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# Downsizing as a sorting device

## Are low-productive workers more likely to leave downsizing firms?

**Abstract:**
Employers cannot always displace workers at their own discretion. In many countries, Employment Protection Legislation (EPL) includes restrictions on laying off workers. This paper studies whether employers use downsizing events, where the rules for dismissal differ from the rules that apply for individual dismissal, to displace workers selectively. We investigate empirically whether workers with low expected productivity relative to co-workers face particularly high exit risks when establishments downsize. Our evidence is consistent with establishments using downsizings as a sorting device to terminate the employment of the least profitable workers who are protected against dismissal under normal times of operation. However, only a minor share of the displacements in downsizings may be attributed to opportunistic sorting by employers, suggesting that EPL may not be an important obstacle to firms' firing of individual workers.

**Keywords:** Downsizing, sickness absence, employment protection

**JEL classification:** I18, J63, J65

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# 1. Introduction

Employers cannot always displace workers at their own discretion. In many countries, Employment Protection Legislation (EPL) includes restrictions on laying off workers. There may also be negotiated and implicit agreements between establishments and workers on firings and layoffs, e.g. dictating a last-in-first-out principle for layoffs. If EPL causes firms to retain unproductive workers that would otherwise have been displaced, it entails a cost to the firm. There is some evidence that this is the case. Autor, Kerr and Kugler (2007) look at variation across American states in the introduction of different employment protection regulations, and conclude that their empirical results "*(...) suggest that adoption of dismissal protections altered short-run production choices and caused employers to retain unproductive workers, leading to a reduction in technical efficiency.*"

To the extent that EPL protects workers from individual dismissal, EPL forms a barrier against optimal workforce adjustment in times of normal operation. Therefore, employers may want to use downsizings, i.e. instances when firms reduce the number of employees in a mass lay-off, but retain some workers and continue production, as opportunities for laying off workers selectively. The reason is that workers who are effectively protected against individual dismissal may lose this special protection when firms downsize. In addition, the real (individual) reasons for displacement may be concealed when many workers are laid off simultaneously.

We investigate whether downsizing events give employers more discretion to displace individual workers. Specifically, do workers who can be expected to have low individual productivity and low individual contribution to profits, relative to co-workers, have a particularly high risk of leaving downsizing firms? Testing how low productivity affects the job loss probability in downsizing serves as a test of whether EPL is a binding restriction on employers' employment decisions under normal terms of operation. If excess separation rates of workers with low productivity are higher in downsizings, this would indicate that EPL does provide some protection, that this protection imposes a costly constraint to employers, and that employers use available opportunities to circumvent this constraint.

Our study covers the private sector in Norway, where individual job security is high. An international comparison of EPL ranks Norwegian EPL as the most restrictive in terms of difficulty of individual dismissal (OECD, 1999), whereas it is not particularly restrictive in terms of access to mass layoff. An important feature of the so-called "Scandinavian model" (cf. e.g. Moene and Wallerstein, 1997) has been small wage differentials both between firms and individuals, to a large extent the outcome of centralized wage determination, combined with a high degree of *individual* job security. The idea is that this would force low-productive firms to exit, and make room for expansion of high-productive firms. In plant closings, there is no sorting of workers. However, if employers are able to use downsizing as a sorting device, thereby increasing their productivity and chance of survival, this may adversely affect the functioning of labour markets of the Scandinavian type, that relies on fast re-employment of displaced workers, because stigma from being negatively selected by the previous employer may prevent this.

We use linked employer-employee data that cover the entire Norwegian private sector in the years 1995 to 2003. The data contain rich information on establishments and persons, and unique person and establishment identification numbers allow us to follow workers across establishments over time. Workers with inferior health are likely to be less productive when at work and more absent from work than persons with "good" health, and we therefore pay particular attention to health, measured by registered sickness absence, as a sorting criterion. Workers who have been absent for health reasons in the past may be less valued by establishments than otherwise identical workers, because sickness absence may signal worsened health, and more future absence. Absence is costly to establishments due to direct costs of sickness benefits paid by employers (in many countries, establishments pay wages for part of the absence period), and indirect costs from failing to find an adequate replacement in the sickness period. Workers with previous sickness absence will then be less attractive, particularly if wages are downward rigid. We also use the residuals from a within-job wage growth regression to proxy other determinants of expected future individual profits than health, assuming that wage growth is positively correlated with the employer's expectation of the future productivity of the employee (see Pfann, 2006).

We assume that a downsizing establishment compares its employees to each other when deciding whom to retain and whom to lay off, in the extreme case ranking workers by expected individual contribution to profits. The probability that a worker exits during a period within which the establishment downsizes, then depends on both the worker's characteristics (age, tenure, education level, individual productivity, etc.) and on the values of these characteristics relative to co-workers. We take this into account in the econometric analysis. We will use the term *peer group* for the group of workers with whom a particular worker competes for jobs. Typically, the competition is between workers with similar qualifications and we will use two alternative definitions of the peer group: (i) all workers within the establishment, and (ii) all workers within the establishment with the same level of education.

Because the data do not distinguish between voluntary quits and layoffs, and because we do not observe the exact timing of downsizing and job termination, some job terminations will be due to other reasons than the downsizing, e.g. quits. We propose a model that allows that exit probabilities vary across workers for other reasons than downsizing. For example, workers with inferior health (in absolute terms) exit into non-participation more often than workers with good health, in all establishments, downsizing and non-downsizing. We therefore use employees of non-downsizing firms as control workers within a regression-based Difference-in-Difference approach, controlling for a number of worker and establishment characteristics. Our identifying assumption is that the mechanisms affecting exits outside the downsizing event are independent of the downsizing status of the establishment. We can then estimate the effect of the part of EPL that may be circumvented when establishments downsize. This may be a small or a large share of the total effect of EPL, but we cannot say how much, because we do not know how binding EPL is when establishments do not downsize.

The results show that persons with health problems face an excess risk of job termination when establishments downsize. Our estimates of the excess probability of displacement with respect to sickness absence relative to colleagues, range from 0.8 to 1.8 percentage points for 100 days absence over a two-year period. The results also show that workers with low within-job wage growth, relative to co-workers, are more likely to exit, indicating that downsizing establishments to some extent manage to retain the most profitable workers. Women face an excess risk of job loss when establishments downsize, whereas long tenure and work experience protect against dismissal. This is in line with seniority being a frequently used criterion for selecting workers, with long-tenure workers being protected. Interestingly, sorting is stronger for downsizing of 20-50 percent of employees than for smaller or larger downsizing shares. This may be due to sorting on absence being more evident when the large majority of employees leave or stay, than when there is a more even split, such that there is more scope for sorting when downsizing is more ‘medium-sized’. The result could also reflect variation in the nature of downsizing (displacing all employees of particular departments vs. displacing an equal share of employees in all parts of the establishment) across downsizing events with different downsizing shares, and that there may be more room for employer discretion when the downsizing is more of an overall reduction of employees.

Our estimates for the excess separation rate due to sickness absence in downsizing firms are quite moderate. A minor share of the displacements in downsizings may be attributed to opportunistic sorting by employers, in the sense that they would have taken place during normal times of operation, had EPL not posed a binding constraint, suggesting that EPL may not be an important obstacle to firms' firing of individual workers.

The rest of this paper is organized as follows. In Section 2 we discuss some relevant previous literature, and Section 3 gives a brief overview of relevant EPL in Norway. Section 4 describes data sources and sample construction. Our econometric framework is presented in Section 5, while Section 6 discusses results. The final section concludes.

# 2. Related literature

There is a large literature documenting that displacement has negative consequences for workers. Together with the the hypothesis that EPL is a binding constraint on firms' employment decisions, this motivates our investigation of sorting in downsizings.

The literature on the consequences of displacement on future wages and employment has shown that (although with some exceptions) there are significant losses following displacement. The losses tend to be larger for women, for the low-skilled and for older workers, and earnings losses are larger for re-employed workers who change sector of occupation. See e.g. the work by Jacobson, LaLonde and Sullivan (1993), and Kletzer (1998) for a survey of empirical evidence for the US, and the cross-country studies in Kuhn (2002) for international evidence. Huttunen, Møen and Salvanes (2006) is a recent study on Norwegian data. Other studies focus on health-related consequences of downsizings or plant closures, measured e.g. by mortality, future sickness absence or disability pension participation, see Kivimäki et al. (2000), Browning, Danø and Heinesen (2003), Vahtera et al. (2004) and Rege, Telle and Votruba (2007). Results vary, but most studies find that job displacement also has significantly negative effects on health.

Another strand of the literature considers downsizings and exits from the perspective of the establishment. Part of this literature analyzes changes in the composition of workers in downsizing firms, see e.g. Abowd, Corbel and Kramarz (1999), Lengermann and Vilhuber (2002) and Schwerdt (2007). One lesson from these papers is that downsizing may be partly foreseen, and that worker exits in a period prior to the downsizing may be attributed to the downsizing event. This suggests that it may be problematic to study exits of workers at the time of downsizing, since workforce composition at that date may already be affected by the downsizing.

Since sorting is a relative phenomenon by definition, it is important to control for the characteristics of colleagues when we model individual exit from downsizing establishments,. We mentioned above that previous sickness absence is one potentially important criterion for sorting workers. In an analysis on Swedish data, Arai and Thoursie (2004) find that even when controlling for detailed individual characteristics, there is substantial variation in sickness absence between establishments. Such establishment effects may have different explanations, e.g. differences in working conditions, different social norms and attitudes towards sickness absence across workplaces, and sorting of workers across establishments. In any case, it clearly suggests that sickness absence *relative* to that of colleagues may be the relevant variable when studying selective layoffs for health reasons in downsizings.

The literature on selective layoffs in downsizing is scarce. Pfann (2006) develops a theoretical model of establishments' layoff policies under uncertainty. Key factors here are heterogeneous firing costs, idiosyncratic productivity growth and uncertainty related to this. In an empirical analysis, idiosyncratic productivity growth is proxied by within-job wage growth. The results are consistent with downsizing establishments selectively retaining workers with the largest expected contribution to future profits. We are not aware of any papers directly relating sickness absence to layoff risk in downsizing. Hesselius (2007), using Swedish panel data, studies the relationship between sickness absence and unemployment. His findings suggest that sickness absence increases the risk of unemployment. Selective layoffs in downsizings is one possible explanation behind this result.

# 3. How do institutions restrict employer discretion in dismissals?

Employees enjoy a relatively high level of formal protection in Norway. In an international comparison of EPLs (OECD, 1999), Norwegian EPL was classified as a high-protection regime. The study ranks Norway as the most restrictive country in terms of difficulty of individual dismissal. Compared to other countries, there are no particular restrictions on downsizings, but there are restrictions regarding who and how many workers an employer can displace. Employer and employee representatives are required to agree upon objective criteria for selecting the workers to be laid off. The selection criteria usually include tenure as an important element, but selection may also be based on a joint assessment of individual worker qualifications and employer needs. The number of displaced workers is also negotiated with employee representatives, and the employer is required to find work for as many as possible in other parts of the firm. This applies even if it requires some re-training of workers. Still, employers can influence the job content that a given employee would be offered after downsizing if he were to stay, and may offer severance payments or retirement packages targeted at older workers. Hence, employers can influence selection directly through negotiated criteria for displacement, and indirectly via affecting individual workers' incentives to quit.

We argued above that employers are likely to consider workers with inferior health less valuable than other workers, such that workers who have been absent for sickness reasons face a higher risk of displacement in downsizings. However, this requires that these workers are relatively less protected in downsizing processes than otherwise. Norwegian EPL states that workers on sickness absence are protected against *individual* dismissal. In case of dismissal of a worker within 6 months after he became sick, the worker should be considered as displaced because of the absence unless some other reason is highly probable. The limit is 12 months for workers with more than 5 years tenure and for workers who were injured or became sick while at work. Otherwise, long-term absence can be a legitimate reason for displacement if it represents an important problem to the firm. Firms that need to cut employment are allowed to displace a worker who is or has been absent for health reasons, if his job has become economically redundant. Because redundancy of jobs is a necessary condition for downsizing, absent workers enjoy no special protection when firms downsize.

Sickness absence may signal lower future idiosyncratic profits due to lower productivity. In addition, absence entails contemporaneous costs for employers, in terms of direct costs and foregone output. Employed workers with more than two weeks tenure and recent earnings above a rather low threshold, are entitled to compensation during sickness for up to 12 months. This is essentially an insurance scheme, with rights depending on recent earned income. The degree of compensation is 100 percent (by law up to a ceiling, but employers often cover the difference up to full compensation). Until 1998 the employer had to pay sickness compensation for the first 14 calendar days of absence, after which Government paid the remaining sickness absence period. Since 1998 the employer payment period has been 16 days.

# 4. Data sources, sample and variable construction

## Main data sources

The data used in this study are taken from Norwegian administrative registers for firms, establishments and individuals. The data are collected by various government agencies for administrative purposes, and cover the entire Norwegian population of persons and firms. Consistent use of firm, establishment and person identifiers across registers facilitates linking of different data sets. Our key data source is the employer-employee register, which is part of the social security system. Employers report information on jobs, such as start and end dates, contracted working hours and changes in working hours along with the dates of these changes to a social security register. Apart from very short job spells and self-employment, the data include all jobs in the Norwegian economy since 1992. We use data for the years 1992 to 2004. The data allow us to follow establishments over time and to follow workers between establishments, giving us our source of information on the creation and termination of employment relationships. It also forms the basis for identifying downsizing events. This procedure is described in detail in Appendix A. Because the employer-employee register contains both establishment and personal identifiers, we are also able to link additional information on employers and employees to the dataset.

We collect information on individuals from several registers. The FD-TRYGD[1] database is a collection of various datasets with information on individuals. The database contains basic demographic information and data on receipt of various benefits and pensions received any given year. We obtain information on annual earnings for each job from the LTO-register[2]. Actual labour market experience is calculated using individual earnings histories from 1967 onwards, see Hægeland (2001) for details. Data on education is taken from the National Education Database, with individual information on all completed educations since 1974. Basic establishment information, such as industry and location, is obtained from the Central Register of Establishments and Enterprises.

## Relative worker characteristics

We argued above that when firms downsize, workers compete for a limited number of jobs, implying that individual displacement probabilities depend on individual characteristics relative to co-workers. We take this into account by defining peer groups of similar workers, and operate with a set of peer group adjusted variables, $\tilde{x}_{ijt} = x_{ijt} - \overline{x}_{jt}$, where $x_{ijt}$ is a generic variable measured for a worker *i* in establishment *j* in year *t*. $\overline{x}_{jt}$ is the average of $x_{ijt}$ over workers employed in establishment *j* in year *t*. Typically, the competition is between co-workers with similar qualifications, because workers are not substitutes in the sense that a worker can perform the tasks that any other worker does. Skill level as defined by length of education is probably the single most important dimension of segregation

[1] Documentation (in Norwegian) of the database can be found at this address: http://www.ssb.no/emner/03/fd-trygd/

[2] The LTO-register (LTO is a Norwegian abbreviation) is the Norwegian Tax Directorate's register of wage sums. All employers are required to report paid wages to the Tax Directorate. Reporting is done at the firm level. There is one report for each contract of employment, each year.

between workers' jobs. We therefore also define a tighter peer group, by considering workers of the same length of education in three categories: Lower secondary school (less than 11 years of education), upper secondary school (11 to 13 years), and tertiary education (14 years or more). We let subscript $s(i)$ index skill group of person *i*, and define the adjusted variables $\tilde{x}_{is(i)jt} = x_{is(i)t} - \overline{x}_{s(i)jt}$, where $\overline{x}_{sjt}$ is the average over workers within skill group *s* employed in establishment *j* in year *t*.

## Sample selection – establishments

In the following we consider nine cohorts of workers, one cohort for each of the years 1995 to 2003, where all workers of a cohort satisfy the sample inclusion criteria in the given year. For a given year $t = 1995,...,2003$, we include in our sample all establishments that did not downsize through the years $t-3$ to $t-1$. The reason for excluding establishments that downsized in the preceding years, is that these establishments may already have laid off workers selectively, and sorting on individual productivity is probably more important in a first wave of downsizing. We exclude establishment-year observations where the establishment downsizes at least 80 percent or closes, noting that there is little or no selection between employees in such events. Because we consider selection of workers based on worker characteristics relative to peers, we re-calculate the downsizing percentage for the relevant peer group, within the sample, i.e. the downsizing percentage is re-defined to equal the share of exiting workers within a peer group. We then apply the criterion for downsizing of at least 10 percent and at most 80 percent within the peer group, on the re-calculated peer group specific downsizing percentages. When the entire establishment is considered the relevant peer group, the downsizing indicator, $D_{jt}$, equals one if establishment *j* downsized in year *t*, zero otherwise. When the peer group is defined as workers with the same education level in the establishment, $D_{sjt}$ is the downsizing indicator.

The procedures described above are likely to be less accurate for small establishments and small downsizing events. We therefore restrict our sample to establishments with at least 100 employees at the beginning of year $t-1$ (it will be clear below why this rule is not applied year *t*), and peer groups with at least 10 employees. Finally, we exclude the largest 1 percent of establishments, in order to avoid that the results are driven by the behaviour of a few very large establishments. This restriction excludes 9.4 percent of the individual observations (after other exclusion criteria are imposed). The empirical results are not sensitive to this exclusion. We restrict the sample to private sector in establishments in six 1-digit NACE categories, see Table 1.

## Sample selection – selection on workers

The exact timing of a downsizing within a calendar year is difficult to observe. Even if different job separations are part of the same downsizing process, the employment relationships may not have the same termination date, e.g. if the downsizing process is stretched over time. We therefore measure workers' transitions into, out of and between establishments at yearly intervals, based on the registered employment relationship on January 1 each year. Downsizing may be anticipated, or at least employees may observe an increased risk of downsizing, before it occurs. As a result, those who leave downsizing firms before the downsizing takes place are likely to not be representative of all employees. However, the direction of selection is not obvious. On the one hand, one would expect more quits from workers with better outside options, but on the other hand, workers who fear (the consequences of) layoff may search more intensively for new jobs. In any case, those employed with the establishment "on the day of" downsizing may not be representative for the workforce prior to the downsizing process. In our sample, the share of workers exiting during year $t-1$ (early leavers) is 9.3 percent in non-downsizing establishments, and 10.9 percent in downsizing establishments.

Although it is possible that those who have not left the downsizing establishment before downsizing occurs are selected sub-sample of all previous employees, including early leavers in our sample may obscure the sorting that occurs among the stayers: regardless of the self-selection out of the establishment prior to downsizing, the employer's behaviour in the downsizing situation may be better described by restricting attention to the sorting into displaced and retained workers of those who are employed in the establishment at the beginning of year *t*. With early exits comprising a non-negligible share of total exits, we use two alternative sample definitions. In the first definition, we include early leavers in the sample, modelling the probability of separating from an establishment during the two years $t-1$ and *t*, for workers employed in the establishment at the beginning of year $t-1$. In the second sample we exclude early leavers, modelling the probability of separating from an establishment during year $t$, for workers employed in the establishment at the beginning of year $t$.

For both data definitions we restrict the "gross" sample to workers with at least two years tenure at the beginning of year $t-1$. This ensures that any estimated effects on exit probabilities do not pick up "marginal worker" effects in job stability, and is in line with the traditional definitions of displaced workers, see Fallick (1996). For the same reasons, we exclude those who were not in a full time job on January 1 in $t-2$, using a code for full time job as reported by establishments. We apply an additional restriction on earnings, excluding workers with annual earnings below a threshold that corresponds to 38 working hours per week for a full year at the minimum wage (there is no statutory minimum wage in Norway, but we apply the lowest negotiated hourly wage for workers employed in the services sector), for each of the years $t-3$ and $t-2$. Finally, we exclude workers below 20 and above 59 years of age.

## Key variables

In our econometric analysis, we model how the excess probability of exit from a downsizing establishment depends on age, labour market experience, tenure, education, gender, sickness absence and residuals from a wage growth regression. We also control for variation in exit rates according to these variables and across sector, year, and region.

Sickness absence is measured by the variable Sickdays that counts number of days covered by the social insurance system during the years $t-3$ and $t-2$, truncated above at 180 days and divided by 100 (we check how our results is affected by different truncation rules). This means that spells shorter than 14 calendar days are not included (16 after 1998). Later absence may occur when the person is employed in a different establishment, if the person changes employer during year $t-1$, and absence (and presence) may be caused by downsizing and the processes that precede downsizing. Hence, if persons with prior knowledge of idiosyncratic displacement risk adapt their absence behaviour accordingly, absence measured during year $t-1$ could be endogenous to exit.

We assume that firms offer higher wage growth to workers who are expected to be more valuable to the firm in the future, and we use within-job wage growth as a proxy for expected idiosyncratic profits, like Pfann (2006). However, wage growth may also reflect productivity shocks, and expected idiosyncratic profits will depend on a range of individual characteristics. Consequently, we allow sorting to depend on a number of individual characteristics (that may also reflect the impact of institutional constraints on layoffs), on sickness absence, and on residual wage growth, defined as the residual from a regression of wage growth on other included variables and absence.[3] Details on the construction of the residual wage growth variable are given in Section 5.

## Sample description

Table 1 reports selected statistics at the establishment-year level, distinguishing establishment-year observations with and without downsizing. Downsizing and non-downsizing establishments are very

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[3] We have also estimated our preferred model using wage growth in place of residual wage growth, and this only yields a very small change in the Difference-in-Difference estimates of sickness absence and idiosyncratic productivity as measured by (residual) wage growth within the job.

similar in terms of size, local economic environment (the labour force and unemployment rates are measured at the municipality level) and distributions across sectors, although downsizing has been less frequent in finance. Table 2 reports means and standard deviation of selected worker characteristics, split by downsizing/non-downsizing establishments, and by workers who exited year $t-1$, year *t*, and workers who did not exit. Relative to exiters, stayers are older and have more experience, longer tenure, shorter education, and less sickness absence. Given exit, late exiters are older and have more experience, longer tenure, shorter education, and less sickness absence, than early leavers. The higher share of persons with sickness absence among early leavers may reflect that these persons are more likely to leave the labour force. There are only minor differences in these patterns between downsizing establishments and other establishments. The means of the peer group adjusted variables are also reported in Table 1. Using these variables we eliminate the difference in employee composition across establishments. Notice that the difference between stayers and exiters in terms of sickness absence increases when we purge fixed establishment effects, stayers having less absence than exiters. However, this is also the case for non-downsizing establishments, and this suggests that part of the higher absence rate among exiters than stayers in downsizing firms is due to other reasons than the downsizing event. This again implies that a Difference-in-Difference method, using employees of non-downsizing establishment as controls, is appropriate for estimating the extent of sorting in downsizings. The table suggests that it is not very important whether the peer group is defined as the establishment or as all workers with the same education level in the establishment.

Figure 1 displays the distribution of sickness absence days accumulated during years $t-3$ and $t-2$. All registered spells exceeded 14 (16) days, but the duration used here includes uninsured days. Given absence, the median duration is 52 days, the mean 89. 24.7 percent of workers have been absent, with the share of absent workers increasing from 20.2 percent in the 1995-cohort to 29.6 percent in the 2003 cohort. This mirrors the overall increase in sickness absence in Norway over this period, when the number of sickness absence days covered by Social Security increased from 8.6 in 1995 to 14.0 in 2003, measured per employed person[4].

# 5. Econometric framework

We formulate a linear probability model (LPM) for worker exit from an establishment during a given period. When early leavers are included in the sample this period is two years, from the beginning of year $t-1$ to the end of year *t*. When we exclude early leavers, the period is during year *t*. We pool

[4] Source: Social Security Statistics Year Book 2004, Table 6.3, url: http://www.nav.no/binary/805321751/file.

observations that satisfy the sample selection criteria in different years. Thus, the subscript $t = 1995, 1996, ..., 2003$ refers to observations from different years. Let $exit_{ijt}$ be a dummy variable that equals one if person *i* who was employed in establishment *j* at the beginning of year $t-1$ (or at the beginning of year *t* in the specification without early leavers) left *j* before the beginning of year $t+1$. We can then express the exit probability in terms of observed worker and establishment variables, as

(1) $$P\left(exit_{ijt} = 1 \mid x_{ijt}, z_{jt}, D_{jt} = 1\right) = \alpha + x_{ijt}\beta + z_{jt}\gamma .$$

$x_{ijt}$ is a vector of worker characteristics that includes age, experience, tenure, education, gender, previous sickness absence and residual wage growth (see below). $z_{jt}$ is a vector of variables that includes dummies for establishment size and industry, local labour market conditions, regional and time effects. We can then estimate the parameters $(\alpha, \beta, \gamma)$ by a least squares regression of *exit* on a constant, *x* and *z*. The LPM is a good approximation of the true exit probability, but the assumption of constant marginal effects can only be valid within a constrained range of the included explanatory variables. If the coefficient on a particular variable is non-zero, then increasing this variable will eventually result in the predicted exit probability becoming negative or larger than one. In addition, the LPM implies that the error terms are heteroskedastic. Still, we choose to work with the LPM due to its convenience and ease of interpretation[5].

Under "ideal" conditions, we would get unbiased estimates of employers' sorting on variables *x* from estimating the model (1) on a sample of workers employed in downsizing firms on the day of downsizing. Ideal conditions corresponds to a situation where downsizing comes as a complete surprise to workers, where all exits within the period of observation are displacements due to the downsizing event, and where sorting depends on the absolute values of *x*. Neither of these conditions are likely to be fulfilled, and the modelling approach needs to take this into account.

Consider first the problem of observing which exits that *are due to* the downsizing. As discussed earlier, the data do not distinguish explicitly between quits and layoffs. Because we measure downsizing over a time interval of one year, this implies that some of the exits in our sample will be initiated by employees, i.e. quits. More generally, some of the exits will be part of an outflow, that

[5] We have also carried out the analysis using a logit model instead of a linear probability model. The results are similar to those we present in the next section.

would have occurred even if the establishment had not downsized. Hence, even if we believe that early exit is exogenous conditional on included variables, such that we can narrow the period of exit to the calendar year when the firm downsizes, some exits are not displacements that are part of the downsizing event of interest, and equation (1) will not yield correct estimates of employer behaviour. If early exit from downsizing firms is endogenous conditional on included variables, i.e. workers with particular unobserved characteristics are more likely to quit before downsizing than other workers, we need to include early leavers when estimating (1) in order to avoid selection bias. But including early leavers implies that a larger share of total exits is due to quits, assuming that the majority of early exits are initiated by employees. We propose to solve this problem by using employees of non-downsizing establishments as controls: If the relation between ordinary outflow and observed variables is the same in downsizing and non-downsizing firms, we can use employees of non-downsizing firms to identify how the included variables relate to this outflow, and thus identify the sorting that occurs in the *additional* outflow from downsizing firms. The difference in the effect of a variable on the exit rates in downsizing versus non-downsizing establishments will then be attributed to the sorting done by downsizing establishments.

The second problem with model (1) is that downsizing firms may sort workers based on relative worker characteristics, in addition to selecting workers based on absolute values of their characteristics. We therefore include the peer group adjusted variables, $\tilde{x}_{ijt} = x_{ijt} - \overline{x}_{jt}$, in the model for exit. We therefore formulate a Difference-in-Difference estimator that uses employees of non-downsizing firms as controls to adjust for "usual outflow", i.e. primarily quits. Then,

(2) $$P\left(exit_{ijt} = 1 \mid x_{ijt}, z_{jt}, \tilde{x}_{ijt}, D_{jt}\right) = \alpha + x_{ijt}\beta + z_{jt}\gamma + \tilde{x}_{ijt}\mu + D_{jt}\delta_1 + D_{jt}\tilde{x}_{ijt}\delta_2 + D_{jt}z_{jt}\delta_3 ,$$

where $D_{jt}$ is the downsizing indicator. Note that the probability of exit depends on $x_{ijt}$ in both downsizing and non-downsizing establishments. We believe that employers may rate workers based on both workers' own characteristics, and on the each worker's characteristics relative to co-workers. We do not include interaction terms between $x_{ijt}$ and $D_{jt}$, assuming that the *absolute* effect on exit of different individual characteristics does not vary between downsizing and non-downsizing establishments. It is the effects of characteristics relative to peers that may have a different impact under downsizing. In (2), the effect of interest is the difference in the exit probability in a downsizing establishment, induced by a change in some variable of interest, $x^k$, over and above the induced difference in exit probability in other establishments. In other words, we are looking for the

Difference-in-Difference effect of a change in $x^k$ of size *d* on the exit probability. Formally, this effect is (ignoring the effect of a change in $x_{ijt}^k$ on $\bar{x}_{jt}^k$),

$$
\begin{aligned}
(3) \qquad DiD\left(x^k,d\right) &= P\left(exit=1 \mid D=1, x^k=b_0+d\right) - P\left(exit=1 \mid D=1, x^k=b_0\right) \\
&\quad -\left[P\left(exit=1 \mid D=0, x^k=b_0+d\right) - P\left(exit=1 \mid D=0, x^k=b_0\right)\right] \\
&= d\delta_2^k
\end{aligned}
$$

Hence, the coefficients $\delta_2$ give direct estimates of the Difference-in-Difference effects of unit changes in the associated variables.

Residual wage growth, which is part of the vector *x*, is calculated from estimates of the following wage growth model

$$
(4) \qquad \Delta \ln w_{ijt} = \beta_0 + y_{ijt}\beta_1 + z_{jt}\beta_2 + e_{ijt},
$$

where $\Delta \ln w_{ijt}$ is the change in log hourly wage from year $t-3$ to $t-2$, i.e. within the job, because all persons in the sample were employed in the same job during these two years. $e_{ijt}$ is a random error term and $y_{ijt}$ is a vector of explanatory variables that includes measures of age, experience, tenure, education, gender and previous sickness absence (defined in more flexible forms than the variables included in the models for exit). The variables included in *z*, that are the same as included in the models for exit, capture that quit rates depend on outside options. A high local unemployment rate will be associated with depressed wages and few job offers, leading to a low quit rate. All else equal, there will be fewer job opportunities in a small labour market, which also generates a lower quit rate. Notice that we have conditioned on the level and the square of Sickdays. Hence, the residual is uncorrelated with Sickdays by construction. The residual $\hat{e}_{ijt}$ from the OLS regression (3), which we label RWG for residual wage growth, is our proxy variable for idiosyncratic productivity shocks. The results from estimating the wage growth regression can be found in Appendix B. We have also estimated the models using raw wage growth, like Pfann (2006), yielding quantitatively very similar estimates.

## 6. Results

We begin with discussing the results for equation (1), estimated separately for downsizing and non-downsizing establishments, including and excluding early leavers. The results are presented in Table 3. We then proceed to the estimates of the parameters of (2).

Table 3 shows that previous sickness absence is a strong predictor for exit. In the sample including early leavers, 100 additional sickdays is associated with an increase in exit probability of 7.2 percentage points in non-downsizing establishments and 7.9 percentage points in downsizing establishments. When we exclude early leavers, the corresponding figures are 4.5 and 3.1 percentage points, respectively. Given that the health status of workers with sickness absence does not differ substantially across downsizing status of establishments conditional on other included variables, the "pure health effect" of sickness absence on exit should be similar in downsizing and non-downsizing establishments, and the results support this assumption[6]. Residual wage growth (*RWG)* is also a strong predictor of exit: A negative coefficient means that higher residual wage growth is associated with a lower exit probability. The standard deviation of *RWG* is 0.09, hence a decrease in residual wage growth of one standard deviation is associated with an increased exit probability of 0.8 (0.09*0.0886) percentage points in downsizing establishments and 0.3 percentage points in non-downsizing establishments. Excluding early leavers, the effects are 0.7 and 0.2 percentage points, respectively.

Higher tenure is associated with lower exit probabilities. Tenure may affect quit and layoff rates in a causal sense, through wage returns to seniority and protection of high-tenure employees by e.g. "last-in first-out" rules. Learning about worker-employer match quality may also lead to a negative relationship between seniority and job exit rates (Jovanovic, 1979). However, exit rates may decrease with tenure even without a causal effect, due to composition effects: If workers differ in latent exit rates, workers with high latent exit rates will leave jobs sooner, such that expected exit rates decrease with tenure. The tenure effect is stronger in downsizing establishments, suggesting that seniority rules may play a role in determining who is laid off in downsizings. Remember that we have restricted the sample to workers with at least two years of tenure at the beginning of year $t-1$, such that the higher tenure effect in downsizing establishments do not merely reflect that marginal workers are typically displaced first.

[6] Note that we do not control for downsizing percentage in the estimations presented. If there is correlation between downsizing percentage and independent variables such as sickness absence, this could drive our results. However, results from specifications including downsizing percentage (not reported) yield similar results.

Women and more educated workers are found to be more mobile regardless of whether the establishment downsizes, but the excess mobility is higher in non-downsizing establishments. The relationships between age and exits is negative and close to linear in both downsizing and non-downsizing establishments, with 10 additional years of age (from 30 to 40) being associated with 3.8 percentage points lower probability of exit for employees of non-downsizing establishments, and 2.1 percentage points in downsizing establishments. Excluding early leavers, the differences are smaller, and essentially zero in downsizing establishments. When we include early leavers, exit rates decrease with experience until 28 and 23 years in downsizing and non-downsizing establishments, respectively. Compared to a worker with 10 years experience, a worker with 20 years experience has 4.1 and 2.7 percentage points lower exit probability in a downsizing and a non/downsizing establishment, respectively. The corresponding numbers in the sample excluding early leavers are 3.9 and 1.5 percentage points. The negative relationships between age and exit follow from job search models with on-the-job search, where job quality becomes positively correlated with age, such that quit rates decline with age (Burdett, 1978). If job destruction risk is seen as an attribute of jobs, then older workers will also have moved to jobs that are less risky on average, causing a negative correlation between age and layoff rates. Similar arguments hold for experience, if non-employment implies a setback in job values. Still, experience (conditional on age and years of education) is also likely to pick up effects of omitted variables that cause, or are correlated with, job exit rates.

Given downsizing status, there seems to be no effect on exit rates of local labor market conditions. Conditional on observed worker characteristics all industries have higher exit rates than manufacturing, which is the reference category. In the sample of downsizing establishments, the industry differences may reflect systematic differences in the size of downsizings. Downsizings in finance, which also are few in number, tend to be smaller in magnitude.

We now turn to our main specification and the Difference-in-Difference estimates. The results in Table 3 suggest that the absolute effects of individual variables do not vary too strongly across downsizing status. We therefore maintain the assumption that they are equal, but investigate whether the effect of individual characteristics relative to those of peers vary across downsizing status. The results are reported Table 4. We present the results from two alternative peer group definitions as defined above, and on samples excluding and including early leavers.

The results show that the effects on exit of individual characteristics relative to peers are different in downsizing establishments. Increasing individual sickness absence by 100 days, keeping the sickness absence of the other employees in the establishment constant, increases the exit probability by 8.0 percentage points (0.1908-0.1112; column 1 of Table 4). There is a strong effect of relative sickness absence: Given previous sickness absence, if average sickness absence of colleagues decreases with 100 days, the exit probability increases with 19 percentage points. In downsizing establishments, the effect is 0.76 percentage points higher (this is the coefficient on peer group adjusted Sickdays interacted with the downsizing indicator, and multiplied by 100). This additional effect has a p-value of 0.059. If we narrow the peer group to colleagues with similar education level, the additional effect of absence is one percentage point, with a p-value of 0.012. If we exclude early leavers from the sample, the excess exit probability is higher: 1.6 percentage points with the establishment peer-group specification, and 1.8 percentage points when we use colleagues with similar education as peer groups. Both these estimates are highly significant. As discussed above, excluding early leavers gives a more correct estimate of employer behaviour if early exit is random conditional on included variables. If this is the case, the larger effect of absence when excluding early leavers suggest that workers with inferior health are particularly unlikely to leave struggling firms before downsizing, perhaps because they lose out in the competition for alternative jobs. However, come the day of downsizing, the employer picks healthy workers before sick workers for continued employment. This interpretation is consistent with previous findings that early leavers tend to be positively selected, see Schwerdt (2007) and Lengermann and Vilhuber (2002).

The excess exit probability for workers with previous sickness absence in downsizing establishments indicates that employers do use downsizing events as opportunities to terminate the employment relationships of workers who are otherwise difficult to displace. However, the effect is quite moderate and relative sickness absence is also a strong predictor for exit in non-downsizing establishments. This may reflect that workers with previous sickness absence have worse average health, and therefore have higher exit rates for pure health-related reasons. Since we use *previous* absence, the workers with the most serious diagnoses may already have left the establishment (and probably the labour force) at the beginning of year $t-1$, and are therefore excluded from the sample. Among employees with previous sickness absence in our sample, people who suffered from less serious illnesses are thus likely to be overrepresented. This means that we expect our estimate to represent a conservative estimate of sorting on absence.

Low residual wage growth may indicate that the employer expects low growth in idiosyncratic profits for this worker, or that the worker has experienced negative productivity growth that was at least partly accomodated in wages. In non-downsizing establishments, the expected direction of the relationship between residual wage growth and exit is ambiguous, depending on whether a low residual represents relatively poor outside options or only reflects low job-specific productivity. The coefficients on *RWG* and on peer group adjusted *RWG* show that there is no clear relationship between residual wage growth and exit from non-downsizing establishments, whereas the effect is negative in downsizing establishments, although the statistical significance varies across samples and peer group definitions. The lower the residual wage growth relative to one's peers, the higher is the exit probability in downsizing establishments. The relation is strongest when we include early leavers in the sample and have a narrow peer group: One standard deviation (0.09) lower residual wage growth is associated with 0.4 percentage points higher exit probability in downsizing establishments relative to establishments that do not downsize. This indicates that individual productivity, or expected contribution to establishment profits, conditional on human capital components related to age, experience, tenure, education and gender, is used for sorting workers in downsizing events.

Tenure is often used as an explicit selection criterion in downsizings. We find that workers with high tenure relative to peers have significantly lower exit probability in downsizing establishments than in establishments that do not downsize, with the excess protection amounting to 1 percentage point lower exit probability for 3 additional years tenure. The same is true for general labour market experience, and the opposite for age. Higher age relative to peers is associated with higher exit rates in downsizing firms. Assuming that re-training is costly to establishments, and downsizing involves re-organization and re-training or transferring some workers to different tasks, older workers may be less attractive to employers. Similarly, if re-training and adaptation to new tasks is costly to workers, older workers may not find it worthwhile to undertake this investment, and may find alternative job opportunities or choose to retire, see Bartel and Sicherman (1993). Workers who have more education than their colleages are somewhat less likely to exit from downsizing firms than from firms that do not downsize. The effect is quite small, and it is interesting to note that it is only significant in the specification where the peer group consists of workers with broadly similar education. This is consistent with the competition for jobs being between workers of similar education level, and that differences in education *within* these levels are more relevant for sorting.

Female workers in male dominated establishments have lower exit probabilities overall, but this difference is significantly lower in downsizing establishments. The excess exit probability for women above that for men is 1.4-1.8 percentage points higher in downsizing establishments than in other establishments with the same gender composition.

The results suggest that there is some extent of sorting in downsizings. Workers with previous sickness absence and low residual wage growth have higher separation rates in downsizing firms, all else equal. The opposite is the case for workers with high tenure, experience or education, whereas there seems to be a weak tendency that older workers leave downsizing firms. The results are qualitatively similar across samples and peer-group definitions. The strongest effect of absence is found when we use the tightest peer-group definition and exclude early leavers from the sample. The former suggest that employers compare workers of with similar levels of schooling, while the latter suggests that it is the workers with best outside opportunities (good health) that tend to leave before downsizing sets in.

## Robustness checks and sensitivity analysis

Including a range of peer group adjusted variables to be interacted with the downsizing indicator may result in a too low estimate of the Difference-in-Difference effect of health, imperfectly proxied by Sickdays. This is because these additional variables may be correlated with health and therefore pick up some of the effect we would really like to attribute to health. For instance, if employers do sort workers according to health unconditional on other characteristics, perhaps not sorting on other variables at all, then including these other characteristics may conceal the gross role of health in sorting. On the other hand, if employers do not sort on health but only on variables that are correlated with health, then dropping these variables will attribute a spurious effect to health as measured by Sickdays. Dropping all other variables than Sickdays among the peer-group adjusted variables in the interaction with *D* gives Difference-in-Difference effects of absence that are around 20 percent higher than in our main specifications. Hence, the excluded variables may together pick up some of the effect of absence on exit probabilities, but the quantitative importance of this is small[7].

***Extent of downsizing***

We now consider variation in the Difference-in-Difference effects of downsizing between downsizing events of different magnitude. One could expect smaller selection effects in smaller downsizings, because it is may be more difficult for establishments to argue that an individual worker is laid off randomly, or according to strictly objective, agreed criteria. If it is not allowed (by law, or as laid down in agreements with employee organisations) to lay off workers based on sickness absence, it is more difficult to get around this when the downsizing is small and it is more obvious who was selected out. In large downsizing events, the scope for selection is also smaller. Entire departments may be closed down, and we expect to find a smaller selection effect of sickness absence. In addition, the

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[7] Excluding only age results in a DiD-effect of absence of 0.0099, that is almost exactly the same as with age included.

larger the downsizing, the deeper is the likely involvement of unions, formal negotiations etc, thus limiting the scope for selection of workers that cannot be justified by rules and agreements.

In order to investigate this empirically, we extend equation (2) by splitting the downsizing indicator into six dummy variables for the downsizing intervals [10,20), [20,30), [30,40), [40,50), [50,60), and [60,80) percent. When the peer group is defined by education level, these intervals account for 27, 26, 17, 11, 11 and 8 percent of the downsizing events, respectively. The results from estimation of this model with the peer group defined at the education group level are presented in Table 5. There is selection on absence in downsizings of up to 50 percent of workers, both with and without early leavers. This result is in line with the expected larger scope for sorting in medium-sized downsizing events. For larger downsizings, the sorting is precisely zero when early leavers are excluded, but negative with early leavers included. We have not been able to explain this by variation in the composition of workers and downsizing percentages across establishments in different sectors.

***Firm size***

One might expect that downsizing processes differ between large and small firms. Large firms will often receive more public attention, and therefore have a stronger incentive to design their downsizing process in a way that has least possible negative effect on reputation. This may imply more frequent use of retirement schemes and severance payments, such that the distinction between a quit and a dismissal becomes less clear; by offering generous compensation for quitting, the firms avoids a number of dismissals. Trade unions are more likely to be involved in downsizings involving a large number of workers. This suggests that downsizing in larger firms, and downsizings involving more workers, probably follow more "regulated" procedures, with formal, objective criteria being relatively more important for the selection of retained and displaced workers. These arguments would imply that sickness absence is less important as a selection criterion when large firms downsize. In downsizing firms that offer attractive compensation packages for leaving, we might expect that workers who do not thrive will be the first to accept such packages, especially older workers who consider early retirement (we have excluded workers older than 59, such that compensation arrangements directly linked to retirement are not relevant for the sample). But then an excess rate of exit among previously absent workers may reflect a choice to leave the firms, rather than be a result of the employer's sorting. Of course, offering compensation packages can also be a strategy for making certain employees leave.

The result of this discussion is that sorting on sickness absence could be either more or less important in large firms than in small firms. We now split the sample into three strata defined by establishment size (at most 200 employees, 201 to 400, and more than 400), and estimate the main specification separately by firms size, with peer groups defined as workers with the same education level, and include early leavers. Table 6 shows that sorting on absence is non-existent in the largest firms, and equally important in firms with less than 200 employees (and more than 100) as in firms with 200 to 400 employees. There is no clear pattern in the relationship with firm size and the relative importance of other variables as sorting criteria. This could indicate that downsizing processes in large firms are indeed more regulated, or at least that sorting is either based on workers deciding to leave with compensation packages, or that large firms sort workers according to other criteria than individual productivity.

***Measures of sickness absence***

The results presented above use a measure of sickness absence that is the total number of absence days covered by Social Security over two years, truncated above at 180 days. However, the effect of absence may be non-linear in absence, e.g. 100 days absence may not be a stronger signal of future productivity than 50 days, and the nature of the underlying illness is also likely to vary with total sickness absence. We calculate the Difference-in-Difference effect of 100 days sickness absence based on the regressions in Table C1, where we have estimated the preferred model for alternative truncation points for sickness absence days, with peer groups defined at the education level, and including early leavers. With truncation at 120 and 60 days, the effects are 1.31 and 1.37 (=0.0228*60), respectively. Using a dummy variable for non-zero sickness absence gives an estimate of 1.23 percentage points. With no truncation, the effect is only 0.48. This suggests that absence beyond a certain duration does not give any additional negative signal to employers, and hence does not affect sorting. It could be that very long absence is not a stronger predictor of future productivity than medium-duration absence, but it might also be the case that employers are more reluctant to dismiss employees with very high historic absence rates.

We have also repeated the analysis using number of sickness absence periods initiated during years $t-3$ and $t-2$ as our measure of absence, using the same sample definition as above. Because firms pay the first 16 days absence, the cost of absence increases in number of absence periods for a given total number of absence days. The Difference-in-Difference effect using absence periods is 0.4 percentage points for an extra absence period when including early leavers(with a standard error of 0.20), 0.85 percentage points when excluding early leavers (standard error 0.19). The average number of absence days per absence period was 79 days in 2003 among absence periods that extended beyond the employer period of 16 days.[8] The Difference-in-Difference effect estimated using sickness absence days truncated at 180 days was 0.98, such that a period of average length would have a Difference-in-Difference effect of 0.8 percentage points. Hence, the results are not very sensitive to the definition of the sickness absence variable.

# 7. Conclusions

Theory predicts, and empirical work suggests, that EPL has negative effects on productivity via limited access to workforce adjustment in times of "normal operation". If this is the case, employers may want to use extraordinary events - where other rules may apply or the real reasons for displacement may be concealed - as opportunities for workforce adjustment. Downsizing, i.e. an instance where an establishment reduces the number of employees substantially without closing down, is one such type of event.

The main contribution of this paper is to exploit a rich and comprehensive worker-establishment dataset to examine to what extent establishments use downsizing events to optimize workforce composition by displacing the least profitable workers. We do this within a regression-based Difference-in-Difference approach where workers of non-downsizing establishments act as controls, such that we estimate the excess probability of exit in downsizing events, for workers with certain characteristics.

We argue that employers expect lower future profits from workers with inferior health because health problems may persist over time, because sickness absence is costly to employers, because unhealthy workers may be less productive when working, and because wages respond slowly and incompletely to changes in individual productivity. Our empirical measure of health is previous sickness absence. In Norway, where the data in this study are from, legislation to some extent protects workers with recent sickness absence from individual dismissal. However, they enjoy no special rights in downsizings. We also include the residual from a within-job wage growth regression as a proxy for the employer's expectation of future individual profits.

We find evidence consistent with a hypothesis that establishments use downsizings as a sorting device to terminate the employment of the least profitable workers, who are protected against dismissal under normal times of operation. Our results also confirm that seniority rules influence who is laid off in

[8] Source: Social Security Statistics Year Book. Url: http://www.nav.no/binary/805321751/file (in Norwegian).

downsizings. The estimated sorting effects are strongest when we compare workers with similar education levels, suggesting that downsizing may be viewed as a competition for a limited number of jobs between workers of similar skills, and that it is worker characteristics *relative to peers* that matter for the chance of keeping your job in downsizings. The effect is largest in small and medium-sized downsizings, both in terms of the share of workers displaced, and in terms of establishment size before downsizing. This may reflect that the scope for employer discretion may be smaller in larger downsizing events, e.g. if these downsizing processes are more regulated and monitored by trade unions, and to a larger extent subject to public interest.

If downsizing provides an opportunity for establishments to behave more freely, downsizing may be a choice, and the occurrence and timing of downsizing may be a function of the composition of the workforce. Indeed, Abowd, McKinney and Vilhuber (2008) find that firms with workers in the lower end of the human capital distribution are more likely to downsize. Whether EPL causes firms with a higher share of effectively protected workers to downsize in order to have more discretion with respect to whom to lay off, is an interesting area for future research. Another unexplored issue is to what extent workers' absence behaviour is affected by the possibility of downsizing and displacement, cf. Yaniv (1991).

Even though we do find evidence consistent with employer sorting, our estimates for the excess separation rate due to sickness absence in downsizing firms are quite moderate. A minor share of the displacements in downsizings may be attributed to opportunistic sorting by employers, in the sense that they would have taken place during normal times of operation, had EPL not posed a binding constraint. This may suggest that employers use the opportunity to lay off workers selectively in downsizing, but that sorting is not the main reason for downsizings, and that EPL may not be an important obstacle to firms' firing of individual workers. The results also suggest that being displaced in a downsizing event does not reveal much information about otherwise unobservable individual productivity, and that there is little reason for statistical discrimination of displaced workers vis-à-vis retained workers among workers in downsizing firms.

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# Tables and figures

**Figure 1. Distribution of sickness absence days (sickdays). See text for definition; for days > 0; truncated above at 400**

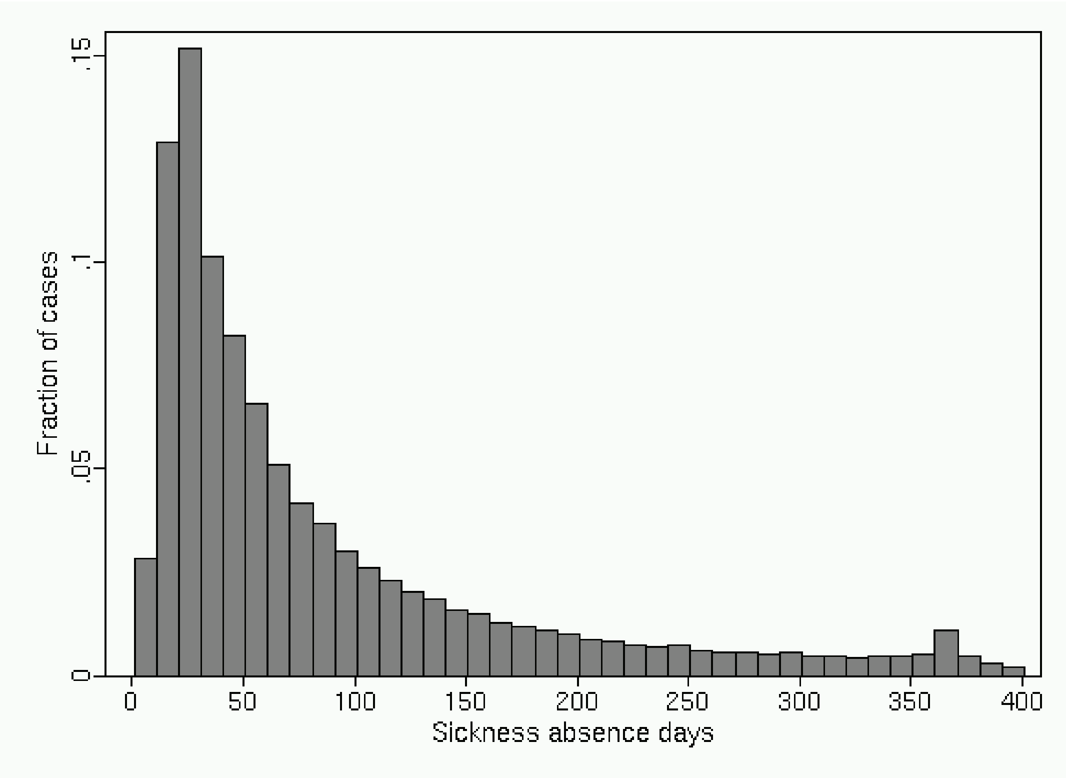

Table 1. Means and standard deviations of selected variables across establishment-year observations

| | Establishment downsizes year *t* | | Other observations | |
|---|---|---|---|---|
| | Mean | S.d. | Mean | S.d. |
| Local unemployment rate | 3.50 | 1.47 | 3.51 | 1.49 |
| Local labour force /1000 | 96.84 | 132.90 | 99.13 | 130.45 |
| Shares by industry | | | | |
| Manufacturing | 0.35 | 0.48 | 0.33 | 0.47 |
| Construction | 0.08 | 0.27 | 0.08 | 0.28 |
| Trade and repair | 0.18 | 0.38 | 0.17 | 0.37 |
| Transport and communications | 0.19 | 0.39 | 0.17 | 0.37 |
| Finance | 0.01 | 0.11 | 0.05 | 0.22 |
| Other services | 0.19 | 0.39 | 0.19 | 0.40 |
| Shares by size | | | | |
| 100-200 employees | 0.63 | 0.48 | 0.64 | 0.48 |
| 201-400 employees | 0.25 | 0.43 | 0.22 | 0.42 |
| More than 400 employees | 0.12 | 0.33 | 0.13 | 0.34 |
| Number of observations | | 1,111 | | 7,620 |

Note: Number of employees measured at beginning of year $t$-1.

Table 2. Means and standard deviations of individual charateristics

| | Establishment downsizes | | | | | | Establishment does not downsize | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Early leavers | | Other exits | | Stayers | | Early leavers | | Other exits | | Stayers | |
| | | | Mean | S.d. | Mean | S.d. | Mean | S.d. | Mean | S.d. | Mean | S.d. |
| Un-adjusted variables | | | | | | | | | | | | |
| Female | 0.26 | 0.44 | 0.27 | 0.45 | 0.23 | 0.42 | 0.29 | 0.45 | 0.28 | 0.45 | 0.24 | 0.43 |
| Age | 38.25 | 9.72 | 39.82 | 9.72 | 41.70 | 9.57 | 38.60 | 9.66 | 39.49 | 9.78 | 42.13 | 9.36 |
| Experience | 18.43 | 10.41 | 20.03 | 10.44 | 22.23 | 10.41 | 18.62 | 10.30 | 19.60 | 10.49 | 22.55 | 10.20 |
| Tenure | 6.68 | 4.97 | 7.74 | 5.33 | 9.05 | 5.75 | 7.12 | 5.14 | 7.47 | 5.31 | 9.48 | 5.81 |
| Education | 12.81 | 2.27 | 12.42 | 2.24 | 12.32 | 2.21 | 13.19 | 2.46 | 13.04 | 2.45 | 12.55 | 2.37 |
| Sick (dummy) | 0.32 | 0.47 | 0.27 | 0.45 | 0.26 | 0.44 | 0.29 | 0.45 | 0.27 | 0.44 | 0.24 | 0.43 |
| Sickdays | 0.31 | 0.58 | 0.22 | 0.48 | 0.19 | 0.43 | 0.27 | 0.55 | 0.22 | 0.48 | 0.17 | 0.41 |
| Variables adjusted for mean within establishment and year | | | | | | | | | | | | |
| Female | 0.02 | 0.40 | 0.02 | 0.41 | -0.01 | 0.38 | 0.01 | 0.42 | 0.01 | 0.41 | 0.00 | 0.39 |
| Age | -2.50 | 9.07 | -0.91 | 9.17 | 0.67 | 9.05 | -2.68 | 9.10 | -1.93 | 9.17 | 0.46 | 8.91 |
| Experience | -2.61 | 9.60 | -1.06 | 9.76 | 0.73 | 9.79 | -2.77 | 9.63 | -2.00 | 9.75 | 0.48 | 9.67 |
| Tenure | -1.26 | 4.42 | -0.61 | 4.60 | 0.38 | 4.79 | -1.32 | 4.58 | -0.99 | 4.64 | 0.23 | 4.87 |
| Education | 0.23 | 1.98 | 0.05 | 1.90 | -0.05 | 1.89 | 0.30 | 2.09 | 0.20 | 2.09 | -0.05 | 2.02 |
| Sick (dummy) | 0.06 | 0.44 | 0.02 | 0.42 | -0.02 | 0.42 | 0.06 | 0.43 | 0.04 | 0.42 | -0.01 | 0.41 |
| Sickdays | 0.10 | 0.56 | 0.03 | 0.46 | -0.02 | 0.42 | 0.10 | 0.52 | 0.05 | 0.46 | -0.01 | 0.39 |
| Number of observations | | 13,697 | | 25,817 | | 86,387 | | 87,932 | | 77,174 | | 826,315 |
| Variables adjusted for mean within establishment, year and education group | | | | | | | | | | | | |
| Female | 0.02 | 0.39 | 0.02 | 0.40 | -0.01 | 0.37 | 0.01 | 0.41 | 0.01 | 0.41 | 0.00 | 0.38 |
| Age | -2.38 | 8.74 | -0.90 | 8.86 | 0.66 | 8.81 | -2.54 | 8.79 | -1.85 | 8.84 | 0.44 | 8.62 |
| Experience | -2.41 | 9.14 | -1.04 | 9.33 | 0.71 | 9.39 | -2.52 | 9.15 | -1.85 | 9.24 | 0.43 | 9.23 |
| Tenure | -1.17 | 4.33 | -0.59 | 4.51 | 0.37 | 4.71 | -1.22 | 4.43 | -0.94 | 4.52 | 0.21 | 4.76 |
| Sick (dummy) | 0.06 | 0.44 | 0.03 | 0.41 | -0.02 | 0.41 | 0.07 | 0.42 | 0.04 | 0.41 | -0.01 | 0.41 |
| Sickdays | 0.11 | 0.54 | 0.03 | 0.45 | -0.03 | 0.41 | 0.10 | 0.51 | 0.05 | 0.45 | -0.02 | 0.39 |
| Number of observations | | 12,740 | | 24,170 | | 78,669 | | 84,479 | | 74,357 | | 808,434 |

Number of observations different when variables are adjusted for mean within establishment-year-education peer group, due to restriction of group size of at least 10, and downsizing being defined at peer group level.

Table 3. Regression models for job separation, by downsizing status

| | Including early leavers | | | | Excluding early leavers | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-downsizing establishments | | Downsizing establishments | | Non-downsizing establishments | | Downsizing establishments | |
| | Est. | t-value | Est. | t-value | Est. | t-value | Est. | t-value |
| Sickdays | 0.0719 | 39.94 | 0.0788 | 18.09 | 0.0308 | 24.54 | 0.0450 | 10.35 |
| RWG | -0.0359 | 4.36 | -0.0886 | 3.59 | -0.0188 | 3.00 | -0.0770 | 2.97 |
| Age/100 | -0.5972 | 6.18 | -0.2784 | 0.96 | -0.3385 | 4.77 | -0.0066 | 0.02 |
| $(Age/100)^2$ | 0.3099 | 2.82 | 0.0952 | 0.28 | 0.2048 | 2.55 | -0.0234 | 0.07 |
| Experience/100 | -0.8023 | 15.49 | -0.8893 | 5.98 | -0.4386 | 11.31 | -0.7519 | 5.00 |
| $(Experience/100)^2$ | 1.7763 | 18.95 | 1.6000 | 5.85 | 0.9753 | 13.84 | 1.2037 | 4.40 |
| Tenure/10 | -0.0543 | 16.28 | -0.0723 | 8.53 | -0.0291 | 11.04 | -0.0481 | 6.00 |
| Education | 0.0083 | 14.94 | 0.0059 | 3.47 | 0.0038 | 9.20 | 0.0015 | 0.84 |
| Female | 0.0111 | 5.47 | 0.0199 | 2.89 | 0.0072 | 4.97 | 0.0166 | 2.44 |
| Local unemployment rate | -0.0021 | 0.92 | 0.0003 | 0.06 | -0.0012 | 0.94 | 0.0055 | 0.99 |
| Log(local labour force/1000) | 0.0022 | 0.83 | 0.0027 | 0.42 | 0.0026 | 1.78 | 0.0036 | 0.62 |
| Construction | 0.0606 | 7.00 | 0.0955 | 3.45 | 0.0357 | 5.08 | 0.0503 | 1.93 |
| Trade and repair | 0.0288 | 5.50 | 0.0476 | 2.42 | 0.0171 | 4.46 | 0.0368 | 1.93 |
| Transport and communication | 0.0565 | 7.31 | 0.1179 | 6.07 | 0.0299 | 5.82 | 0.0949 | 4.62 |
| Finance | 0.0778 | 4.77 | -0.0723 | 2.21 | 0.0437 | 3.62 | -0.0657 | 1.93 |
| Other services | 0.0250 | 3.76 | 0.0494 | 2.85 | 0.0148 | 3.06 | 0.0394 | 2.25 |
| 201-400 employees | 0.0187 | 4.95 | 0.0051 | 0.42 | 0.0074 | 2.59 | -0.0018 | 0.16 |
| More than 400 employees | 0.0196 | 3.68 | 0.0056 | 0.40 | 0.0064 | 1.69 | 0.0093 | 0.65 |
| R-square | | 0.0571 | | 0.0553 | | 0.0271 | | 0.0416 |
| Number of clusters | | 7,620 | | 1,111 | | 7,620 | | 1,111 |
| Number of observations | | 991,421 | | 125,901 | | 903,489 | | 112,204 |

Models estimated using OLS with robust covariance matrix adjusted for correlation within establishment (using cluster option in STATA). All models include 8 dummies for year, 17 dummies for county and a constant term.

Table 4. Regression models for job separation, by peer group definiton, with and without early leavers

| | Peer group: workers in same establishment, same year. | | | | Peer group: workers with same education level in same establishment, same year. | | | |
|---|---|---|---|---|---|---|---|---|
| | Including early leavers | | Excluding early leavers | | Including early leavers | | Excluding early leavers | |
| | Est. | t-value | Est. | t-value | Est. | t-value | Est. | t-value |
| Peer group adjusted variables * D | | | | | | | | |
| Sickdays * D | 0.0076 | 1.89 | 0.0164 | 4.36 | 0.0098 | 2.50 | 0.0182 | 4.84 |
| RWG * D | -0.0396 | 1.92 | -0.0322 | 1.55 | -0.0445 | 2.41 | -0.0376 | 2.01 |
| Age/100 * D | 0.1051 | 2.08 | 0.0843 | 1.83 | 0.0874 | 1.80 | 0.0664 | 1.46 |
| Experience/100 * D | -0.1154 | 2.42 | -0.1279 | 2.80 | -0.1102 | 2.41 | -0.1242 | 2.84 |
| Tenure/10 * D | -0.0321 | 4.28 | -0.0326 | 4.49 | -0.0331 | 5.13 | -0.0337 | 5.44 |
| Education * D | -0.0020 | 1.49 | -0.0019 | 1.34 | -0.0035 | 2.11 | -0.0032 | 2.01 |
| Female * D | 0.0157 | 2.69 | 0.0137 | 2.45 | 0.0179 | 3.25 | 0.0153 | 2.97 |
| Peer group adjusted variables | | | | | | | | |
| Sickdays | 0.1908 | 6.36 | 0.0944 | 4.40 | 0.1484 | 8.55 | 0.0714 | 5.50 |
| RWG | 0.0073 | 0.13 | 0.0591 | 1.37 | -0.0441 | 1.06 | 0.0190 | 0.61 |
| Age/100 | 0.9627 | 3.34 | 0.4523 | 1.98 | 0.1748 | 1.23 | 0.0328 | 0.30 |
| Experience/100 | -0.9528 | 3.32 | -0.4604 | 2.17 | -0.3466 | 2.33 | -0.1446 | 1.30 |
| Tenure/10 | 0.0311 | 3.52 | 0.0232 | 3.28 | 0.0317 | 5.06 | 0.0216 | 4.55 |
| Education | -0.0038 | 1.09 | -0.0015 | 0.62 | -0.0008 | 0.60 | 0.0003 | 0.29 |
| Female | -0.0801 | 4.51 | -0.0370 | 2.62 | -0.0454 | 4.04 | -0.0189 | 2.09 |
| Un-adjusted variables | | | | | | | | |
| Sickdays | -0.1112 | 3.70 | -0.0606 | 2.81 | -0.0686 | 3.95 | -0.0374 | 2.87 |
| RWG | -0.0532 | 0.94 | -0.0798 | 1.86 | -0.0055 | 0.13 | -0.0429 | 1.37 |
| Age/100 | -1.5488 | 5.27 | -0.7706 | 3.32 | -0.7870 | 4.65 | -0.3819 | 2.96 |
| $(Age/100)^2$ | 0.3203 | 3.08 | 0.1958 | 2.39 | 0.3134 | 3.02 | 0.2144 | 2.68 |
| Experience/100 | 0.1130 | 0.40 | -0.0276 | 0.13 | -0.5001 | 3.21 | -0.3378 | 2.88 |
| $(Experience/100)^2$ | 1.7577 | 19.91 | 1.0109 | 14.58 | 1.8001 | 20.46 | 1.0130 | 14.75 |
| Tenure/10 | -0.0756 | 8.40 | -0.0448 | 6.14 | -0.0743 | 11.74 | -0.0424 | 8.70 |
| Education | 0.0103 | 2.97 | 0.0045 | 1.85 | 0.0065 | 4.83 | 0.0024 | 2.57 |
| Female | 0.0851 | 4.85 | 0.0418 | 3.01 | 0.0507 | 4.62 | 0.0243 | 2.75 |
| Local unemployment rate | -0.0019 | 0.86 | -0.0010 | 0.70 | -0.0027 | 1.60 | -0.0015 | 1.43 |
| Log(local labour force/1000) | 0.0027 | 1.13 | 0.0029 | 1.97 | 0.0023 | 1.19 | 0.0025 | 2.16 |
| Construction | 0.0486 | 5.50 | 0.0301 | 4.16 | 0.0505 | 7.58 | 0.0312 | 5.79 |
| Trade and repair | 0.0263 | 5.04 | 0.0169 | 4.39 | 0.0259 | 6.60 | 0.0161 | 5.58 |
| Transport and communication | 0.0535 | 6.90 | 0.0289 | 5.55 | 0.0530 | 9.08 | 0.0284 | 7.41 |
| Finance | 0.0576 | 3.39 | 0.0349 | 2.72 | 0.0593 | 5.14 | 0.0353 | 4.22 |
| Other services | 0.0156 | 1.98 | 0.0107 | 1.71 | 0.0163 | 3.06 | 0.0112 | 2.74 |
| 201-400 employees | 0.0212 | 5.65 | 0.0093 | 3.23 | 0.0201 | 6.88 | 0.0086 | 3.86 |
| More than 400 employees | 0.0228 | 4.21 | 0.0088 | 2.21 | 0.0235 | 6.03 | 0.0092 | 3.28 |
| Construction * D | 0.0368 | 1.27 | 0.0078 | 0.30 | 0.0322 | 1.35 | 0.0092 | 0.38 |
| Trade and repair * D | 0.0202 | 0.94 | 0.0230 | 1.06 | 0.0225 | 1.27 | 0.0234 | 1.28 |
| Transport and communication * D | 0.0763 | 3.54 | 0.0900 | 4.24 | 0.0743 | 4.57 | 0.0862 | 5.18 |
| Finance * D | -0.1302 | 5.36 | -0.0907 | 3.70 | -0.1350 | 6.99 | -0.0967 | 4.99 |
| Other services * D | 0.0152 | 0.86 | 0.0186 | 1.06 | 0.0045 | 0.30 | 0.0080 | 0.56 |
| 201-400 employees * D | -0.0142 | 1.11 | -0.0109 | 0.90 | -0.0159 | 1.56 | -0.0112 | 1.14 |
| More than 400 employees * D | -0.0080 | 0.48 | 0.0087 | 0.52 | -0.0046 | 0.35 | 0.0105 | 0.79 |
| D | 0.1251 | 12.59 | 0.1186 | 12.37 | 0.1328 | 16.27 | 0.1256 | 15.53 |
| R-square | | 0.0715 | | 0.0503 | | 0.0711 | | 0.0503 |
| Number of clusters | | 8,731 | | 8,731 | | 18,109 | | 18,109 |
| Number of observations | | 1,117,322 | | 1,015,693 | | 1,082,849 | | 985,630 |

Models estimated using OLS with robust covariance matrix adjusted for correlation within peer group (using cluster option in STATA). All models include 8 dummies for year, 17 dummies for county and a constant term.

Table 5. Regression models for job separation, with effect of absence by extent of downsizing

| | Including early leavers | | Excluding early leavers | |
|---|---|---|---|---|
| | Est. | t-value | Est. | t-value |
| Peer group adjusted variables * D | | | | |
| Sickdays * D1020 | 0.0109 | 1.99 | 0.0137 | 2.74 |
| Sickdays * D2030 | 0.0243 | 3.22 | 0.0250 | 3.49 |
| Sickdays * D3040 | 0.0178 | 1.63 | 0.0228 | 2.03 |
| Sickdays * D4050 | 0.0136 | 1.15 | 0.0300 | 2.13 |
| Sickdays * D5060 | -0.0207 | 2.01 | -0.0008 | 0.08 |
| Sickdays * D6080 | -0.0386 | 3.30 | -0.0017 | 0.11 |
| RWG * D | -0.0441 | 2.39 | -0.0415 | 2.24 |
| Age/100 * D | 0.0908 | 1.88 | 0.0561 | 1.23 |
| Experience/100 * D | -0.1128 | 2.47 | -0.1201 | 2.76 |
| Tenure/10 * D | -0.0332 | 5.15 | -0.0331 | 5.34 |
| Education * D | -0.0035 | 2.11 | -0.0031 | 1.92 |
| Female * D | 0.0177 | 3.19 | 0.0152 | 2.94 |
| Peer group adjusted variables | | | | |
| Sickdays | 0.1330 | 8.15 | 0.0585 | 5.27 |
| RWG | -0.0556 | 1.43 | 0.0006 | 0.02 |
| Age/100 | 0.2391 | 1.83 | 0.1066 | 1.13 |
| Experience/100 | -0.4230 | 3.07 | -0.2324 | 2.45 |
| Tenure/10 | 0.0266 | 4.37 | 0.0177 | 3.96 |
| Education | -0.0017 | 1.30 | -0.0007 | 0.72 |
| Female | -0.0440 | 4.21 | -0.0183 | 2.32 |
| Un-adjusted variables | | | | |
| Sickdays | -0.0532 | 3.25 | -0.0245 | 2.20 |
| RWG | 0.0059 | 0.15 | -0.0244 | 0.90 |
| Age/100 | -0.9177 | 5.76 | -0.5096 | 4.47 |
| $(Age/100)^2$ | 0.3906 | 3.85 | 0.2772 | 3.57 |
| Experience/100 | -0.3935 | 2.71 | -0.2260 | 2.23 |
| $(Experience/100)^2$ | 1.7398 | 20.28 | 0.9649 | 14.51 |
| Tenure/10 | -0.0692 | 11.27 | -0.0387 | 8.36 |
| Education | 0.0074 | 5.82 | 0.0034 | 4.08 |
| Female | 0.0493 | 4.83 | 0.0236 | 3.09 |
| Local unemployment rate | -0.0024 | 1.48 | -0.0014 | 1.43 |
| Log(local labour force/1000) | 0.0019 | 1.03 | 0.0020 | 1.91 |
| Construction | 0.0517 | 7.82 | 0.0321 | 5.99 |
| Trade and repair | 0.0272 | 7.00 | 0.0171 | 6.02 |
| Transport and communication | 0.0540 | 9.22 | 0.0288 | 7.58 |
| Finance | 0.0616 | 5.36 | 0.0371 | 4.47 |
| Other services | 0.0194 | 3.66 | 0.0136 | 3.37 |
| 201-400 employees | 0.0196 | 6.74 | 0.0081 | 3.65 |
| More than 400 employees | 0.0231 | 5.93 | 0.0088 | 3.14 |
| Construction * D | -0.0770 | 8.06 | -0.0791 | 6.06 |
| Trade and repair * D | -0.0421 | 6.94 | -0.0346 | 4.92 |
| Transport and communication * D | -0.0531 | 6.53 | -0.0335 | 4.25 |
| Finance * D | -0.0879 | 5.64 | -0.0568 | 3.43 |
| Other services * D | -0.0575 | 8.01 | -0.0454 | 6.33 |
| 201-400 employees * D | -0.0139 | 3.14 | -0.0060 | 1.16 |
| More than 400 employees * D | -0.0195 | 3.46 | -0.0009 | 0.15 |
| D1020 | 0.0371 | 9.16 | 0.0464 | 11.19 |
| D2030 | 0.1179 | 24.22 | 0.1100 | 21.87 |
| D3040 | 0.2037 | 35.67 | 0.1793 | 26.11 |
| D4050 | 0.2845 | 43.43 | 0.2663 | 31.15 |
| D5060 | 0.4292 | 62.84 | 0.4115 | 35.00 |
| D6080 | 0.5410 | 64.92 | 0.5298 | 38.14 |
| R-square | | 0.0862 | | 0.0712 |
| Number of clusters | | 18,109 | | 18,109 |
| Number of observations | | 1,082,849 | | 985,630 |

Models estimated using OLS with robust covariance matrix adjusted for correlation within peer group (using cluster option in STATA). Models include 8 dummies for year, 17 dummies for county and a constant term. Peer group is workers with same education level in same establishment, same year.

Table 6. Regression models for job separation, by establishment size

| | Estimation by establishment size | | | | | |
|---|---|---|---|---|---|---|
| | 100-200 employees | | 201-400 employees | | More than 400 employees | |
| | Est. | t-value | Est. | t-value | Est. | t-value |
| Peer group adjusted variables * D | | | | | | |
| Sickdays * D | 0.0164 | 2.68 | 0.0165 | 2.22 | -0.0006 | 0.09 |
| RWG * D | -0.0263 | 0.92 | -0.1299 | 3.96 | -0.0071 | 0.22 |
| Age/100 * D | 0.0824 | 1.12 | 0.0285 | 0.34 | 0.1365 | 1.59 |
| Experience/100 * D | -0.0964 | 1.36 | -0.0606 | 0.77 | -0.1557 | 1.91 |
| Tenure/10 * D | -0.0334 | 4.31 | -0.0399 | 3.94 | -0.0276 | 2.19 |
| Education * D | -0.0004 | 0.14 | -0.0101 | 3.27 | -0.0017 | 0.61 |
| Female * D | 0.0041 | 0.50 | 0.0067 | 0.71 | 0.0366 | 3.70 |
| Peer group adjusted variables | | | | | | |
| Sickdays | 0.0632 | 4.95 | 0.1024 | 4.14 | 0.2862 | 6.85 |
| RWG | 0.0560 | 1.33 | -0.1922 | 2.70 | -0.0345 | 0.36 |
| Age/100 | 0.0531 | 0.43 | 0.3989 | 1.67 | -0.0387 | 0.11 |
| Experience/100 | -0.0911 | 0.74 | -0.5999 | 2.44 | -0.2842 | 0.75 |
| Tenure/10 | 0.0187 | 3.34 | 0.0333 | 3.86 | 0.0438 | 3.07 |
| Education | -0.0019 | 1.41 | -0.0028 | 1.22 | 0.0023 | 0.68 |
| Female | -0.0289 | 2.88 | -0.0174 | 0.94 | -0.0768 | 2.97 |
| Un-adjusted variables | | | | | | |
| Sickdays | 0.0213 | 1.67 | -0.0284 | 1.15 | -0.2064 | 4.94 |
| RWG | -0.1154 | 2.80 | 0.1533 | 2.17 | -0.0141 | 0.15 |
| Age/100 | -0.8764 | 5.10 | -0.8388 | 2.96 | -0.5388 | 1.38 |
| $(Age/100)^2$ | 0.4987 | 3.51 | 0.1059 | 0.56 | 0.3277 | 1.77 |
| Experience/100 | -0.6092 | 4.46 | -0.2957 | 1.14 | -0.6278 | 1.61 |
| $(Experience/100)^2$ | 1.5277 | 12.71 | 1.8810 | 11.70 | 1.9160 | 12.32 |
| Tenure/10 | -0.0668 | 12.72 | -0.0697 | 8.34 | -0.0860 | 5.86 |
| Education | 0.0080 | 6.99 | 0.0099 | 4.68 | 0.0020 | 0.61 |
| Female | 0.0336 | 3.42 | 0.0252 | 1.37 | 0.0812 | 3.21 |
| Local unemployment rate | -0.0035 | 2.60 | -0.0012 | 0.44 | -0.0036 | 1.08 |
| Log(local labour force/1000) | -0.0002 | 0.10 | 0.0067 | 2.24 | 0.0031 | 0.73 |
| Construction | 0.0371 | 6.78 | 0.0571 | 4.79 | 0.0583 | 3.45 |
| Trade and repair | 0.0347 | 9.12 | 0.0138 | 1.92 | 0.0455 | 3.63 |
| Transport and communication | 0.0393 | 8.65 | 0.0711 | 7.23 | 0.0468 | 4.08 |
| Finance | 0.0497 | 7.12 | 0.0395 | 2.87 | 0.0614 | 2.83 |
| Other services | 0.0463 | 9.04 | 0.0303 | 3.84 | -0.0179 | 1.65 |
| 201-400 employees | | | | | | |
| More than 400 employees | | | | | | |
| Construction * D | 0.0175 | 0.83 | 0.0488 | 1.10 | 0.0410 | 0.66 |
| Trade and repair * D | -0.0015 | 0.09 | -0.0114 | 0.49 | 0.0608 | 1.54 |
| Transport and communication * D | 0.0904 | 4.68 | 0.0360 | 1.59 | 0.0947 | 3.05 |
| Finance * D | -0.0963 | 3.48 | -0.0795 | 3.42 | -0.1888 | 6.90 |
| Other services * D | 0.0173 | 0.88 | -0.0151 | 0.67 | 0.0095 | 0.35 |
| 201-400 employees * D | | | | | | |
| More than 400 employees * D | | | | | | |
| D | 0.1324 | 17.44 | 0.1292 | 11.26 | 0.1156 | 7.52 |
| R-square | | 0.0730 | | 0.0700 | | 0.0789 |
| Number of clusters | | 10,288 | | 4,603 | | 3,218 |
| Number of observations | | 355,527 | | 276,986 | | 450,336 |

Models estimated using OLS with robust covariance matrix adjusted for correlation within peer group (using cluster option in STATA). All models include 8 dummies for year, 17 dummies for county and a constant term. Peer group is workers with same education level in same establishment, same year. Early leavers included.

**Appendix A**

# Construction of the downsizing indicators

For the purpose of studying downsizing, we are interested in cases when an establishment lays off a number of employees in one single event, a mass layoff. Hence, we should eliminate changes in establishment employment that are not due to true exit or downsizing. The data series are free of such errors in principle, but with establishment identification numbers being continuously updated according to rules that include change of address, industry and legal owner, errors remain. False establishment exit may occur due to (temporary) attrition of establishments from registers, mergers and takeovers, changes in the internal organization of establishments within a firm, or changes in identification number series that are due to administrative reasons alone. In our data, there are two additional potential sources of spurious downsizing. First, there was a change in the establishment identification number series in 1995. This is adjusted for in the data available to researchers. Second, the data are constructed using two raw data sets that contain information on all jobs for the periods 1992-1999 and 1999-2005, respectively. The latter data set was extracted from registers in 2005, and therefore contains the establishment identification numbers as they were at that date, whereas the former data set has establishment identification numbers as they were in 1999. If we are not careful in constructing our downsizing indicator, we could risk finding a spurious spike in the rate of downsizing in 1999-2000.

Previous studies of worker and job flows, firm dynamics, and displaced workers, have also been concerned with constructing consistent firm/establishment identification series and eliminating false firm/establishment death and spurious downsizing from data. The usual approach is to condition on the flows of workers between firms/establishments (clustered moves). The reasons is that events with a large share of workers simultaneously moving between the same employer identification numbers likely reflect other events than downsizing. Dale-Olsen and Rønningen (2000) add criteria relating to worker flows to the criteria of location, owner and industry that form the basis for the series, namely relating to whether or not at least 30, 50 or 60% of employees remain in the plant and whether or not the employees of year 1 make up at least 30, 50 or 60% of employees of year 2. The Danish IDA database incorporates a similar correction using a threshold of 30%, see Albæk, van Audenrode and Browning (2002). Abowd, McKinney and Vilhuber (2007) apply an 80% threshold to rule out downsizing. Benedetto et al. (2007) examine the patterns of clustered worker moves between firm identification numbers in US data, finding that a threshold of 80% co-movers is supported by their data. Schwerdt (2007) applies a similar rule to identify firm death, eliminating events when at least

50% of employees move in one cluster. After careful investigation of the data and alternative rules, we have chosen to apply a threshold of 85% clustered moves, but allow for up to three clusters of joint movers per initial establishment. Hence, we are able to pick up false downsizing that occurs as a result of the establishment being split in up to three new establishments. We describe the rules in details below.

Given that the firm/establishment number series have been adjusted for false changes, we need to define downsizing events. Some studies have applied a 30%-rule, where a unit is defined as downsizing if employment drops by at least 30% from one period to the next, or if employment drops at least 30% from the maximum of employment over the period of interest, see e.g. Jacobson, LaLonde and Sullivan (1993), Lengermann and Vilhuber (2002), Abowd, McKinney and Vilhuber (2007), Albæk, Van Audenrode and Browning (2002). We define downsizing as a reduction in the number of employees of at least 10 percent during a calendar year, and at most 80%.

We take two steps to adjust the establishment number series for errors. First, if two establishments that exist on January 1 a given year have a large fraction of common employees, we merge them to a single establishment if more than 50 percent of the employees of the smaller establishment (measured by the number of employees) are also in the larger establishment[9]. Jobs for the same person in the same establishment that are at most 60 days apart are merged into one job. This is done sequentially for each year from 1992 to 2004. In the second step, we merge different establishment identification numbers that have a large fraction of common employees in two consecutive years. We use the same procedures as described above in correcting establishment identification numbers[10].

Using the corrected establishment number series, we define an establishment as downsizing a given year when the stock of employees declines by at least 10 percent from January 1 one year to January 1 the following year. Since the adjustments of establishment identification numbers described above may not have eliminated all spurious downsizing, we include the additional restriction that the workers who left the downsizing establishments did not move in clusters to one new employer or at most three new employers. Consider an establishment A that loses *k* workers (which is more than 10 percent of its employees) from year 0 to year 1, and let $m_j$ be the number of workers employed in establishment A, year 0, that are employed in establishment *j* year 1, where $m_1 > m_2 > m_3$. Then, if $m_1$ is large relative

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[9] This procedure reduces the number of establishments from 382,270 to 361,980. Note that this includes all establishments with one or more employees.

[10] Merging establishments across years further reduces the number of establishments to 348,860.

to *k*, or $m_1 + m_2$ or $m_1 + m_2 + m_3$ are large relative to *k*, the negative change in the stock of employees may not have been due to downsizing. We apply the rule that the establishment downsizes if the number of employees is reduced by at least 10 percent and $m / k < 0.85$ or $m < 6$, where

$$m = \begin{cases} m_1 & \text{if} \quad m_2 < \max(6, 0.15k) \\ m_1 + m_2 & \text{if} \quad m_3 < \max(6, 0.15k) \le m_2 \\ m_1 + m_2 + m_3 & \text{if} \quad m_3 \ge \max(6, 0.15k). \end{cases}$$

This condition states that an establishment does not downsize if 85 percent of those who left establishment A move in clusters (to one or at most three receiving establishments), and where at least six workers move together. A receiving establishment must at least receive 15 percent of those who left A, and at least six workers, in order to be counted. The rule implies that we do not pick up spurious downsizing when the employees of an establishment spread on more than three other establishments. As a final condition we require that at least 5 percent of the employees (and at least 2 employees) who left A began an unemployment spell within the same calendar year, or before the end of February the following year. If this condition is not met, the establishment is not defined as downsizing. Unemployment spells are identified from register data containing all spells of workers registered as unemployed at local unemployment offices.

# Auxiliary wage growth regression

Table B1. Wage growth regressions

| | Peer group: Establishment | | Peer group: Education level | |
|---|---|---|---|---|
| | Est. | t-value | Est. | t-value |
| lnw(*t-3* ) | -0.0705 | 45.40 | -0.0715 | 53.33 |
| Age/100 | -1.3875 | 15.55 | -1.4063 | 15.85 |
| $(Age/100)^2$ | 3.6533 | 17.50 | 3.7120 | 17.91 |
| $(Age/100)^3$ | -3.1090 | 19.33 | -3.1647 | 19.86 |
| Experience/100 | -0.1959 | 14.76 | -0.1970 | 15.89 |
| $(Experience/100)^2$ | 0.3358 | 14.07 | 0.3406 | 15.12 |
| Tenure/10 | -0.0182 | 10.81 | -0.0181 | 12.54 |
| $(Tenure/10)^2$ | 0.0061 | 8.71 | 0.0060 | 10.15 |
| Education | -0.0028 | 5.11 | -0.0024 | 3.01 |
| $Education^2$ | 0.0003 | 12.87 | 0.0003 | 8.87 |
| Female | -0.0135 | 26.23 | -0.0136 | 30.39 |
| Sickdays | -0.0197 | 22.28 | -0.0197 | 23.36 |
| $Sickdays^2$ | -0.0012 | 2.28 | -0.0012 | 2.33 |
| Local unemployment rate | -0.0008 | 1.40 | -0.0009 | 1.69 |
| Log (local labor force/1000) | -0.0002 | 0.31 | -0.0002 | 0.42 |
| Construction | -0.0051 | 2.85 | -0.0054 | 3.41 |
| Trade and repair | 0.0000 | 0.01 | 0.0001 | 0.08 |
| Transport and communication | -0.0032 | 2.48 | -0.0033 | 3.22 |
| Finance | 0.0003 | 0.17 | 0.0000 | 0.00 |
| Other services | 0.0001 | 0.11 | -0.0002 | 0.16 |
| 201-400 employees | -0.0002 | 0.26 | 0.0001 | 0.11 |
| More than 400 employees | -0.0010 | 0.98 | -0.0007 | 0.79 |
| R-square | | 0.0714 | | 0.0718 |
| Number of clusters | | 8,731 | | 18,109 |
| Number of observations | | 1,117,322 | | 1,082,849 |

Estimated using OLS with robust covariance matrix adjusted for correlation within establishment-education clusters (using cluster option in STATA). Dependent variable is change in log wage from year *t*- 3 to *t*- 2. The regression also includes 8 year dummies, 17 county dummies and a constant term.

**Appendix C**

# Variations in truncation point for sickness absence days

Table C1. Regression models for job separation, with alternative truncation points for sickness days

| | Upper truncation point for sickness absence in days | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 (dummy) | | 60 | | 120 | | 180 | | None | |
| | Est. | t-value | Est. | t-value | Est. | t-value | Est. | t-value | Est. | t-value |
| Peer group adjusted variables * D | | | | | | | | | | |
| Sickdays * D | 0.0123 | 3.40 | 0.0228 | 2.95 | 0.0131 | 2.67 | 0.0098 | 2.50 | 0.0048 | 1.67 |
| RWG * D | -0.0456 | 2.46 | -0.0448 | 2.42 | -0.0446 | 2.41 | -0.0445 | 2.41 | -0.0447 | 2.42 |
| Age/100 * D | 0.0910 | 1.87 | 0.0885 | 1.83 | 0.0879 | 1.81 | 0.0874 | 1.80 | 0.0844 | 1.74 |
| Experience/100 * D | -0.1129 | 2.46 | -0.1109 | 2.43 | -0.1105 | 2.42 | -0.1102 | 2.41 | -0.1072 | 2.35 |
| Tenure/10 * D | -0.0329 | 5.11 | -0.0329 | 5.11 | -0.0330 | 5.12 | -0.0331 | 5.13 | -0.0331 | 5.15 |
| Education * D | -0.0035 | 2.13 | -0.0035 | 2.10 | -0.0035 | 2.12 | -0.0035 | 2.11 | -0.0036 | 2.16 |
| Female * D | 0.0182 | 3.29 | 0.0179 | 3.24 | 0.0179 | 3.23 | 0.0179 | 3.25 | 0.0185 | 3.35 |
| Peer group adjusted variables | | | | | | | | | | |
| Sickdays | 0.1571 | 8.74 | 0.3243 | 8.99 | 0.1935 | 8.76 | 0.1484 | 8.55 | 0.0999 | 7.87 |
| RWG | -0.0342 | 0.82 | -0.0385 | 0.92 | -0.0425 | 1.02 | -0.0441 | 1.06 | -0.0416 | 1.00 |
| Age/100 | 0.2110 | 1.49 | 0.1861 | 1.31 | 0.1758 | 1.24 | 0.1748 | 1.23 | 0.1825 | 1.28 |
| Experience/100 | -0.3588 | 2.43 | -0.3468 | 2.34 | -0.3437 | 2.32 | -0.3466 | 2.33 | -0.3595 | 2.42 |
| Tenure/10 | 0.0315 | 5.05 | 0.0318 | 5.09 | 0.0318 | 5.07 | 0.0317 | 5.06 | 0.0317 | 5.05 |
| Education | 0.0004 | 0.30 | 0.0002 | 0.11 | -0.0004 | 0.31 | -0.0008 | 0.60 | -0.0017 | 1.20 |
| Female | -0.0441 | 3.95 | -0.0457 | 4.09 | -0.0457 | 4.08 | -0.0454 | 4.04 | -0.0445 | 3.96 |
| Un-adjusted variables | | | | | | | | | | |
| Sickdays | -0.1022 | 5.70 | -0.1859 | 5.16 | -0.0974 | 4.40 | -0.0686 | 3.95 | -0.0385 | 3.04 |
| RWG | -0.0129 | 0.31 | -0.0103 | 0.25 | -0.0075 | 0.18 | -0.0055 | 0.13 | -0.0026 | 0.06 |
| Age/100 | -0.8127 | 4.81 | -0.7853 | 4.65 | -0.7816 | 4.62 | -0.7870 | 4.65 | -0.8054 | 4.76 |
| $(Age/100)^2$ | 0.3166 | 3.04 | 0.3062 | 2.95 | 0.3090 | 2.98 | 0.3134 | 3.02 | 0.3217 | 3.10 |
| Experience/100 | -0.4986 | 3.22 | -0.5088 | 3.28 | -0.5068 | 3.26 | -0.5001 | 3.21 | -0.4823 | 3.09 |
| $(Experience/100)^2$ | 1.8106 | 20.50 | 1.8115 | 20.55 | 1.8050 | 20.50 | 1.8001 | 20.46 | 1.7955 | 20.40 |
| Tenure/10 | -0.0742 | 11.75 | -0.0744 | 11.78 | -0.0744 | 11.75 | -0.0743 | 11.74 | -0.0743 | 11.71 |
| Education | 0.0049 | 3.61 | 0.0054 | 3.94 | 0.0060 | 4.46 | 0.0065 | 4.83 | 0.0073 | 5.54 |
| Female | 0.0518 | 4.74 | 0.0516 | 4.72 | 0.0510 | 4.65 | 0.0507 | 4.62 | 0.0503 | 4.58 |
| Local unemployment rate | -0.0025 | 1.52 | -0.0025 | 1.53 | -0.0026 | 1.57 | -0.0027 | 1.60 | -0.0028 | 1.65 |
| Log(local labour force/1000) | 0.0023 | 1.20 | 0.0024 | 1.26 | 0.0024 | 1.22 | 0.0023 | 1.19 | 0.0022 | 1.14 |
| Construction | 0.0458 | 6.86 | 0.0478 | 7.18 | 0.0495 | 7.44 | 0.0505 | 7.58 | 0.0518 | 7.77 |
| Trade and repair | 0.0249 | 6.33 | 0.0254 | 6.47 | 0.0257 | 6.56 | 0.0259 | 6.60 | 0.0260 | 6.63 |
| Transport and communication | 0.0516 | 9.08 | 0.0525 | 9.11 | 0.0529 | 9.10 | 0.0530 | 9.08 | 0.0531 | 9.04 |
| Finance | 0.0576 | 4.99 | 0.0581 | 5.03 | 0.0589 | 5.10 | 0.0593 | 5.14 | 0.0599 | 5.20 |
| Other services | 0.0138 | 2.59 | 0.0149 | 2.79 | 0.0158 | 2.96 | 0.0163 | 3.06 | 0.0171 | 3.21 |
| 201-400 employees | 0.0206 | 7.03 | 0.0204 | 6.97 | 0.0202 | 6.91 | 0.0201 | 6.88 | 0.0199 | 6.80 |
| More than 400 employees | 0.0243 | 6.22 | 0.0239 | 6.15 | 0.0237 | 6.07 | 0.0235 | 6.03 | 0.0231 | 5.94 |
| Construction * D | 0.0357 | 1.49 | 0.0341 | 1.43 | 0.0329 | 1.38 | 0.0322 | 1.35 | 0.0313 | 1.31 |
| Trade and repair * D | 0.0208 | 1.19 | 0.0215 | 1.23 | 0.0221 | 1.25 | 0.0225 | 1.27 | 0.0232 | 1.31 |
| Transport and communication * D | 0.0719 | 4.39 | 0.0729 | 4.47 | 0.0738 | 4.54 | 0.0743 | 4.57 | 0.0752 | 4.63 |
| Finance * D | -0.1352 | 7.03 | -0.1350 | 7.01 | -0.1351 | 7.00 | -0.1350 | 6.99 | -0.1350 | 6.99 |
| Other services * D | 0.0044 | 0.30 | 0.0043 | 0.30 | 0.0043 | 0.30 | 0.0045 | 0.30 | 0.0045 | 0.30 |
| 201-400 employees * D | -0.0160 | 1.58 | -0.0158 | 1.56 | -0.0159 | 1.56 | -0.0159 | 1.56 | -0.0157 | 1.55 |
| More than 400 employees * D | -0.0055 | 0.42 | -0.0052 | 0.40 | -0.0048 | 0.37 | -0.0046 | 0.35 | -0.0042 | 0.32 |
| D | 0.1334 | 16.33 | 0.1331 | 16.31 | 0.1330 | 16.29 | 0.1328 | 16.27 | 0.1324 | 16.23 |
| R-square | | 0.0677 | | 0.0681 | | 0.0691 | | 0.0704 | | 0.0710 |
| Number of clusters | | 18,109 | | 18,109 | | 18,109 | | 18,109 | | 18,109 |
| Number of observations | | 1,082,849 | | 1,082,849 | | 1,082,849 | | 1,082,849 | | 1,082,849 |

Model estimated using OLS with robust covariance matrix adjusted for correlation within peer groups (using cluster option in STATA). The regression also includes 8 year dummies , 17 county dummies and a constant term. Peer group is workers with same education level in same establishment, same year. Early leavers included.