replacement of white-collar specialists can easily cost the equivalent of six months' salary. Higher-level managers are significantly more expensive to replace. Hence, irrespective of the type of employee, there are substantial costs associated with turnover, and an improved ability to reduce employee turnover will therefore lead to significant cost savings – cost savings that, with a high probability, will exceed the costs of running a survey and conducting a quantitative analysis.

From descriptive to predictive analysis

The presented results show how companies can reduce uncertainty by improving their predictive power. In fact, the present analysis illustrates one way for companies to move from a descriptive and backward-looking approach to becoming predictive and forward-looking in nature.

In most companies, the HR department reports on employee turnover rates. In the present company, the average turnover rate (in the regression sample) is 8.4%. It is straightforward to conduct a 'drill-down' of employee turnover and present turnover rates at, for example, the department level. The result would be of the type: Department X had a quit rate of, say, 8% last year, while department Y had a quit rate of 8.8%. This information is useful, but it is also backward-looking and descriptive; it would be common for companies to focus their attention on department Y with the highest (historical) quit rate.

The analysis presented here allows companies to look forward instead of backwards. Based on the analysis, each individual can be associated with an expected quit rate, which is a function of the employees' characteristics and the characteristics of the departments in which they work. Hence, an immediate leap forward for any company is to focus on individuals and departments with high predicted quit propensities (instead of high historical quit propensities). If the data reveal that department X has an expected quit rate of 8.8% and department Y has an expected quit rate of 8%, it would be inefficient to focus attention on department Y (as the backward-looking analysis would suggest); instead the focus should be on department X.

A second way to use the data is to compare expected (predicted) quit rates with actual quit rates. Imagine that department X has an expected quit rate for the year to come of 8.8, but the actual quit rate that year is lower at only 8.4%, whereas department Y with its expected quit rate of 8% has a realized quit rate of 8.3%. The conclusion is obvious: if employee turnover is used as a key performance indicator (KPI) for department managers, it should be the manager of department X who should be rewarded the most despite the realized higher quit rate in her department.

An additional way to create value for companies is to visualize the results. For a given set of thresholds, departments can be grouped into, for example, departments with low, satisfactory and high quit propensities. These groups could be represented by green, yellow and red dots on a map. A variety of online and offline programs are available. In Figure 4 I have used Google Maps. While the dots on the map for confidentiality reasons do not represent the actual data from the analysis, the benefits of visualization become clear immediately: the branches in Aalborg and Aarhus are in red and Copenhagen, among others, is in green. With a continuous update of the data, the map becomes dynamic, as the colors will change over time. In this way, the map can serve as an early warning system.

Conclusion

It is often observed that firms delegate the implementation of job satisfaction surveys to external consulting companies. This has the benefit that the firm commits to preserving the employees' anonymity and, in turn, can expect to receive more reliable answers in the survey. In the first part of the article I provided a theoretical motivation for this mechanism. In the second part I studied the value of conducting job satisfaction surveys in the context of a quit analysis. It is clear from the analysis that companies can improve their ability to predict quitters if they complement their personnel records with information from job satisfaction surveys. This is the case even when firms can only use the survey data in ways that preserve the employees' anonymity, that is as means and standard deviations at the department level. It is also clear, however, that survey information at the level of the individual is superior to the department-level information when it comes to identifying quitters.

Additional practical issues arise when companies are interested in obtaining information from job satisfaction surveys. For years the focus has been on the response rate in surveys, but because the issue of anonymity plays a big role in relation to job satisfaction surveys when they are used by management and for analysis, there will also be a lower bound on 'group size' for which the company can obtain survey information. More specifically, in small groups there will be almost no difference between individual survey answers and group averages. Consequently, firms will typically not receive information about job satisfaction on the smallest groups. This concern becomes real when reading Frederiksen et al. (2016), who show that the average span of control in the company they

Figure 4. Visual representation of the results.

study is around 10 employees, and when one realizes that the average department size in the firm studied in this paper is 16. Maybe the increasing demand for HR data and analytics will have consequences for organizational design in the future; perhaps the smallest groups will become larger so that companies can retrieve information about their employment satisfaction.

While the empirical results show significant gains derived from conducting job satisfaction surveys and applying these in quit models, the presented estimates of the firm's gains from such surveys are likely to be a lower bound. The survey was originally implemented to elicit information from the employees about their job satisfaction for management purposes, not to reduce turnover costs per se. For example, the job satisfaction scores constitute KPIs for managers and, as such, play a role in how they are remunerated, and furthermore, they are used as input in promotion decisions. These additional uses of the survey information also provide benefits for the firm.

In this article I have combined personnel records with job satisfaction surveys at the individual level. This unique combination of data has allowed for a detailed assessment of the value of surveys. The results and examples show how companies can reduce uncertainty, and how they can move from being descriptive to becoming predictive. This focus on new data sources from companies and statistical analysis thus seems to be a particularly fruitful path to pursue in future research as it will allow us to 'draw pictures' of the world not yet seen – pictures that will not only advance our academic knowledge of employer–employee relations, but will also be relevant for managers in firms. This study therefore contributes to the recent HR analytics movement.

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Notes

1. For recent theory and evidence on the drivers for employee turnover, see Lee et al. (2008).
2. Anderson and Meyer (1994) identify the characteristics of high employee turnover firms. Royalty (1998) focuses on how job separation rates differ by demographic characteristics. More recently, Frederiksen et al. (2007) as well as Frederiksen (2008) use employer–employee data to estimate the job separation process, and by doing so, they are able to study the importance of firm and individual characteristics simultaneously. Studies using firm-level data similar to those used in this study include Weiss (1984) and Sicherman (1996). The focus of these papers is on how demographics (e.g. gender and age), education and task assignments correlate with employee quits. However, the literature on employee turnover is vast, and a comprehensive overview can be found in the meta-analysis by Griffeth et al. (2000).
3. These models have been studied extensively in economics. Often, the discussion is cast in the context of the prisoner's dilemma where a better outcome can be achieved if the parties involved cooperate, and I will follow that lead. For a broader, yet very interesting discussion of strategic behaviour in the labour market (and elsewhere), the reader is referred to the book *The Art of Strategy* by Dixit and Nalebuff (2010).
4. The set-up used in the analysis is the conventional prisoner's dilemma. For additional details, the reader is referred to the excellent textbooks by Gibbons (1992), Barron and Kreps (1999) and Campbell (2006).
5. Note that this result is obtained without repeated game arguments.
6. This is at best because the response rate also plays a role. When focusing on the significant survey variables in a quit regression (details given below), 69.4% of employees respond to all relevant survey questions.
7. The average employee is a 44-year-old woman with 18 years of tenure. She works in one of the branches at job level 5.
8. Note that an alternative to this approach would be to conduct a factor analysis or a principal component analysis in which case the factor scores would be extracted and used in a subsequent regression analysis. The performance of such models is discussed in more detail below.
9. Alternative measures of model performance such as the Mean Absolute Distance (MAD) or the Mean Squared Distance (MSD) can also be used. These measures compare the actual outcome (quit or no quit) to the model's predicted quit probability. The main difference between the two measures is that the MSD penalizes more heavily the larger differences. The ordering of the models based on their MAD or MSD resembles previous results. For example, the

MAD for Model 1 is 0.146, the MAD for Model 2 is 0.117, and the MAD for Model 5 is 0.133. One could also use a principal component analysis (PCA). Using this approach I can extract seven factors, and when used in a regression model, it produces an MAD of 0.122. Hence, the regression and PCA approaches perform at the same level. In fact, this is not too surprising since the variables, which are selected when the model is tested down, are representative of the factors identified in the PCA. As to the principle component model, there are two noteworthy observations in the present context. First, the model has the advantage that the factors included in the regression model are uncorrelated, but this does not lead to a higher predictive power in the present context. Second, the principal component model has the disadvantage that it is more sensitive to the response rate as it requires that an employee answers all questions in the survey before a factor can be predicted.

10. I also study a restricted version where only the variables identified as significant in Model 2 are used. That is, in Models 3–5 I use the means and standard deviations of the seven survey variables included in Model 2. These models naturally perform worse on the R^2 criterion and they all have lower R^2 than the original models, but Models 3–4 do marginally better in terms of classification and positive predictive value, whereas Model 5 performs worse on all measures. The results are shown in Table 8 in the Appendix.
11. Note that the relatively few employees classified as ‘quitters’ in Model 5 are in part the result of the lower number of observations. If we scale the number of 112, that is the number of individuals classified as ‘quitters’, with (43,637/32,814) we arrive at 149.

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Appendix

Table 6. The employee survey.

Satisfaction	Overall, how satisfied are you as an employee at your workplace?
	Imagine a place of work which is perfect in all aspects. How far from or close to this ideal do you consider your place of work to be?
Loyalty	I would like to be working in the company in two years' time
	I would recommend others to seek employment with the company
	I rarely look for other jobs outside the company
	I feel that I would have many alternative job opportunities, if I were to leave the company
Motivation	I feel motivated in my job
	I always look forward to going to work
Salary and benefits	My salary (including allowances and bonuses) compared to what I could get in a similar position elsewhere
	My general benefits (holidays, pension, and other benefits) compared to what I could get in a similar position elsewhere
	My job security
Corporate leadership	The ability of the Senior Manager to make the right decisions
	The ability of the Senior Manager to inform the employees
Immediate manager	The professional skills of my immediate superior
	The leadership skills of my immediate superior
	My immediate superior is energetic and effective
	My immediate superior gives constructive feedback on my work
	My immediate superior delegates responsibility and authority so I can complete my work effectively
	My immediate superior helps me to develop personally and professionally
	What my immediate superior says is consistent with what he/she does
Cooperation	The professional cooperation with my colleagues
	The general atmosphere among my colleagues
	Social relations and interaction with my colleagues
	In my unit, we are good at learning from each other
Conditions at work	My job objectives and work content
	The physical working environment at my place of work
	I feel good about the workload in my job
	I have sufficient influence over the setting of my job objectives
	I am able to observe and adhere to the core values
	I am satisfied with the way job objectives and work is distributed in my unit
	My work tasks present me with appropriate challenges
Career development	My opportunities for professional and personal development
	The attention given to my professional and personal development
	My job enhances my future career opportunities
	My appraisal conversation supports my further development
Image	The company has a good image
	I am proud to tell other people that I work for the company
	Other people consider the company to be a good place to work in
	The company has a good image

The scale used is a 10-point Likert scale with 1 corresponding to low, not satisfied, do not agree, and 10 corresponding to high, satisfied, agree.

Table 7. Logit estimates of employee quit behaviour as modelled by the firm.

	Model 3	Model 4	Model 5
	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
	Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
Personnel records			
Wage residuals	−0.583***	−0.658***	−0.742***
	(0.101)	(0.104)	(0.112)
Age	−1.600***	−1.606***	−1.794***
	(0.275)	(0.276)	(0.299)
Age^2	6.918***	6.955***	7.636***
	(1.016)	(1.023)	(1.106)
Age^3	−1.291***	−1.298***	−1.406***
	(0.162)	(0.163)	(0.176)
Age^4	0.088***	0.088***	0.094***
	(0.009)	(0.009)	(0.010)
Tenure	−0.086***	−0.087***	−0.086***
	(0.004)	(0.005)	(0.005)
Tenure^2	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Woman	−0.162***	−0.166***	−0.158***
	(0.034)	(0.034)	(0.037)
Education: university	−0.080**	−0.091**	−0.093**
	(0.037)	(0.037)	(0.040)
Supervisor	0.006	0.005	−0.010
	(0.064)	(0.064)	(0.074)
Branches	−0.223***	−0.193***	−0.240***
	(0.040)	(0.040)	(0.046)
Central staff	0.004	0.053	0.009
	(0.069)	(0.069)	(0.073)
Market functions	0.029	0.113	0.068
	(0.069)	(0.069)	(0.076)
Employee survey (scale 1–10) Averages for departments			
I rarely look for other jobs outside the company	−0.084*** (0.031)	−0.117*** (0.031)	−0.122*** (0.040)
The company is an organization characterized by sincerity	−0.171*** (0.047)	−0.185*** (0.044)	−0.207*** (0.061)

Table 7. (Continued)

	Model 3	Model 4	Model 5
	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
	Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
My general benefits (holidays, pension and other benefits) compared with what I could get in a similar position elsewhere	0.057*** (0.020)	0.042** (0.021)	0.056** (0.025)
I feel that I would have many alternative job opportunities if I were to leave the company	0.102*** (0.025)	0.093*** (0.025)	0.120*** (0.034)
I would like to be working in the company in two years' time	−0.176*** (0.039)		
My job security	−0.066** (0.031)		
The professional cooperation with my colleagues	0.160** (0.064)		
My opportunities for professional and personal development	−0.103*** (0.037)		
I am proud to tell other people that I work for the company	0.120*** (0.038)		
Overall, how satisfied are you as an employee at your workplace?		−0.206*** (0.064)	−0.259*** (0.089)
I always look forward to going to work		0.110** (0.051)	0.206*** (0.064)
My immediate superior gives constructive feedback on my work		0.128** (0.053)	0.248*** (0.066)
My immediate superior helps me to develop personally and professionally		−0.179*** (0.055)	
The general atmosphere among my colleagues		0.130*** (0.048)	
I have sufficient influence over the setting of my job objectives		−0.120** (0.051)	

(Continued)

Table 7. (Continued)

	Model 3	Model 4	Model 5
	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
	Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
I have the opportunity to complete/present my own work		0.195*** (0.057)	
I would recommend others to seek employment with the company			0.201*** (0.059)
The leadership skills of my immediate superior			−0.301*** (0.068)
My immediate superior is energetic and effective			0.121** (0.054)
The professional cooperation with my colleagues			0.242*** (0.088)
My opportunities for professional and personal development			−0.257*** (0.060)
Std. dev. for departments			
Overall, how satisfied are you as an employee at your workplace?		−0.180*** (0.054)	−0.297*** (0.073)
I would like to be working in the company in two years' time		0.131*** (0.037)	0.236*** (0.047)
I would recommend others to seek employment with the company		0.136*** (0.046)	0.283*** (0.064)
The leadership skills of my immediate superior		−0.104** (0.048)	−0.216*** (0.070)
My immediate superior gives constructive feedback on my work		0.147*** (0.057)	0.176** (0.070)
My job security		0.085** (0.039)	
My immediate superior helps me to develop personally and professionally		−0.122** (0.055)	

Table 7. (Continued)

	Model 3	Model 4	Model 5
	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
	Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
I have sufficient influence over the setting of my job objectives		−0.148*** (0.054)	
I am able to observe and adhere to the core values		0.196*** (0.061)	
I am proud to tell other people that I work for the company		−0.135*** (0.052)	
My salary (including allowances and bonuses) compared with what I could get in a similar position elsewhere			−0.123** (0.049)
The ability of my senior manager to make the right decisions			0.126*** (0.043)
My opportunities for professional and personal development			−0.152** (0.067)
Dummies for job level	YES	YES	YES
Year dummies	YES	YES	YES
Observations	62,663	62,083	52,015

*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

Table 8. Evaluation of model predictions (same sample and same covariates).

	Personnel records	Personnel records and employee survey information (individual level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)	Personnel records and employee survey information (department level)
			Means	*Means and std. dev.*	*Means and std. dev. Departments sized 10+*
Employees classified as 'quitters'	140	163	145	148	113
Correctly classified	92.59	92.61	92.60	92.59	92.49
Positive predictive value	34.29	39.26	36.55	35.81	34.51
Negative predictive value	92.77	92.81	92.78	92.78	92.69

The 43,637 observations available to estimation of Model 2 are used in Models 1–4. Only 32,814 observations are used in Model 5.