

Drivers of Effort: Evidence from Employee Absenteeism*

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Abstract

We use detailed information on individual absent spells of all employees in 4,140 firms in Denmark to document large differences across firms in average absenteeism. Using employees who switch firms, we decompose days absent into an individual component (e.g., motivation, work ethic) and a firm component (e.g., incentives, corporate culture). We find the firm component explains a large fraction of the difference in absenteeism across firms. We present suggestive evidence of the mechanisms behind the firm effect. After controlling for selection of employees into firms, family firm status and concentrated ownership are strongly correlated with decreases in absenteeism. Taken together, the evidence supports the importance of firm-level mechanisms in eliciting effort from existing employees.

Keywords: family firms; organizational structure; employee effort

JEL Classification:

1 INTRODUCTION

Practices to encourage employee effort are widespread among firms. Incentive pay, for example, is widely used and its prevalence is increasing over time. Lemieux et al. (2009) find that 38% of workers were covered by performance pay in the 1970s, and by the 1990s, this number had increased to 45%. Black & Lynch (2001) find that in addition to incentive pay, other human resource practices (e.g., Total Quality Management, benchmarking, profit sharing with all employees, and employee participation in decision making) are also very common among a representative sample of U.S. firms.

Despite the considerable resources that firms spend trying to elicit effort from employees, scant evidence compares employee effort across a representative sample of firms. Do any significant differences exist across firms in the level of effort employees exert? Are these differences driven by the type of employees who choose to work in each firm or by the incentives the firm provides? What firm features are more important for employees' effort provision?

We use employee absenteeism at the individual level to address these questions. Admittedly, absenteeism captures only one dimension of employee behavior.¹ Yet it has two important advantages.² The first is that it is an aspect of employee behavior that can be consistently measured for all employees in all occupations and firms. This aspect is crucial for analyzing differences across firms. The second advantage is that it can be measured at the individual level. This feature allows us to follow employees as they switch firms, and to use these movers to identify firm effects.³

Our data come from an administrative survey conducted by Statistics Denmark covering employees at all medium and large Danish corporations. The data contain detailed information of every absence spell of over 674,000 unique individuals over the period 2007 to 2013.⁴

We start by showing large differences in average absenteeism across firms. The difference

1. For example, it does not pick up variation in effort when the employee is at the workplace.

2. Ichino & Maggi (2000) previously used absenteeism as measure of effort, in investigating what drives shirking differential in a large Italian bank.

3. Absenteeism is also economically important on its own. The European Commission estimated in 2011 that work-related ill health can cost EU member states anything from 2.6% to 3.8% of their GDP (European Commission (2011)).

4. The total number of employees in the private sector in year 2013 was 1,146,391.

between firms in the top and bottom decile is 15 days, corresponding to 6% of annual working days. Importantly, this variation persists even within industry.

Next, we analyze the role played by two broad sets of explanations in accounting for this difference. On the one hand, firms can affect effort of its existing labor force by paying employees as a function of output, promoting them based on their performance relative to peers, structuring the organization of work (e.g., rotation policies, team formation), and developing on-the-job training programs, among others. We refer to this broad set of explanations as “incentives.” On the other hand, the difference in employee absenteeism across firms might be driven by variation in employee characteristics (motivation, loyalty, work ethic). We refer to this second set of explanations as “selection.”

To separate the effect of these two sets of theories, we estimate a model at the employee level of days absent as a function of individual and firm fixed effects following the methodology of Abowd et al. (1999) (henceforth AKM). The firm fixed effect in this model captures the impact of all firm policies and its environment that equally affects all employees working at the firm, that is, incentives.⁵ The individual fixed effect captures the role of individual traits on effort provision regardless of the firm at which the employee works. We aggregate this individual fixed effect to the firm level to capture the effect of selection on firm absenteeism.

We identify individual and firm fixed effects by relying on movers. To build intuition, consider an employee who moves from a firm with high absenteeism to a firm with low absenteeism, and focus on the extreme cases in which only incentives or individual traits explain differences in absenteeism across firms. If the sole driver of absenteeism is incentives, we would expect the mover’s days absent to drop immediately to a level close to that of the employees of the destination firm. After all, the mover and all her co-workers at the destination firm will be affected by the same set of policies that fully determine absenteeism. If, on the contrary, absenteeism is driven primarily by individual characteristics, we would expect the mover’s days absent to remain constant after the move because, in this case, the potential new set of policies does not impact employee behavior. Away from these extreme cases, the change in absenteeism around a move is informative about the relative importance of firm

5. The firm fixed effect would also capture peer effects.

and individual drivers of absenteeism.

Next, we aggregate the individual fixed effects (and also, as we explain below, the effect of time-varying individual characteristics) at the firm level to examine the role of selection. Although individual fixed effects can play a large role in behavior at the employee level, their contribution to explaining differences in average firm absenteeism depends on how employees sort into firms. For example, if all firms hire a similar set of workers, the effect of selection would be minimal even in the presence of significant differences across individual employees. When we compare firms with above-the-median average days absent with firms below the median, we find incentives drive 53% of the difference in average days absent, and selection explains the rest. Our results are robust to considering only absences around national holidays and weekends, which are likely to reflect discretionary absences.

A key assumption to obtain unbiased estimates is that shocks to absenteeism around a move are not correlated with the level of absenteeism in origin and destination firms. For example, if workers that experience an increase in motivation move to firms with lower absenteeism, we would attribute the effect of motivation to the firm fixed effect, leading to a larger role for the incentive explanation. This possible endogeneity channel predicts that, to the extent motivation changes slowly over time, we should observe employee behavior moving toward that of the average in the destination firm prior to the move. However, our results suggest that this is not the case.

Although the results so far are informative about the quantitative importance of incentives explanations in driving cross-firm differences in employee absenteeism, they are silent about the precise policies or features of the environment that create such incentives. To gain some insight, we turn to studying firm attributes that correlate with firm fixed effects. We classify these attributes into four categories: career considerations, firm organizational structure, market forces, and ownership and control. Moreover, to better understand the drivers of effort, we split the sample into workers and managers and estimate a firm fixed effect for each of these two groups of employees.

We investigate which variables are more important for predicting the firm fixed effect in

a multivariate setting. We first focus on variables related to career concerns. We develop firm-level sensitivities of wage increases, separations, and promotions to days absent. Career incentives do not appear to be important.

Next we turn to the effect of product market competition on effort. This effect is ambiguous, as Hart (1983) and Schmidt (1997) pointed out. On the one hand, competition increases the probability of bankruptcy, sharpening incentives. On the other hand, competition mutes incentives as it reduces profits. We measure competition using the the Herndahl-Hirschman index (HHI). (The higher the HHI index, the lower the competition.) We find that higher competition correlates with higher absences. However, managers drive this result: their absenteeism is higher when firms face more competition.

We find that organizational structure also has important effects on employee efforts, with flatter firms having employees with lower absenteeism. The effect of organizational structure, however, is only statistically significant for workers.

The theoretical predictions of the role of family control point to different directions. First, family firms might have a more difficult time motivating non-family employees, because these workers might be concerned that nepotism, rather than meritocracy, would determine promotions. Additionally, non-family employees might also be discouraged if they end up having to spend time embroiled in family conflicts (Poza (2013)). Second, family firm status could instead boost employee motivation. Family owners, due to their long-term horizons, might have a comparative advantage at sustaining implicit labor contracts, which workers might reciprocate with cooperative behavior (Sraer & Thesmar (2007), Ellul et al. (2014)). Also, their large ownership stakes could motivate family owners to monitor more or be tougher with labor (Mueller & Philippon (2011)), leading to higher effort provision. We find a strong positive effect (lower absences) for family firms for the average employee. However, the effect is only present for workers. One possible explanation for this result is that a positive incentive effect of family firms exists and affects all employees (loyalty, stricter monitoring), and the negative effects of nepotism are only present at the top of the firm hierarchy because family members are typically promoted to top positions. We find family firm status is related to

lower absenteeism, and the effect is driven by non-managers.

Our paper relates to a large empirical literature on the effects of incentives on employees. Most studies focus on a single mechanism in one or a few firms (Lazear (2000*a*); Shearer (2004); Bandiera et al. (2005); Bandiera et al. (2007); Bandiera et al. (2009)). The advantage of this approach is that, by focusing on one or on a small set of similar firms, these studies can use performance measures that are comparable across employees. For example, Lazear (2000*a*) uses the units of glass installed by workers in a firm specialized in automobile glass installation, Shearer (2004) uses the number of tree planted by workers in a tree-planting firm in British Columbia, and Bandiera et al. (2005) use kilograms of fruit picked per hour. Identification in these studies is obtained by focusing on a policy change (e.g., from fixed wages to piece rates) that either the firm adopts as part of its normal course of business or by the researcher’s randomization. A few studies do analyze multiple firms, but focus primarily on developing countries (Karlan & Valdivia (2011), Bruhn et al. (2010) and Bloom et al. (2010)).⁶ Although these studies are convincing about the causal effect of mechanisms used by firms to elicit effort, they are, by design, only informative about the specific firms studied. To date, we have limited evidence on employee effort provision in a large sample of representative firms in a developed economy.⁷ Our paper provides such evidence.

A second difference is our focus on movers. Most of the previous literature analyzes policy changes at the firm level and traces their effect on firm productivity.⁸ In this paper, we instead identify firm effects using job switchers who are affected by different firm policies before and after the move. We are able to follow this strategy because we have a measure of effort at the individual level. Using switchers makes pointing to the specific policy difference that causes the change in employee behavior more difficult. However, it allows us to estimate firm effects

6. One exception is Black & Lynch (2004), who use a panel of U.S. firms and find the introduction of human resource management practices have almost no effect on firm productivity. These results, however, can be biased downwards if the introduction of human resource management practices are correlated with low productivity.

7. Bloom & Van Reenen (2011) in their survey of this literature comment that “[t]he future of the field may be to move away from purely single firm studies to consider larger numbers of firms who are subject to [human resource management] policy interventions.”

8. An exception is Ichino & Maggi (2000), who also use absenteeism as a measure of effort, and focus on movers across different branches of the same bank. Ichino & Maggi (2000), however, study only one firm, whereas the focus of our paper is on differences across firms in employee behavior.

for a large number of firms because policy changes are infrequent and likely correlated with firm productivity.

A final advantage of our approach is that, because our measure of performance is at the individual level, we are not only able to estimate the average effect of firm policies, but also their effect on different groups of employees. In this paper, we only investigated the effect of policies on workers and managers, but the empirical methodology is applicable to other classifications as well.

The finance literature has many examples of using movers for identification. Bertrand & Schoar (2003) use CEOs who switch firms to separate the effect of CEO from the firm effects to study CEO effects. Graham et al. (2012) decompose executive compensation into the individual and firm components. Ewens & Rhodes-Kropf (2015) study the role of individual venture capitalists' human capital versus the importance of the venture capital firms. Also, Kim et al. (2009) use movers to separately identify the university effect on researcher productivity from individual effects.

The rest of the paper is organized as follows. The next section describes how we estimate the individual and firm components of absenteeism and discusses the assumptions required. Section 3 describes the data with a special focus on the absenteeism measure. Section 4 contains the main empirical results, and Section 5 concludes.

2 EMPIRICAL STRATEGY

2.1 Decomposition into individual and firm components

In this section, we describe our approach to decomposing days absent into a component that is driven by individual characteristics and a part that is explained by incentives provided by the firm. We follow closely Abowd et al. (1999), Card et al. (2013), and Finkelstein et al. (2016). We assume days absent, y_{it} , can be described by the following model:

$$(1) \quad y_{it} = \alpha_i + \beta x_{it} + \gamma_{J(i,t)} + \mu_t + e_{it},$$

where $J(i, t)$ is the firm for which person i works at time t . The person fixed effect, α_i , captures the contribution of unobservable time-invariant individual traits (motivation, discipline, sense of responsibility, etc.) on days absent. βx_{it} captures the effect of time-varying factors. We include age, number of children, wage, and importantly, health status measured as number of days spent at the hospital. We define $c_{it} = \alpha_i + \beta x_{it}$ as the contribution of individual traits on days absent. This is the portable component of employee behavior and is assumed to be the same for individual i , regardless of the firm j in which he works. The term γ_j captures the effect of pay for performance, monitoring, corporate culture, organizational structure, and so forth, on all employees of firm j (all i with $J(i, t) = j$). As previously mentioned, we refer to these explanations collectively as “incentives.” Finally, e_{it} is the error term.

Identification of this model requires employees to switch firms. In the absence of movers, separating the effect of individual characteristics from firm effects would be impossible. For example, we would not be able to ascertain whether a firm with low employee absenteeism has policies that promote work, or has a workforce consisting of motivated employees. Yet the presence of movers does not guarantee identification of all fixed effects. AKM provides an algorithm based on these moves to construct sets of firms and employees whose fixed effects are identifiable (the “connected set”). In our case, the largest connected set includes 98.7% of employees and 82.6% of firms. Focusing on this set is therefore not a significant limitation.

2.2 Identification

We estimate the model using OLS. Identifying the parameters of the model requires the usual assumption that the error term be orthogonal to all covariates. Of these assumptions, the key one is that the error term be uncorrelated with origin- and destination-firm characteristics. This “exogenous mobility” assumption can fail for a number of reasons. To systematize these reasons, we write the error term as

$$(2) \quad e_{it} = \eta_{iJ(i,t)} + \epsilon_{it}.$$

The term ϵ_{it} measures the time-varying unobservable component of employee behavior. For example, motivation can be time varying, perhaps affected by life events we do not observe. The match component of the error term, $\eta_{iJ(i,t)}$, is the effect on behavior of individual i specific to firm $J(i,t)$. This component could arise when the same work environment provides heterogeneous incentives to individuals. For example, firms could have varying corporate cultures and individuals could have different rankings over these cultures. If, in addition, individuals are more motivated to work in firms that offer a corporate culture that is a better fit for them, the match component η_{ij} would be low (contributing to lower absenteeism) for individual i if he happens to be a good fit for the culture offered by firm j .

The first concern is that the ϵ_{it} component of the error term for movers is correlated with the origin- and destination-firm characteristics. As an illustration, suppose ϵ_{it} captures shocks to motivation, with increases in motivation leading to lower absenteeism. If employees who experience an increase to their motivation move to firms with low absenteeism (and vice versa), we would attribute part of the effect of motivation to the firm fixed effect, effectively overstating the importance of the incentive explanations. Our event study analysis in Section 2.5 provides some evidence against this hypothesis. If motivation changes slowly over time, this potential endogeneity channel would predict that employees with positive shocks exhibit a decline in their days absent prior to their move to a low-absenteeism firm. However, we do not find this effect. In the years prior to the move, employees' absenteeism does not tend toward the average of the destination firm.⁹ Of course, this result does not address the possibility that the change in motivation is sudden and correlated with origin and destination average absence.

The second concern relates to the idiosyncratic match component of the error term, η_{ij} . Consider the example in which η_{ij} represents the match between a worker's personal preferences and the firm's culture. Suppose workers have lower absences when the fit is better. That is, in the model, a better fit corresponds to a lower η . Absent the match component, we would expect the change in absenteeism for workers moving from firm j to firm j' to be

9. As an additional robustness test, we repeat the event study in Figure A2, using only employees who move due to plant closures and find similar patterns as our main event study.

equal to but with the opposite sign to the change in absenteeism for workers moving in the opposite direction. After controlling for time-varying covariates, this change in absenteeism would be driven by the differences in firm fixed effects, and any error terms would average out to zero. However, when the match component is present, this relation no longer holds because the group of employees who move from firm j to j' are those with especially low $\eta_{ij'}$, and the employees moving in the opposite direction are those with a low η_{ij} . Hence differences in absenteeism for movers will not reflect a pure firm fixed effect. We test this potential concern in Figure 3 by plotting the change in days absent for movers against the difference in average absenteeism between the destination and origin firm. Importantly, the relationship is symmetric above and below zero as predicted by a model without a match component in the error term.

2.3 Contribution of the individual and firm components to employee days absent

We estimate the individual and firm fixed effect of our model from a regression at the individual level. However, we are ultimately interested in estimating the fraction of the variation *across* firms in *average* employee behavior. Even if individual characteristics played a large role in explaining behavior at the employee level, this result might not translate to the firm level; for example, when the distribution of employee characteristics is similar across firms.

We follow Finkelstein et al. (2016) in estimating the fraction of the difference in days absent across firms that is due to employees and the fraction that is due to firm policies/environment.

We write equation (1) collecting the terms related to employee characteristics into c_{it} as

$$(3) \quad y_{it} = c_{it} + \gamma_j + \mu_t + e_{it}.$$

For each firm j , we average y_{it} across all employees i in year t and then we average across

time to obtain

$$(4) \quad \bar{y}_j = \bar{c}_j + \gamma_j + \frac{1}{T} \sum_t \mu_t + \bar{e}_j,$$

where \bar{y}_j is computed by averaging y_{it} across all employees in firm j in year t and then averaging across time. We define \bar{c}_j and \bar{e}_j analogously. T is the number of years in the panel.

In expectations, the difference in average absence between any two firms j and j' is the sum of the differences of the firm and the employee components $\bar{y}_j - \bar{y}_{j'} = \gamma_j - \gamma_{j'} + \bar{c}_j - \bar{c}_{j'}$. Also, we define $y_J = \frac{1}{\#J} \sum_{j \in J} \bar{y}_j$ to refer to the average \bar{y}_j across a set of firms J . We define \bar{c}_J and γ_J analogously. Hence, the difference in days absent in two different groups of firms, M and N , is given by $\bar{y}_M - \bar{y}_N = \gamma_M - \gamma_N + \bar{c}_M - \bar{c}_N$.

Finally, the share of the difference in days absent between groups of firms M and N attributable to incentive explanations is

$$(5) \quad S_{incentives} = \frac{\gamma_M - \gamma_N}{\bar{y}_M - \bar{y}_N},$$

and the share attributable to selection is

$$(6) \quad S_{selection} = \frac{\bar{c}_M - \bar{c}_N}{\bar{y}_M - \bar{y}_N}.$$

2.4 Determinants of the firm effect

From the model in equation (1), we obtain estimates of the firm effects, $\hat{\gamma}_j$. These estimates capture the effect of the firm environment on employee absenteeism. In a second stage, we investigate firm characteristics that correlate with these firm fixed effects by estimating the following model:

$$(7) \quad \hat{\gamma}_j = \delta z_j + \psi_j,$$

where z_j are firm characteristics. We include characteristics related to career considerations, market forces, internal organization, and ownership and control. The result of these regres-

sions are suggestive of the mechanisms through which policies and its environment affect employees' behavior. However, the results of this part are not conclusive, because we do not use exogenous variation in these firm characteristics.

2.5 Event study

Following Finkelstein et al. (2016), we re-arrange equation (1) so that we can collect the firm fixed effects into a single coefficient. Focusing only on movers who switch employers only once, equation (1) can be re-written as

$$(8) \quad y_{it} = \alpha_i + \beta x_{it} + \gamma_{o(i)} + \mathbf{1}(t > T_i) \frac{\gamma_{d(i)} - \gamma_{o(i)}}{\bar{y}_{d(i)} - \bar{y}_{o(i)}} (\bar{y}_{d(i)} - \bar{y}_{o(i)}) + \mu_t + e_{it},$$

where $o(i)$ and $d(i)$ are the origin and destination firm of employee i , and T_i is the year in which the employee moves. We estimate the following equation:

$$(9) \quad y_{it} = \tilde{\alpha}_i + \beta x_{it} + \theta \mathbf{1}(t > T_i) (\bar{y}_{d(i)} - \bar{y}_{o(i)}) + \mu_t + e_{it},$$

where the employee fixed effect is $\tilde{\alpha}_i = \alpha_i + \gamma_{o(i)}$ and the coefficient θ captures the average across all movers of $\frac{\gamma_{d(i)} - \gamma_{o(i)}}{\bar{y}_{d(i)} - \bar{y}_{o(i)}}$, which is the fraction of the difference in average absenteeism that is explained by incentives. We further modify this regression by using a different θ coefficient for each year relative to the move as follows:

$$(10) \quad y_{it} = \tilde{\alpha}_i + \beta x_{it} + \sum_{\tau=-\bar{\tau}}^{\bar{\tau}} \theta_{\tau} \mathbf{1}(t = T_i - \tau) (\bar{y}_{d(i)} - \bar{y}_{o(i)}) + \mu_t + e_{it}.$$

The interpretation of θ_{τ} is the fraction of the gap in absenteeism between the origin and destination firm (i.e., the fraction of $\bar{y}_{d(i)} - \bar{y}_{o(i)}$) that, after controlling for individual characteristics and time fixed effects, the employee closed each year relative to the move.

3 DATA AND DESCRIPTIVE STATISTICS

3.1 Data sources

Administrative Survey of Employee Absenteeism. Our main dataset is the administrative Survey of Employee Absenteeism conducted in Denmark. Statistics Denmark collects absence data for employees in the central government, local governments, and private firms.

The survey of private firms covers a representative sample of firms with 10 to 250 employees and all firms with more than 250 employees.¹⁰ Firms report absence spells for each employee. For each spell, the data contain the employee national identification number (CPR number), firm identifier, workplace identifier, start day, end day, and absence category. There are four absence categories: “Own Sickness,” “Child Sickness,” “Work Accident,” and “Maternity/Paternity related absence.” In the analysis below, we focus on the category “Own Sickness” because the reporting of other categories is rare.¹¹

Reporting is not costly to firms. Statistics Denmark has developed software that firms can integrate into their payroll system to facilitate collecting absence information. In addition, the reimbursement policy of sickness benefits provides firms with incentives to report employees’ absences as soon as they start, because the firm is required to pay sickness benefits the first 30 days with the Danish government paying only after this initial period.

It is important to note that days absent does not include vacation days. In Denmark, the number of vacation days is, to a large extent, determined by a combination of the law and collective bargaining. The law establishes the right to 5 weeks (25 days) of holidays every year. In some cases, collective bargaining between the central employer and employee organizations adjusts this general vacation policy. However, these adjustments are negotiated with the unions and not with individual firms.¹²

Integrated Database for Labour Market Research. We also use the matched employer-employee dataset from the Integrated Database for Labour Market Research (IDA

10. Not all firms are included in every year.

11. Our results do not change when we include the other absence categories as well.

12. Furthermore, when we compare days absent across countries in Appendix Figure A1, Denmark is similar to the U.S., just below the 2.8% average in absenteeism in terms of employment time lost due to absenteeism.

database) at Statistics Denmark. In addition to the employer’s identification number (CVR), the IDA dataset contains employees’ demographic information, such as age and gender and the employee’s position in the organization. The position in the firm is based on the Danish occupational code, defined based on the international standard classification of occupations (ISCO). We have access to this dataset for every year in the period 1995 - 2013.

National Patient Registry. Data on hospitalizations are from the National Patient Registry (NPR) at Statistics Denmark. This dataset records public hospital interactions of all Danish citizens and contains the individual national identification number (CPR number) and the number of hospitalization days per calendar year.

Firm Financials. This dataset covers all firms incorporated in Denmark and includes the information these firms are required to file with the Ministry of Economics and Business Affairs, including the value of total assets and operating and net income. *Experian*, a private data provider, collects these reports. Even though most firms in this dataset are privately held, external accountants audit firm financials in compliance with Danish corporate law. We link information in the *Experian* dataset to our other sources using the firm identifier (CVR number).

3.2 Sample construction and summary statistics

We start with all the private firms and their employees included in the Survey of Employee Absenteeism. For ease of comparison, we eliminate part-time workers and only retain full-time workers. We lose 22.5% of the firm-years when we require firms to have financial information. Our final sample contains 4,140 unique firms and 665,661 employees, representing approximately 60% of full-time employees in the private sector in Denmark.

Table 1 presents summary statistics for the universe of Danish firms and for firms in our sample. To assess firm performance, we use operating return on assets (OROA). The average OROA of limited liability firms in Denmark for the years 2007-2012 is 7.6%. Firms in our sample have 2.7 percentage points lower OROA than the average firm in the population. We find a similar pattern in net income to assets. We also report significant differences in log

assets and the number of employees with firms in our sample being larger. This result is expected because the survey is tilted towards larger firms. Finally, Table 1 reports that firms in our sample are older.

A total of 19.67% of employees are classified as “movers,” that is, people who appear in different firms in consecutive years. Table 2 shows movers are younger, more educated, and less likely than non-movers to be female. These differences are small in magnitude and, in any case, we control for education and age and include individual fixed effects that subsumed gender.

3.3 Variation in days absent across firms

Table 3 shows the difference in average days absent for different classifications of firms. Our main measure of absenteeism at the firm level is computed by first averaging days absent across all employees in the firm in a given year and then averaging over years.

The difference in average days absent between firms above and below the median is 6.3 days, whereas the difference between firms in the top and bottom quartile is 10.4 days. This difference widens to 15 days, corresponding to approximately 6% of annual working days, when we compare firms at the top and bottom decile of the distribution.

Furthermore, these differences persist within industries as Figure 1 shows. The industry classification is based on the NACE 1-digit code. Each box plot presents the minimum, first quartile, median, third quartile, and maximum days absent for each industry. The median days absent across industries is remarkably stable, and considerable variation exists within all industries.¹³

Table 3 conveys information similar to that in Figure 1. Table 3 presents the difference in average days absent for different classifications of firms for the different industries in our sample. The difference in average days absent between manufacturing firms above and below the median is 5.4 days, whereas it is 6.2 days in construction. The same difference is 10.7 days for public and personal services. The differences in average days absent of firms within

13. Public and personal services has a higher median than the rest, because it contains health care and education.

industry are even larger (range from 8.8 to 18 days) when we compare the top and bottom quartiles, and they range from 13.4 to 29.6 days when we compare the top and bottom deciles. Overall, Figure 1 and Table 3 show substantial variation in days absent across firms, even within the same industry.

3.4 Discretionary component of days absent

Our main variable is the number of sick days an employee takes in a year. Admittedly, factors beyond effort provision affect this variable. In the models we estimate, we control for many of these factors, including health shocks. As a result, our measure of effort can be seen as the residual, after controlling for determinants of absenteeism.

Critically for our purposes, absenteeism must have a discretionary component. Figure 2 shows preliminary evidence for this component. The figure presents the relationship between hospitalization days and days absent for employees in different positions in the firm. To the extent that a discretionary component exists in days absent, we would expect employees with more responsibility to return to work sooner. Indeed, throughout the distribution of hospitalization days, employees with senior positions have shorter absence spells than employees in junior positions. The difference disappears for long hospitalizations, perhaps because our sample is very limited in this part of the distribution or because incentives play a small role for extremely severe illnesses.

Furthermore, in Section 4.3 we present evidence using days absent only in absent spells that start on Monday or Friday or within two days around a national holiday. This measure is more likely to capture the discretionary component of days absent.

3.5 Does absenteeism matter?

We present suggestive evidence that employees' absences matter for the firm. Flabbi & Ichino (2001) state that "workers who are more often and for longer periods absent are less productive for the firm." Yet employees might be able to compensate for the lost labor supply by working from home or by working overtime when they return to the workplace.

We show two different sets of results. The first one is the relation between average absenteeism at the firm level and OROA. We regress OROA on average days absent at the firm level and a number of controls including firm and year fixed effects. The results are in the appendix (Table A1). This table shows a negative correlation between the average days absent and performance for medium and large firms.¹⁴ These results are only preliminary evidence of the effect of days absent on performance, because interpreting this correlation in a causal way is difficult. For example, employees might decide to take more days off in response to poor firm performance. Because estimating this relation is not the purpose of this paper, we leave this task for future work. We note, however, that in a different setting, Herrmann & Rockoff (2012) find a large causal effect of teacher absence on productivity.

The second set of results focuses on the consequences to employees of being absent. To the extent that firms care about absenteeism, they should penalize employees who lose more days of work. We present these results in the appendix (Table A2). We show that employees with longer absence spells are less likely to be promoted. In an attempt to measure firings, we code separation as situations in which an employee changes firms or becomes unemployed. We find that the longer the absence spell, the more likely employees are to become separated from the firm. Again, these results are not conclusive. For example, the promotion result can be explained by reverse causality as employees lose motivation if they learn they will not be promoted. Because this causality mechanism is not the focus of the paper, we leave more careful analysis to future work.

4 MAIN RESULTS

4.1 Results on decomposition into individual and firm components

Our goal is to quantify the contribution of the incentives and selection components in accounting for the difference in average employee absenteeism between different groups of firms. Table 4 presents the main results of the paper. Each column presents results for a

¹⁴ We do not find a correlation for firms with less than 100 employees. Smaller firms have noisier data on performance.

different pair of groups formed by their average employee absenteeism. In the first column, one group is formed by the firms with above-median employee absenteeism and the other group consists of firms that fall below the median. The groups in the other columns are formed by using firms in the top and bottom quartiles, top and bottom 10%, and top and bottom 5%.

We estimate the model in equation (1) and use the estimates to construct the share of the difference explained by the incentive and selection effects using equations (5) and (6). Panel A presents the results when equation (1) is estimated without including time-varying employee characteristics, whereas panel B results are estimated with individual time-varying characteristics.

The overall difference in absenteeism between firms above and below the median is 6.29 days (column 1). We find that incentives explain 53% (3.39 days) of this difference, whereas selection drives the rest (2.9 days). The estimate is quite precise. We find similar results when comparing other groups (columns 2-5). Incentive explanations account for 58% of the difference between the top and bottom quartiles (column 2), 60% of the difference between the top and bottom deciles (column 3), and 65% of the difference between the top and bottom 5% (column 4). Panel B shows the results are similar when we also control for time-varying employee characteristics, specifically age and hospitalization. The incentive explanations account for 53% to 64%.

These results show the importance of the incentive channel. A way to interpret our results is that even in a hypothetical world in which firms have the same distribution of workers, we would still find significant differences across firms in employee absenteeism. Indeed, we would find the difference between the top and bottom half of the distribution of firms to be 3.39 days.

At the same time, the selection effect is also large, accounting for slightly less than half of the variation in employee absenteeism. This result underscores our emphasis on disentangling the incentive and selection effects. It also highlights an interesting fact about absenteeism: the selection and incentive effect go in the same direction. That is, firms with

policies/environments that discourage absenteeism (the incentive effect) also attract employees who are intrinsically more motivated (selection effect).

4.2 Occupational differences

The type of occupation might affect employees' absenteeism. For example, workers might take fewer days off when a backlog of work will be waiting for them when they return (Aronsson & Gustafsson (2005)). Alternatively, workers are known to take fewer sick days when they can control their work tasks (Johansson & Lundberg (2004)).

If occupation is relatively stable over time, it will not bias our firm fixed effect estimates, because occupational choices will be subsumed in the individual fixed effect. However, if workers commonly change occupations when they switch jobs, our estimation will attribute differences in absenteeism due to occupational changes to the firm fixed effects. To address this concern, we include a set of occupation fixed effects. We have the occupational code of the position of the employee. The occupational code is defined based on the international standard classification of occupation (ISCO). In Table A3, we repeat the analysis of equation (1), including occupation fixed effects in addition to time-varying employee characteristics. The results are similar to the main results in Table 4, mitigating concerns that occupation switching around the move might be driving the firm fixed effects. Furthermore this analysis ameliorates concerns that the results might be driven by firms having a different distribution of occupations.

4.3 Absence spells more likely to be discretionary

In our main results, we use the number of days absent as the dependent variable. We repeat this analysis using days absent only in absent spells that start on Monday or Friday or within two days around a national holiday. This measure is more likely to capture the discretionary component of days absent. Table A4 presents the results. Both the results based on the basic model (panel A) and the results using employee time-varying controls show the firm share ranges from 57% to 70%, consistent with our main results in Table 4.

4.4 Event study

An alternative way to present the results is by using the event study methodology described previously. We estimate equation (10) using movers who switch firms only once, and plot the estimated θ_τ in Figure 6. The interpretation of θ_τ is the fraction of the gap in absenteeism between the origin and destination firm (i.e., the fraction of $\bar{y}_{d(i)} - \bar{y}_{o(i)}$) that, after controlling for individual characteristics and time fixed effects, the employee closes each year relative to the move. As shown in Section 2.5, θ is also an estimate of $S_{incentives}$, the share of the difference in absence days explained by incentives.

The figure shows a sharp, discontinuous jump at the time of the move, from 0 to approximately 0.6. This magnitude is consistent with the results in Tables 4 and A4 that show incentives account for slightly above 50% of the difference in absenteeism across firms.

This figure also allows us to assess the severity of a potential endogeneity problem described in Section 2.2. Recall that if employees with positive shocks to motivation move to firms with low absenteeism, this move would magnify the effect of incentives explanations. If, in addition, motivation changes slowly over time, we should see days absent moving closer to the average in the destination firm even prior to the move. However, Figure 3 shows that this is not the case. If anything, a small movement away from the average in the destination firm occurs prior to the move.

As an additional robustness test, we repeat the event study in Figure A2, using only employees who move due to plant closures. This analysis mitigates concerns about the endogenous choice of moving, since these employees are forced to move. During our sample period, we have 673 plants closing (2.94% of all plants). The event study based on plant-closure-related moves shows similar patterns as our main event study (it is noisier though, due to the much smaller sample size).

4.5 Absence variation due to firms and firm characteristics

We examine observable firm characteristics that correlate with the firm fixed effects, $\gamma'_j s$, in order to shed light on the mechanisms behind the incentive effect. For this task, we estimate

equation (7). Because we have effectively controlled for selection in estimating the firm fixed effects, selection does not drive our results in this section.¹⁵ However, we do not use exogenous variation in firm characteristics and hence cannot rule out bias in the estimates coming from correlated unobserved characteristics.

We first focus on variables related to career concerns. We develop firm-level sensitivities of wage increases, separations, and promotions to days absent.¹⁶ To create the sensitivity of wage increases to absenteeism, for each firm, we regress an indicator variable that takes the value 1 if the employee received a wage increase, and 0 otherwise, on employees' days absent. The coefficient on days absent obtained from each of these regressions is our measure of such sensitivity. We follow a similar procedure for promotions and separations.

Next, we investigate how market forces, specifically, product market competition, relate to the firm fixed effects. Prior literature suggests the effect of product market competition on incentives is ambiguous. On the one hand, the higher probability of bankruptcy and its negative consequences for employees provides employees with strong incentives to exert effort. On the other hand, the lower profits that result from more intense competition discourage effort (e.g., Hart (1983), Schmidt (1997)). Our main measure of product market competition is the Herfindahl-Hirschman index (HHI). The HHI is a commonly used measure of competition and is well grounded in theory (see Tirole (1988), pp. 221-223).

We furthermore investigate the role of organizational characteristics of the firm. We proxy size by the logarithm of assets. We follow Caliendo et al. (2015) and Friedrich et al. (2015) in constructing a measure on how hierarchical a firm is. The measure is based on the number of different occupational layers represented by workers in a firm. We use workers' occupations as reported in the Danish occupational code DISCO (DISCO is a modified version of the ILO international standard classification of occupations). The first layer (highest level) consists of directors, CEOs, and general managers. The second layer includes department managers and professionals. The third layer consists of technicians and associate professionals. White-collar

15. We would have this problem had we directly estimated a regression of employee effort on a firm characteristic, such as size. In such a regression, concluding whether size causes high effort or whether highly motivated employees work for large firms would be difficult.

16. For separations, we cannot separate whether the employee was fired or departed willingly.

and blue-collar workers constitute the lowest layer. Friedrich et al. (2015) provide detailed information on the construction of the measure.

Finally, we focus on measures of firm ownership and control. A large body of academic and anecdotal evidence suggests ownership structure of the firm shapes employee behavior. We first examine the role of ownership by a private equity firm. Jensen (1989) argues that leveraged buyouts are a superior governance form leading to better-managed companies. Specifically, PE firms mitigate management-agency conflicts through the disciplinary role of debt and concentrated and active ownership. To identify firms that have PE ownership, we match the data on firm ownership with the database of all PE firms operating in Denmark.

We also study the role of family firm status. Using information from the Danish Civil Registration system on family trees of managers and board members, we identify family ties among them. Using these ties, we define firms as family controlled if (1) two board members are related to the CEO by blood or marriage or (2) any three board members are related (even if none of them is a CEO).

The direction of the effect of the family presence, however, is ambiguous. On the one hand, employees of family firms might exert less effort. Family firms might have a more difficult time motivating non-family employees, because these workers might be concerned nepotism, rather than meritocracy, would determine promotions. Non-family employees might also be discouraged if they end up having to spend time embroiled in family conflicts (Poza (2013)). On the other hand, family firm status could boost employee motivation. Family owners, due to their long-term horizons, might have a comparative advantage in sustaining implicit labor contracts, which might be reciprocated by workers with cooperative behavior (Sraer & Thesmar (2007), Ellul et al. (2014)). Their large ownership stakes might also motivate family owners to more closely monitor or be tougher with labor (Mueller & Philippon (2011)), leading to higher effort provision.

We also investigate whether employees in single-owned firms exert more effort as one would expect if concentrated ownership leads to greater monitoring. Finally, we analyze the role of debt. Higher levels of debt require the firms to generate more cash flow to avoid bankruptcy,

hence sharpening employee incentives (Jensen & Meckling (1976) and Jensen (1986)).

Figure 4 presents the results. The points are coefficients from a multivariate regression of the firm fixed effect on the firm characteristics described above (equation (7)). All covariates have been standardized to have mean zero and standard deviation one; therefore, the coefficients report the relationship between a one standard deviation change in the covariate and the respective outcome. Horizontal bars show 90% confidence intervals.

Figure 4 column 1 presents the results of a regression without industry fixed effects, whereas column 2 includes these fixed effects. A negative coefficient implies higher levels of the variable are negatively associated with the firm fixed effect, that is, lower employee absenteeism.

Career incentives do not appear to be important. The variables wage increase, end, and promotion are constructed so that higher values correlate with more severe penalties for the employees (e.g., a firm with a high value of the wage variable is among the least likely to raise employees' wages after long absences). All else being equal, firms that impose higher penalties for absences in terms of a low probability of wage increases and promotions, and a higher probability of separation do not have lower firm fixed effects.

Higher HHI (lower competition) does appear to have a positive effect on effort as it reduces the firm fixed effect. Because competition is defined at the industry level, we cannot identify its effect when we include industry fixed effects in the second column.

In terms of organizational design, size does not affect the firm fixed effect, whereas hierarchy does. Firms with more hierarchical structures have higher firm fixed effects (more absences). The result is borderline significant.

Finally, of the variables in the ownership and control category, only family firm significantly affects the firm fixed effect. The result indicates family firms provide an environment that leads to lower absences.

One potential (and trivial) explanation for our results is that firms have specific policies to address absenteeism (e.g., a high sensitivity of “punishments” to days absent) and these targeted policies explain most of the variation we find in firm fixed effects. However, our

results in the multivariate estimation do not support this theory. Note the incentive variables in terms of promotions, wage increases, and separations measure the direct punishment for absenteeism. Nevertheless, none of them is significant. More importantly, after controlling for the direct punishment of absenteeism, we still find competition and family firm status are important in explaining employee behavior.

4.6 Variation between managers and non-managerial employees

In this section, we repeat our analysis separately on two subsets of employees: non-managerial and managerial employees. Although in the main analysis the model assumes that the firm effects affect similarly all firm employees, one of the strengths of our setting is that our measure of absences is at the individual level, thus we can examine whether firm policies might have different effect for different groups of employees.

In Table 5, we repeat the analysis of Section 4.1. Focusing on panel A, column 1 decomposes the difference in average days absent for managers between above-median and below-median firms. The overall difference is 4.5 days. We find that 58.6% of the difference in average absenteeism is due to incentives, whereas 41% of the difference is due to selection. The estimate is quite precise. Columns 2-5 present different partitions of firms and show the results on share explained by incentives remain roughly similar. Incentive explanations drive 65% of the difference in managers' days absent between the top and bottom quartiles, 63% of the difference between the top and bottom deciles, and 80% of the difference between the top and bottom 5%.

Panel B presents the same analysis for non-managerial employees. We also observe that incentives explanations drive a substantial part of the variation in non-managerial employees' days absent across firms with values ranging from 51 to 68%. The table shows more variation in days absent for non-managers. For example, when comparing firms above and below the median, the difference in days absent for managers is 4.5 days, but it is 6.9 for non-managers. Similarly, the number of days in this difference explained by incentives is larger for non-managers. However, as a fraction of the difference, incentive explanations drive a larger share

in the managers sample.

We also repeat the covariate analysis for managers and non-managerial employees and report the results in Figure 5. The first column uses the firm fixed effects estimated in the subsample of managers, and the second column uses the coefficients estimated using the subsample of employees.

We observe that for managers, the estimated firm fixed effects relate negatively to HHI. This finding is consistent with theoretical models in which product market competition lowers profits and discourages effort. For managers, this variable is the only one with a statistically significant coefficient.

Family firm status leads to lower firm fixed effects for non-managers, but has no statistically significant effect for managers. One possible explanation for this result is a positive incentive effect of family firms (loyalty, stricter monitoring) and a negative incentive effect due to nepotism. Because family members are typically promoted to top positions, nepotism only affects managers negatively, cancelling the positive loyalty effect.¹⁷

5 CONCLUSION

We propose a new measure of employee effort that can we calculate for all employees in a large panel of firms in Denmark. We find significant variation in the average effort across firms.

Using employees who move, we are able to calculate the contribution to the overall variation of effort of two broad sets of theories. We find that “incentives” (firm policies/environment) explain a large fraction of the variation. A lower fraction, although still considerable, is attributed to the types of employees that work at different firms (“selection”).

We also find suggestive evidence that the firm policies/environment that matter are organizational characteristics, family control, and product market competition. However, employ-

17. In a recent paper, Bandiera et al. (2013) study differences in CEO behavior in family and non-family firms, and find family CEOs record 8% fewer working hours relative to professional CEOs. Figure 5 shows our results are not inconsistent with theirs, because non-managerial employees drive the negative correlation of family status with the estimated firm effects.

ees are affected differently by these policies. We find that the most important determinant of managers' behavior is product market competition, while for non-managers, family control and organizational structure are key.

REFERENCES

- Abowd, J. M., Kramarz, F. & Margolis, D. N. (1999), 'High wage workers and high wage firms', *Econometrica* **67**(2), 251–333.
- Allen, S. G. (1983), 'How much does absenteeism cost?', *Journal of Human Resources* pp. 379–393.
- Aronsson, G. & Gustafsson, K. (2005), 'Sickness presenteeism: prevalence, attendance-pressure factors, and an outline of a model for research', *Journal of Occupational and Environmental Medicine* **47**(9), 958–966.
- Bandiera, O., Barankay, I. & Rasul, I. (2005), 'Social preferences and the response to incentives: Evidence from personnel data', *The Quarterly Journal of Economics* **120**(3), 917–962.
- Bandiera, O., Barankay, I. & Rasul, I. (2007), 'Incentives for managers and inequality among workers: evidence from a firm-level experiment', *The Quarterly Journal of Economics* **122**(2), 729–773.
- Bandiera, O., Barankay, I. & Rasul, I. (2009), 'Social connections and incentives in the workplace: Evidence from personnel data', *Econometrica* **77**(4), 1047–1094.
- Bandiera, O., Barankay, I. & Rasul, I. (2010), 'Social incentives in the workplace', *The Review of Economic Studies* **77**(2), 417–458.
- Bandiera, O., Prat, A. & Sadun, R. (2013), Managing the family firm: Evidence from ceos at work, Technical report, National Bureau of Economic Research.
- Barmby, T. A., Orme, C. D. & Treble, J. G. (1991), 'Worker absenteeism: An analysis using microdata', *The Economic Journal* **101**(405), 214–229.
- Barney, J. B. (1986), 'Organizational culture: can it be a source of sustained competitive advantage?', *Academy of management review* **11**(3), 656–665.

- Bertera, R. L. (1990), ‘The effects of workplace health promotion on absenteeism and employment costs in a large industrial population.’, *American journal of public health* **80**(9), 1101–1105.
- Bertrand, M. & Schoar, A. (2003), ‘Managing with style: The effect of managers on firm policies’, *The Quarterly Journal of Economics* **118**(4), 1169–1208.
- Black, S. E. & Lynch, L. M. (2001), ‘How to compete: the impact of workplace practices and information technology on productivity’, *The Review of Economics and Statistics* **83**(3), 434–445.
- Black, S. E. & Lynch, L. M. (2004), ‘What’s driving the new economy?: the benefits of workplace innovation’, *The Economic Journal* **114**(493).
- Bloom, N., Sadun, R. & Van Reenen, J. (2010), ‘Does product market competition lead firms to decentralize?’, *American Economic Review* **100**(2), 434–38.
- Bloom, N. & Van Reenen, J. (2011), ‘Human resource management and productivity’, *Handbook of labor economics* **4**, 1697–1767.
- Bonato, M. L. & Lusinyan, L. (2004), *Work absence in Europe*, number 4-193, International Monetary Fund.
- Bonnier, K.-A. & Bruner, R. F. (1989), ‘An analysis of stock price reaction to management change in distressed firms’, *Journal of Accounting and Economics* **11**(1), 95–106.
- Bridges, S. & Mumford, K. (2001), ‘Absenteeism in the uk: a comparison across genders’, *The Manchester School* **69**(3), 276–284.
- Bruhn, M., Karlan, D. & Schoar, A. (2010), The effect of mentorship on sme growth in mexico, university of chicago, Technical report, mimeo.
- Caliendo, L., Monte, F. & Rossi-Hansberg, E. (2015), ‘The anatomy of french production hierarchies’, *Journal of Political Economy* **123**(4), 809–852.

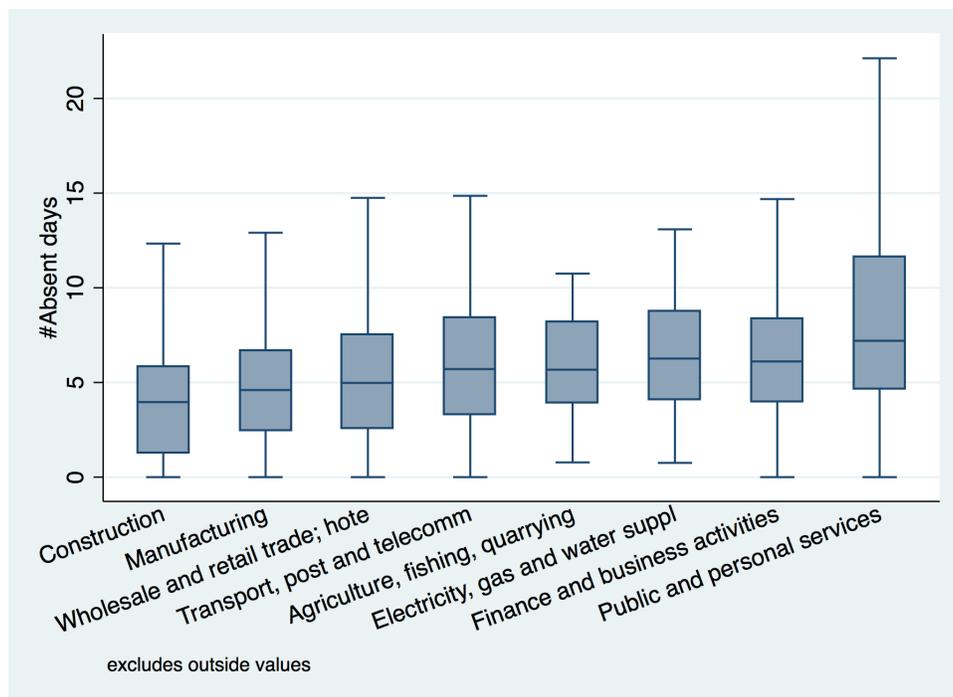
- Card, D., Heining, J. & Kline, P. (2013), ‘Workplace heterogeneity and the rise of west german wage inequality’, *The Quarterly Journal of Economics* **128**(3), 967–1015.
- Cuñat, V. & Guadalupe, M. (2005), ‘How does product market competition shape incentive contracts?’, *Journal of the European Economic Association* **3**(5), 1058–1082.
- Cuñat, V. & Guadalupe, M. (2009), ‘Globalization and the provision of incentives inside the firm: The effect of foreign competition’, *Journal of Labor Economics* **27**(2), 179–212.
- De Boer, E. M., Bakker, A. B., Syroit, J. E. & Schaufeli, W. B. (2002), ‘Unfairness at work as a predictor of absenteeism’, *Journal of Organizational Behavior* **23**(2), 181–197.
- Ellul, A., Pagano, M. & Schivardi, F. (2014), ‘Employment and wage insurance within firms: Worldwide evidence’, *Kelley School of Business Research Paper* (2014-23).
- Ewens, M. & Rhodes-Kropf, M. (2015), ‘Is a vc partnership greater than the sum of its partners?’, *The Journal of Finance* **70**(3), 1081–1113.
- Finkelstein, A., Gentzkow, M. & Williams, H. (2016), ‘Sources of geographic variation in health care: Evidence from patient migration’, *The Quarterly Journal of Economics* **131**(4), 1681–1726.
- Flabbi, L. & Ichino, A. (2001), ‘Productivity, seniority and wages: new evidence from personnel data’, *Labour Economics* **8**(3), 359–387.
- Frankel, E. (1921), ‘Labor absenteeism’, *The Journal of Political Economy* pp. 487–499.
- Friedrich, B. et al. (2015), ‘Trade shocks, firm hierarchies and wage inequality’, *Unpublished working paper. Yale University*.
- Gellatly, I. R. (1995), ‘Individual and group determinants of employee absenteeism: Test of a causal model’, *Journal of organizational behavior* **16**(5), 469–485.
- Graham, J. R., Li, S. & Qiu, J. (2012), ‘Managerial attributes and executive compensation’, *Review of Financial Studies* **25**(1), 144–186.

- Hart, O. (2008), 'The market mechanism as an incentive scheme, *bell journal of economics*, 14 (2), autumn, 366-82', *International Library of Critical Writings in Economics* **214**(3), 388.
- Hart, O. D. (1983), 'The market mechanism as an incentive scheme', *The Bell Journal of Economics* pp. 366–382.
- Herrmann, M. A. & Rockoff, J. E. (2012), 'Worker absence and productivity: Evidence from teaching', *Journal of Labor Economics* **30**(4), 749–782.
- Ichino, A. & Maggi, G. (2000), 'Work environment and individual background: Explaining regional shirking differentials in a large italian firm', *The Quarterly Journal of Economics* **115**(3), 1057–1090.
- Jensen, M. C. (1986), 'Agency cost of free cash flow, corporate finance, and takeovers', *Corporate Finance, and Takeovers. American Economic Review* **76**(2).
- Jensen, M. C. (1989), 'Eclipse of the public corporation'.
- Jensen, M. C. & Meckling, W. H. (1976), 'Theory of the firm: Managerial behavior, agency costs and ownership structure', *Journal of Financial Economics* **3**(4), 305–360.
- Johansson, G. & Lundberg, I. (2004), 'Adjustment latitude and attendance requirements as determinants of sickness absence or attendance. empirical tests of the illness flexibility model', *Social science & medicine* **58**(10), 1857–1868.
- Johansson, P. & Palme, M. (1996), 'Do economic incentives affect work absence? empirical evidence using swedish micro data', *Journal of Public Economics* **59**(2), 195–218.
- Johansson, P. & Palme, M. (2002), 'Assessing the effect of public policy on worker absenteeism', *Journal of Human Resources* pp. 381–409.
- Johnson, W. B., Magee, R. P., Nagarajan, N. J. & Newman, H. A. (1985), 'An analysis of the stock price reaction to sudden executive deaths: Implications for the managerial labor market', *Journal of Accounting and Economics* **7**(1-3), 151–174.

- Karlan, D. & Valdivia, M. (2011), ‘Teaching entrepreneurship: Impact of business training on microfinance clients and institutions’, *Review of Economics and statistics* **93**(2), 510–527.
- Khanna, N. & Poulsen, A. B. (1995), ‘Managers of financially distressed firms: Villains or scapegoats?’, *The Journal of Finance* **50**(3), 919–940.
- Kim, E. H., Morse, A. & Zingales, L. (2009), ‘Are elite universities losing their competitive edge?’, *Journal of Financial Economics* **93**(3), 353–381.
- Lazear, E. P. (1986), ‘Salaries and piece rates’, *Journal of business* pp. 405–431.
- Lazear, E. P. (1998), *Personnel economics for managers*, Wiley New York.
- Lazear, E. P. (2000a), ‘Performance pay and productivity’, *American Economic Review* **90**(5), 1346–1361.
- Lazear, E. P. (2000b), ‘The power of incentives’, *The American Economic Review* **90**(2), 410–414.
- Lazear, E. P. & Rosen, S. (1981), ‘Rank-order tournaments as optimum labor contracts’, *The Journal of Political Economy* **89**(5), 841–864.
- Lemieux, T., MacLeod, W. B. & Parent, D. (2009), ‘Performance pay and wage inequality’, *The Quarterly Journal of Economics* **124**(1), 1–49.
- Lucas, R. (1996), ‘On the size distribution of business firms, bell journal of economics, 9 (2), autumn, 508-23’, *International Library of Critical Writings in Economics* **61**, 175–190.
- Manne, H. G. (1965), ‘Mergers and the market for corporate control’, *Journal of Political economy* **73**(2), 110–120.
- Mueller, H. M. & Philippon, T. (2011), ‘Family firms and labor relations’, *American Economic Journal: Macroeconomics* **3**(2), 218–245.
- Nicholson, N. & Johns, G. (1985), ‘The absence culture and psychological contract—who’s in control of absence?’, *Academy of Management Review* **10**(3), 397–407.

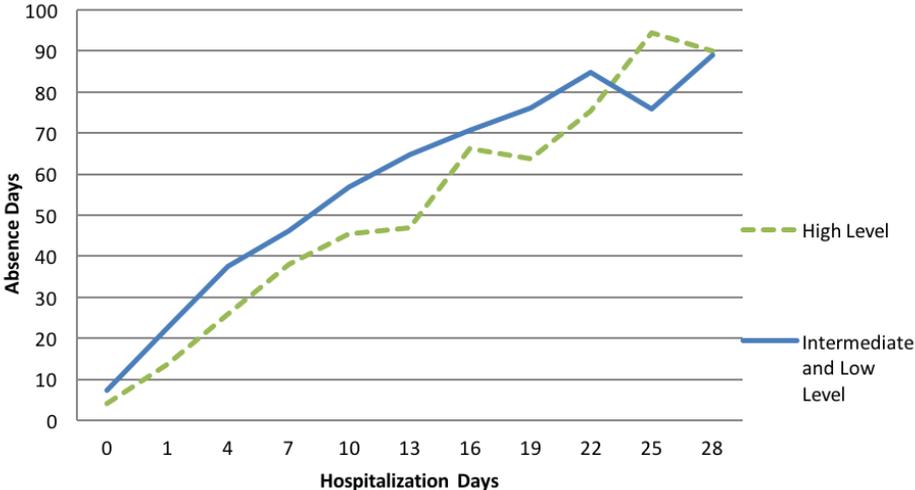
- Paringer, L. (1983), ‘Women and absenteeism: health or economics?’, *The American economic review* **73**(2), 123–127.
- Porter, L. W. & Steers, R. M. (1973), ‘Organizational, work, and personal factors in employee turnover and absenteeism.’, *Psychological bulletin* **80**(2), 151.
- Poza, E. J. (2013), *Family business*, Cengage Learning.
- Reinganum, M. R. (1985), ‘The effect of executive succession on stockholder wealth’, *Administrative Science Quarterly* pp. 46–60.
- Scheil-Adlung, X. & Sandner, L. (2010), ‘Wage continuation during sickness: Observations on paid sick leave provisions in times of crises’, *Working Paper, International Labour Organisation* .
- Schmidt, K. M. (1997), ‘Managerial incentives and product market competition’, *The Review of Economic Studies* **64**(2), 191–213.
URL: <http://www.jstor.org/stable/2971709>
- Shearer, B. (2004), ‘Piece rates, fixed wages and incentives: Evidence from a field experiment’, *The Review of Economic Studies* **71**(2), 513–534.
- Sraer, D. & Thesmar, D. (2007), ‘Performance and behavior of family firms: Evidence from the french stock market’, *Journal of the European economic Association* **5**(4), 709–751.
- Tirole, J. (1988), *The theory of industrial organization*, MIT press.
- Warner, J. B., Watts, R. L. & Wruck, K. H. (1988), ‘Stock prices and top management changes’, *Journal of Financial Economics* **20**, 461–492.
- Weisbach, M. S. (1988), ‘Outside directors and ceo turnover’, *Journal of Financial Economics* **20**, 431–460.

FIGURE 1: DISTRIBUTION OF DAYS ABSENT BY INDUSTRY



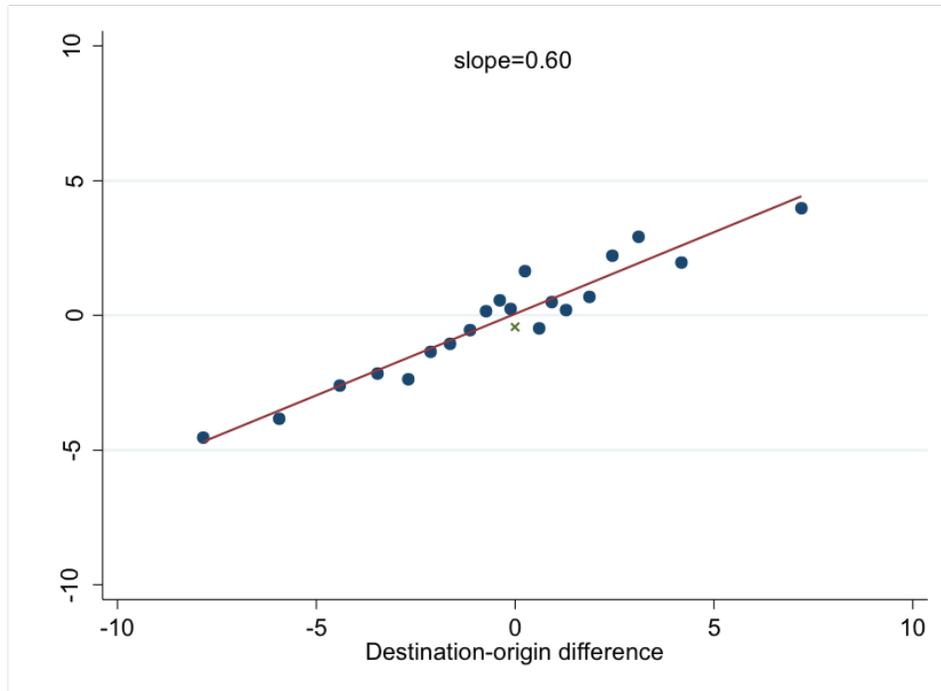
Note: This figure presents box plots of average employee days absent for firms in different industries. Industries are classified based on NACE 1-digit classification. Each box plot presents the minimum, first quartile, median, third quartile, and maximum of days absent for each industry.

FIGURE 2: HOSPITALIZATION AND ABSENT DAYS BY POSITION IN ORGANIZATION



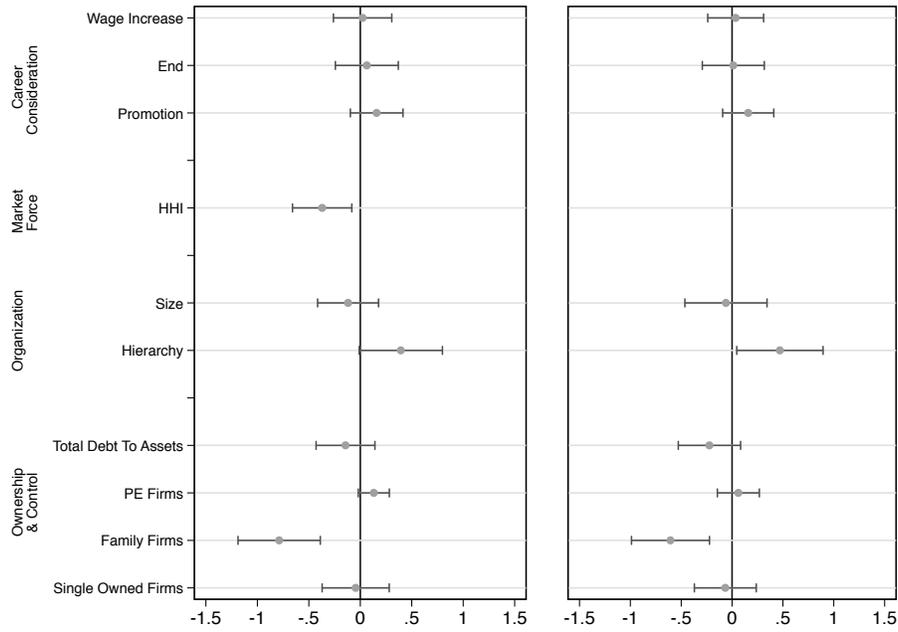
Note: This figure presents the average days absent per year for different days of hospitalization that year for employees with high positions in the organization (green dashed line) and employees with intermediate or low positions in the organization (solid blue line).

FIGURE 3: CHANGE IN DAYS ABSENT BY SIZE OF MOVE



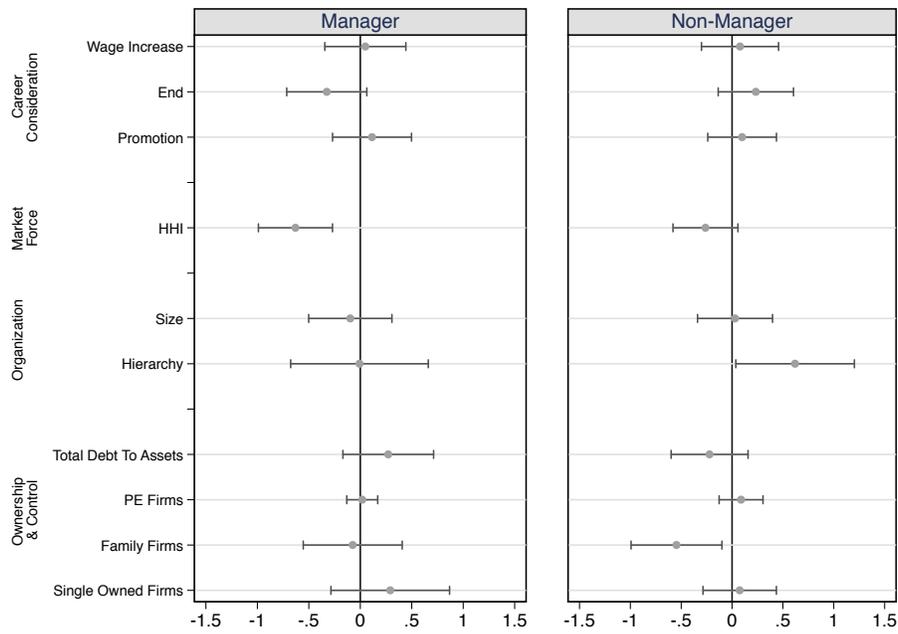
Note: This figure shows the change in days absent before and after the move. For each mover, we calculate the difference δ in average absence between their origin and destination firms, and then group the difference into ventiles. The x-axis displays the mean of δ for movers in each ventile. The y-axis shows, for each ventile, average absence post-move minus average absence pre-move. The line of best fit is obtained from simple OLS regression using the 20 data points corresponding to movers, and its slope is reported on the graph. For comparison, we also compute the average change in absence for a sample of matched non-movers, which we show with the “X” marker on the graph. We construct the sample of non-movers by matching each mover with another employee who does not move and is in the same firm in the year of the move and has the same gender and belongs to the same five-year age bin.

FIGURE 4: FIRM CHARACTERISTICS THAT CORRELATE WITH AVERAGE FIRM EFFECTS



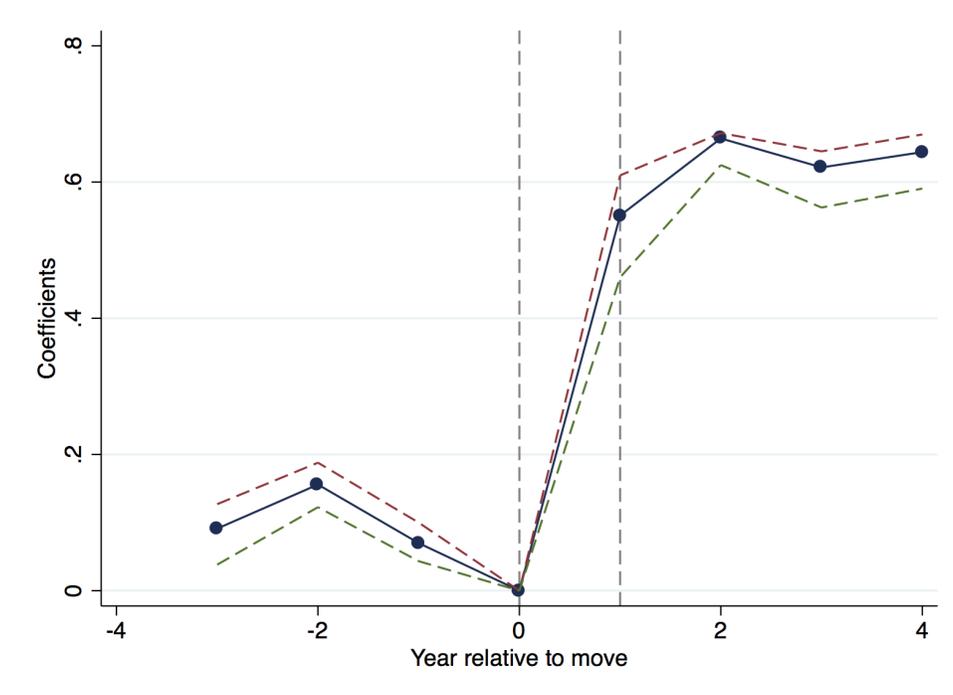
Note: The figure presents multivariate OLS regression results of firm fixed effects on a set of firm- and industry-level characteristics, using the full sample. The second column removes the industry-level variable “competition” and adds industry fixed effect as controls. All covariates have been standardized to have mean zero and standard deviation one. The career consideration variables represent the corresponding event’s sensitivity measure to absence for the firm. Competition is measured using the HHI. Size is measured as the log of assets. Hierarchy is measured using the number of the firm’s different occupational layers, following Caliendo et al. (2015) and Friedrich et al. (2015). PE (private equity) firms, family firms, and single-owned firms are indicator variables that correspond to the firm’s ownership structure. Horizontal bars show 90% confidence intervals.

FIGURE 5: FIRM CHARACTERISTICS THAT CORRELATE WITH AVERAGE FIRM EFFECTS.
ANALYSIS BASED ON MANAGERS AND NON-MANAGERIAL EMPLOYEES



Note: The figure presents multivariate OLS regression results of firm fixed effects on a set of firm- and industry-level characteristics, based on the managers sample and the non-managers sample, respectively. All covariates have been standardized to have mean zero and standard deviation one. Horizontal bars show 90% confidence intervals. The considered variables and specification are the same as in Figure 4.

FIGURE 6: EVENT STUDY



Note: The figure shows the coefficient $\hat{\theta}_{\tau(i,t)}$ estimated from equation (10) in Section 2.5. θ_{τ} captures the fraction of the gap in absenteeism between the origin and destination firm that the employee closes each year relative to the move, after controlling for individual characteristics and time fixed effects. θ_{τ} corresponds to the estimate $S_{incentives}$, the share of the difference in days absent explained by incentives. The sample includes only movers who switch firms once. The dashed lines correspond to upper and lower bounds at the 95% confidence interval. The coefficient for relative year 0 is normalized to 0. Section 2.5 contains details on the graph construction. The mover sample has 390,521 observations, with 98,351 movers in total and 2,544 firms from which employees leave.

TABLE 1: CHARACTERISTICS OF SAMPLE FIRMS VS. ALL DANISH FIRMS

	All	Sample firms	Difference All vs. Sample
OROA	0.0757 (0.0007) [257,397]	0.0599 (0.0025) [13,575]	0.0158*** (0.0026) [257,397]
Net Income/Assets	0.0433 (0.0005) [257,392]	0.0349 (0.0022) [13,575]	0.0084*** (0.0023) [257,392]
Assets	51.8463 (0.8400) [257,432]	364.1203 (9.7585) [13,575]	-312.274*** (9.7870) [257,432]
log(Assets)	2.8465 (0.0082) [257,431]	4.9601 (0.0340) [13,575]	-2.11136*** (0.0349) [257,431]
No. of Employees	38.5082 (0.3553) [257,636]	179.0560 (3.5823) [13,575]	-140.5478*** (3.5965) [257,636]
Firm Age	22.9027 (0.1416) [256,356]	35.0215 (0.5679) [13,575]	-12.1188*** (0.5860) [256,356]

Note: This table presents firm characteristics for all limited liability firms in Denmark during 2007-2012 (column 1) as well as firm characteristics for our sample firms (column 2). Column 3 presents differences. OROA represents the operating return on assets, defined as the ratio of operating income to total assets. Assets and income are measured in real DKK. Firm age is based on the firm foundation date. Sample standard deviation is presented in parentheses. Observation count is reported in brackets. *** indicates significance at the 1% level.

TABLE 2: CHARACTERISTICS OF MOVERS AND NON-MOVERS

	Non-movers			Movers		
	Mean	S.D.	Observations	Mean	S.D.	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.4025	-	1,535,132,	0.3705	-	563,801
Bachelor degree	0.3209	-	1,415,973	0.3647	-	526,534
No. of children	1.27	1.14	1,492,715	1.22	1.13	556,401
<i>Age</i>						
≤ 30	0.1879	-	1,535,132	0.1954	-	563,801
30 - 40	0.2682	-	1,535,132	0.3133	-	563,801
40 - 50	0.2937	-	1,535,132	0.2993	-	563,801
50 - 60	0.203	-	1,535,132	0.1669	-	563,801
Age	41.81	11.47	1,535,132	40.48	10.53	563,801
<i>Absence</i>						
No. of days absent	7.92	22.47	1,535,123	7.06	20.36	563,801
Hospital event	0.0551	-	1,535,123	0.0512	-	563,801

Note: Female, bachelor degree, and age bins report the proportion of the non-movers and movers sample that match the criteria. Hospital event reports the proportion of the sample that experienced a hospital event. S.D. reports the sample standard deviation.

TABLE 3: ABSENCE DIFFERENCE BY FIRM CLASSIFICATION

	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
All	6.295	10.372	15.696	20.080
Manufacturing	5.453	8.894	13.455	17.729
Construction	6.206	10.03	15.225	20.277
Whole and retail trade; hotels & restaurants	6.280	10.089	14.689	18.391
Transport, post and telecomm	6.473	10.749	16.751	23.007
Finance and business activities	6.734	11.260	18.514	26.554
Public and personal services	10.701	18.099	29.638	41.286

Note: This table reports the difference in average days absent for different industries. Each column defines a set of firms R and R' based on percentiles of average absence. The rows report the difference in average days absent overall between the two groups $y_R - y_{R'}$ for the various industries. The industry classification is based on NACE 1-digit code.

TABLE 4: DECOMPOSITION OF EMPLOYEE ABSENCE

Panel A: Base				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	6.2948	10.3718	15.6956	20.0801
Due to Incentives	3.3922	6.0216	9.4964	13.1734
Due to Selection	2.9026	4.3502	6.1992	6.9067
<i>Share of Difference</i>				
Due to Incentives	0.5389 (0.0614)	0.5806 (0.0524)	0.6050 (0.0765)	0.6560 (0.0951)
Due to Selection	0.4611	0.4194	0.3950	0.3440
Panel B: w/ Person Controls				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	6.2881	10.3535	15.6565	20.0462
Due to Incentives	3.3613	5.9583	9.4164	12.9796
Due to Selection	2.9268	4.3952	6.2401	7.0666
<i>Share of Difference</i>				
Due to Incentives	0.5345 (0.0582)	0.5755 (0.0507)	0.6014 (0.0791)	0.6475 (0.0978)
Due to Selection	0.4655	0.4245	0.3986	0.3525

Note: The dependent variable is the annual number of days absent. The sample includes movers and non-movers. Panel A is based on estimation of equation (1) without including the employee time-varying controls and panel B is based on estimation of equation (1), which includes controls for age, number of children, wage and hospitalization. Each column defines a set of firms R and R' based on percentiles of average absence. The first row reports the difference in average days absent overall between the two groups $y_R - y_{R'}$; the second row reports the difference due to incentives $\gamma_R - \gamma_{R'}$; the third row reports the difference due to selection $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two sets of firms that is due to incentives $S_{incentives}(R; R')$. The last row reports the share of the difference in average absence between two sets of firms that is due to selection $S_{selection}(R; R')$. The standard error of the share is calculated by bootstrap of 50 repetitions, and reported in parentheses. The values of R^2 of the AKM of panel A and B are 0.4737 and 0.4884, respectively.

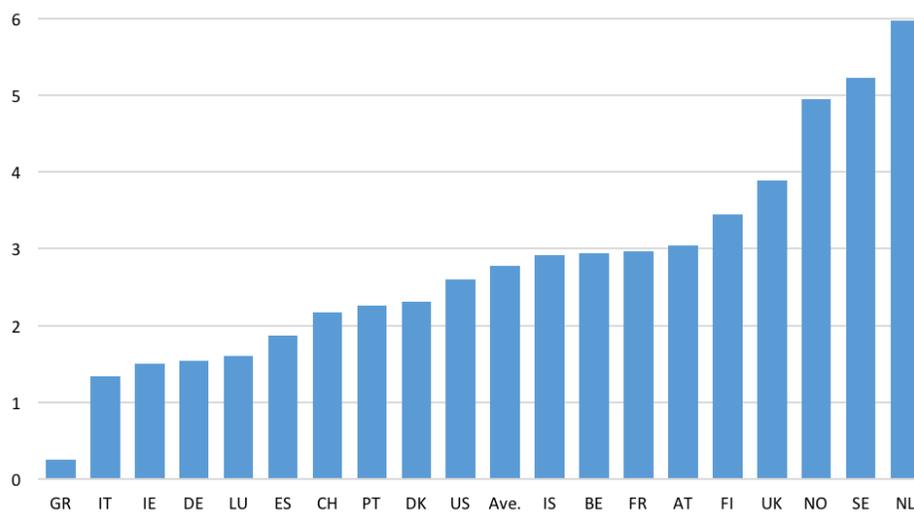
TABLE 5: DECOMPOSITION OF ABSENCE OF MANAGERS AND NON-MANAGERS

Panel A: Managers				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	4.4991	7.4119	11.0616	14.3781
Due to Incentives	2.6365	4.8521	7.0343	11.5621
Due to Selection	1.8626	2.5598	4.0273	2.8160
<i>Share of Difference</i>				
Due to Incentives	0.5860 (0.1066)	0.6546 (0.0955)	0.6359 (0.0911)	0.8041 (0.1274)
Due to Selection	0.4140	0.3454	0.3641	0.1959
Panel B: Non-managers				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	6.8551	11.3225	17.1227	22.1998
Due to Incentives	3.5217	6.2083	10.6866	15.1222
Due to Selection	3.3334	5.1142	6.4361	7.0776
<i>Share of Difference</i>				
Due to Incentives	0.5137 (0.0582)	0.5483 (0.0507)	0.6241 (0.0791)	0.6812 (0.0978)
Due to Selection	0.4863	0.4517	0.3759	0.3188

Note: The dependent variable is the annual number of days absent. The sample includes movers and non-movers. Both panels are based on estimation of equation (1) and also includes controls for age, number of children, wage, and hospitalization. Panel A is based on managers and panel B is based on non-managerial employees. Each column defines a set of firms R and R' based on percentiles of average absence. The first row reports the difference in average days absent overall between the two groups $y_R - y_{R'}$; the second row reports the difference due to incentives $\gamma_R - \gamma_{R'}$; the third row reports the difference due to selection $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two sets of firms that is due to incentives $S_{incentives}(R; R')$. The last row reports the share of the difference in average absence between two sets of firms that is due to selection $S_{selection}(R; R')$. The standard error of the share is calculated by bootstrap of 50 repetitions, and reported in parentheses. The values of R^2 of the AKM of panel A and B are 0.5316 and 0.5349, respectively.

APPENDIX A ADDITIONAL FIGURES AND TABLES

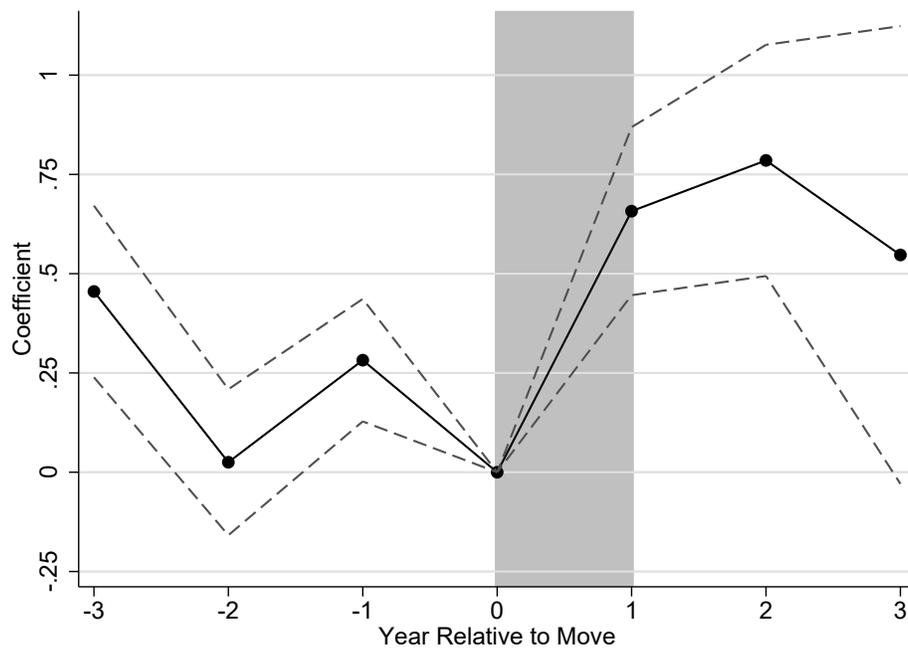
FIGURE A1: SICKNESS ABSENCE, AVERAGE FOR 1995-2003 (AS A PERCENTAGE OF EMPLOYMENT)



Note: AT=Austria; BE=Belgium; CH=Switzerland; DE=Germany; DK=Denmark; ES=Spain; FI=Finland; FR=France; GR=Greece; IE=Ireland; IS=Iceland; IT=Italy; LU=Luxembourg; NL=Netherlands; NO=Norway; PT=Portugal; SE=Sweden; UK=United Kingdom; US=United States.

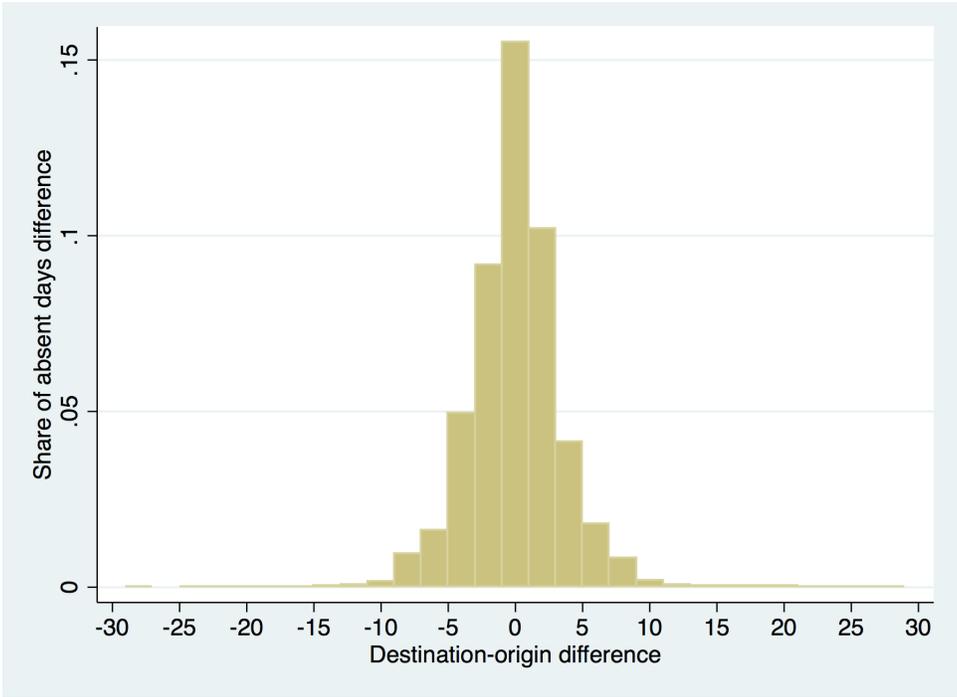
Source: Bonato, L., and L. Lusinyan, 2004, Work Absence in Europe, IMF Working Paper WP/04/193, International Monetary Fund.

FIGURE A2: EVENT STUDY OF MOVES DUE TO PLANT CLOSING



Note: The figure shows the coefficient $\hat{\theta}_{\tau(i,t)}$ estimated from equation (10) in Section 2.5. The sample includes only movers who move due to plant closing. The dashed lines correspond to upper and lower bounds at the 95% confidence interval. The coefficient for relative year 0 is normalized to 0. Section 2.5 contains details on the event study graph construction. Over our sample period, 673 plants (2.94% of all plants) closed.

FIGURE A3: DISTRIBUTION OF DIFFERENCE IN AVERAGE DAYS ABSENT BETWEEN DESTINATION FIRM AND ORIGIN FIRM



Note: This figure presents the distribution of differences in average days absent between origin firm and destination firm (destination - origin) for movers, which is $\bar{y}_{d(i,t)} - \bar{y}_{o(i)}$ for mover i . $d(i,t)$ and $o(i)$ represent the destination and origin firm of mover i . Notation follows what we derived in the main article. The sample is all movers.

TABLE A1: EMPLOYEE ABSENCE AND FIRM PERFORMANCE

Dependent Variable: OROA	<100 employees	>100 employees	>300 employees
Absence	0.0000 (0.0007)	-0.0008** (0.0004)	-0.0011* (0.0006)
Firm Age	-0.0079*** (0.0030)	-0.0079*** (0.0015)	-0.0065*** (0.0020)
Assets	0.0004 (0.0029)	-0.0000 (0.0000)	-0.0000 (0.0000)
Constant	0.3120*** (0.0935)	0.3740*** (0.0586)	0.3228*** (0.0815)
Observations	4,028	4,777	2,238
R-squared	0.8058	0.7127	0.7035
Year FE	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Note: This table presents the effect of employee absence on firm performance. We estimate the following regression: $OROA_{jt} = \gamma_j + \mu_t + \eta absence_{jt} + x_{it}\theta + \zeta_{jt}\delta + e_{ijt}$, where $OROA_{jt}$ is each firm-year observation of operating return on assets, defined as the ratio of operating income to total assets. γ_j is the firm fixed effect, μ_t is the year fixed effect, and ζ_{jt} are firm controls. $Absence_{jt}$ is the mean days absent at the firm-year level. Column 1 presents results for firms with less than 100 employees, column 2 presents results for firms with more than 100 employees, and column 3 presents results for firms above 300 employees. In each column, we report estimated coefficients and their standard errors. Heteroscedasticity-robust standard errors (in parentheses) are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% percent levels, respectively.

TABLE A2: PROMOTION AND SEPARATION WITH ABSENCE

	Promotion		Separation	
	(1)	(2)	(3)	(4)
Days Absent _{t-1}	-0.0003*** (0.0001)	-0.0002*** (0.0001)	0.0005*** (0.0001)	0.0004*** (0.0001)
Observations	925,894	925,894	943,210	943,210
R-squared	0.0597	0.3921	0.0180	0.6925
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Employee Characteristics	Yes	Yes	Yes	Yes
Employee FE	No	Yes	No	Yes
Firm Controls	Yes	Yes	Yes	Yes

Note: The following table reports the estimated effect of absence on promotion and separation. Columns (1) and (3) do not include employee fixed effects. Heteroscedasticity-robust standard errors (in parentheses) are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE A3: DECOMPOSITION OF EMPLOYEE ABSENCE INCLUDING OCCUPATION FIXED EFFECT

w/ Person Controls	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	6.1128	10.185	15.6244	20.5616
Due to Incentives	3.192	5.8015	9.0415	13.3229
Due to Selection	2.9208	4.3835	6.5829	7.2387
<i>Share of difference</i>				
Due to Incentives	0.5222 (0.04219)	0.5696 (0.0519)	0.5787 (0.0644)	0.6480 (0.0760)
Due to Selection	0.4778	0.4304	0.4213	0.3520

Note: The dependent variable is the annual number of days absent. The sample is movers and non-movers. The results are based on estimation of equation (1), which includes controls for age, number of children, wage, and hospitalization. We also augment the equation including occupation fixed effects. Each column defines a set of firms R and R' based on percentiles of average absence. The first row reports the difference in average days absent overall between the two sets of firms $y_R - y_{R'}$; the second row reports the difference due to incentives $\gamma_R - \gamma_{R'}$; the third row reports the difference due to selection $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two sets of firms that is due to incentives $S_{incentives}(R; R')$. The last row reports the share of the difference in average absence between two sets of firms that is due to selection $S_{selection}(R; R')$. The standard error of the share is calculated by bootstrap of 50 repetitions, and reported in parentheses. The value of R^2 of the AKM is 0.5052.

TABLE A4: DECOMPOSITION OF EMPLOYEE ABSENCE ON MONDAY, FRIDAY, AND AROUND HOLIDAY

Panel A: Base				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	3.0089	4.965	7.5295	9.7189
Due to Incentives	1.7393	3.0919	5.0956	6.8686
Due to Selection	1.2696	1.8731	2.4339	2.8503
<i>Share of Difference</i>				
Due to Incentives	0.5781 (0.0571)	0.6227 (0.0544)	0.6768 (0.0672)	0.7067 (0.0928)
Due to Selection	0.4219	0.3773	0.3232	0.2933
Panel B: w/ Person Controls				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
<i>Difference in Absence</i>				
Overall	3.0023	4.9497	7.4964	9.6809
Due to Incentives	1.7279	3.0922	5.0937	6.8265
Due to Selection	1.2744	1.8575	2.4027	2.8544
<i>Share of Difference</i>				
Due to Incentives	0.5755 (0.0563)	0.6247 (0.0535)	0.6795 (0.0702)	0.7052 (0.0978)
Due to Selection	0.4245	0.3753	0.3205	0.2948

Note: The dependent variable is the annual number of days absent from absence spells that start on Monday or Friday or around a national holiday. The sample is movers and non-movers. Panel A is based on estimation of equation (1) without including the employee time-varying controls, and panel B is based on estimation of equation (1), which includes controls for age, number of children, wage, and hospitalization. Each column defines a set of firms R and R' based on percentiles of average absence. The first row reports the difference in average days absent overall between the two sets of firms $y_R - y_{R'}$; the second row reports the difference due to incentives $\gamma_R - \gamma_{R'}$; the third row reports the difference due to selection $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two sets of firms that is due to incentives $S_{incentives}(R; R')$. The last row reports the share of the difference in average absence between two sets of firms that is due to selection $S_{selection}(R; R')$. The standard error of the share is calculated by bootstrap of 50 repetitions, and reported in parentheses. The values of R^2 of the AKM of panel A and B are 0.4894 and 0.5049, respectively.

APPENDIX B MOVERS

In the paper, we rely on movers to identify individual and firm fixed effects. The goal of Appendix B is to describe the movers and provide additional comparisons of movers and non-movers.

In Figure A3, we plot the difference between average absence in the destination firm and average absence in the origin firm. The figure shows this variable is centered at zero and the distribution is roughly symmetric. That is, a mover is equally likely to move to a firm that has one more day absent on average (or any other number of days absent) than the origin firm than to move to a firm that has one fewer day absent on average.

In Figure 3, we present evidence of the individual change in behavior as a function of the average days absent at the origin and destination firm. The x-axis displays the difference in average days absent between the destination and origin firm. The y-axis shows average change in the mover's absenteeism. The slope of the line of best fit is 0.6. In other words, the mover changes his days absent by 0.6 times the difference in days absent between the destination and origin firm. This finding suggests that common factors at the firm level have a large impact on employee behavior.

Figure 3 shows changes in absenteeism around a move are symmetric. The figure indicates the change in absenteeism associated with a move from firm j to firm j' is similar in magnitude but opposite in sign to the change induced by a move in the opposite direction. As we explained before, this symmetry is reassuring because it is inconsistent with moves being driven by the match component in the error term.

We also compare the behavior of non-movers to movers. We construct a sample of non-movers by matching each mover with another employee who does not move and is in the same firm in the year of the move and has the same gender and belongs to the same five-year age bin. Non-movers are displayed with an "x" in Figure 3. By definition, the change in days absent between the destination and origin firm for non-movers is zero. The relevant movers against which to compare the non-movers are those whose destination and origin firm have the same level of absenteeism so that the change in destination- and origin-firm absenteeism is also

zero. As we can see from the figure, both groups experience the same change in absenteeism (zero), suggesting movers and non-movers are similar.

APPENDIX C

TABLE C1: DEFINITIONS OF VARIABLES

Variable	Definition
<i>Firm Level Variables</i>	
Family firm	An indicator variable that takes the value 1 if the firm is a family firm, and 0 otherwise.
PE firm	An indicator variable that takes the value 1 if PE firms hold ownership in the firm, and 0 otherwise.
Single owned firm	An indicator variable that takes the value 1 if the firm has a single owner who holds 100% of the firm, and 0 otherwise.
Assets	Measured in real DKK. The source is KOB.
OROA	Source is KOB.
Firm age	Firm age based on the firm foundation date. The information source is the business registry.
Hierarchy	We follow Caliendo et al. (2015) and Friedrich et al. (2015) in constructing a measure on how hierarchical a firm is. The measure is based on the number of different occupational layers represented by workers in a firm. We use workers' occupations as reported in the Danish occupational code DISCO. The source is IDA
<i>Industry Level Variables</i>	
HHI	Herfindahl-Hirschman index.
<i>Employee Level Variables</i>	
Male	An indicator variable that takes the value 1 if the person is male, and 0 otherwise. The source is the Danish Civil Registration System.
Age	Employee age. The source is the Danish Civil Registration System.
No. of Children	The number of the employee's living children. The source is the Danish Civil Registration System.
Wage	Total annual wage of the employee. The information comes from the administrative-matched employer-employee dataset (IDA).
College degree	An indicator variable that takes the value 1 if an employee has completed a bachelor's degree. The variable is constructed based on information from the official Danish registry.
Promotion	An indicator variable that takes the value 1 if the employee got a promotion that year, and 0 otherwise. The promotion variable is constructed based on information of employee position from IDA.
Separation	An indicator variable that takes the value 1 if the employee left the company that year, and 0 otherwise. The separation variable is constructed based on information from IDA.