Drivers of Effort: Evidence from Employee Absenteeism *

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Abstract

We use detailed information on individual absent spells of all employees in 2,600 firms in Denmark to document large differences across firms in average absenteeism. Using employees who switch firms, we decompose absent days into an individual component (e.g., motivation, work ethic) and a firm component (e.g., incentives, corporate culture). We find that 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, McCleod and Parent (2009) find that 38% of workers were covered by performance pay in the 1970s, and by the 1990s, this number had increased to 45%. In addition to incentive pay, Black and Lynch (2001) find that other human resource practices (such as 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, there is scant evidence comparing employee effort across a representative sample of firms. Are there significant differences 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 provided by the firm? What firm features are more important for employees' effort provision?

We use employee absenteeism at the individual level to address these questions. While absenteeism captures only one dimension of employee behavior, it has two important advantages.[1] 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 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 use these movers to identify firm effects.[2]

Our data comes from an administrative survey conducted by Statistics Denmark covering employees at all medium and large Danish corporations. The data contains detailed information of every absence spell of over 665,000 unique individuals over the period 2007 to 2013.[3]

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

1. Absenteeism has been previously used as measure of effort by Ichino & Maggi (2000*a*) in investigating what drives shirking differential in a large Italian bank.

2. 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)).

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

work (e.g., rotation policies, team formation), 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 absent days 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, what we call incentives.[4] 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 average days absent 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 which 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 since, 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 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. While 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 to firms below the median, we find that 53% of the difference in average days absent is driven by incentives with the rest explained by selection. Our results are robust to considering

4. Peer effects would also be captured by the firm fixed effect

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 larger role for the incentive explanation. This possible endogeneity chanel predicts that, to the extent motivation changes slowly over time, we should observe employee behavior moving towards that of the average in the destination firm prior to the move. However, our results suggests that this is not the case.

While 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.

Not surprisingly, we find that career considerations are an important force shaping employee incentives. Firms in which wage increases, promotions and separations react more strongly to absences discourage employee absenteeism. Interestingly, the effect is only present for workers and not for managers. This differential effect is suggestive of the fact that firm have better performance measures for managers in addition to absenteeism.

Next we turn to the effect of product market competition on effort. This effect is ambiguous, as pointed by Schmidt (1997) and Hart (1983). On the one hand, competition increases the probability of bankruptcy, sharpening incentives. On the other hand, competition mutes incentives as it reduces profits. We find no effect on average. However, when we focus on the sample of managers only, we find a strong effect: Their absenteeism is lower when firms face more competition consistent with Hart (1983).

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 as 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. It is possible that family owners, due to their long-term horizons, have a comparative advantage at sustaining implicit labor contracts, which might be reciprocated by workers with cooperative behavior (Sraer & Thesmar (2007), Ellul et al. (2014)). It could also be that their large ownership stakes motivates 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 there is a positive incentive effect of family firms that affects all employees (loyalty, more strict monitoring) and that the negative effects of nepotism are only present at the top of the firm hierarchy since family members are typically promoted to top positions.

In the final step we investigate which variables are more important for predicting the firm fixed effect using the lasso technique. In the sample of all workers, five variables are selected, but only product market competition and family firm status are statistically significant.

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 number of tree planted by workers in tree-planting firm in Bristish 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 is either adopted by the firm as part of its normal course of business or is randomized by the researchers. A few studies do analyze multiple firms, but mostly focusing on developing countries (Karlan & Valdivia (2009), Bruhn et al. (2010) and Bloom et al. (2010)).[5]

While 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.[6].

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

6. Bloom & Van Reenen (2011) in their survey of this literature comment that "[t]he future of the field may be

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.[7] 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 do this because we have a measure of effort at the individual level. Using switchers has the disadvantage that it is more difficult to point to the specific policy difference that causes the change in employee behavior. However, it has the advantage that it allows us to estimate firm effects for a large number of firms as 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 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. (2014).[8] We assume that days absent, y_{it}, can be described by the following model:

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

to move away from purely single firm studies to consider larger numbers of firms who are subject to [human resource management] policy interventions..."

7. An exception is Ichino & Maggi (2000*a*) that also uses absenteeism as a measure of effort and focuses on movers across different branches of the same bank. Ichino & Maggi (2000*a*), however, studies only one firm while the focus of our paper is on differences across firms in employee behavior.

8. In the finance literature this approach has been used by

where the $J(i,t)$ 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. The term 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, etc. on all employees of firm j (all i with $J(i,t) = j$). As we said before, 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, it would be impossible to separate the effect of individual characteristics from firm effects. For example, we would not be able to ascertain whether a firm with low employee absenteeism has policies that promote work or alternatively has a workforce comprised 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. To identify the parameters of the model the usual assumption that the error term be orthogonal to all covariates is required. Of these assumptions, the key one is that the error term be uncorrelated to 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

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

The term ϵ_{it} measures time-varying unobservable component of employee behavior. For example, motivation can be time varying, perhaps affected by life events that 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, it could be that firms have varying corporate cultures and individuals 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, then 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 that ϵ_{it} captures shocks to motivation with increases in motivation leading to lower absenteeism. If employees that 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, this is not what we find. In the years prior to the move, employees' absenteeism does not tend towards the average of the destination firm. 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 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 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 effect and any error terms would average out to zero. However, when the match component is present, this relation no longer holds as the group of employees who move from firm j to j' are those with especially low $\eta_{ij'}$ and those 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. This would be the case if, for example, the distribution of employee characteristics is similar across firms.

We follow Finkelstein et al. (2014) 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:

$$y_{it} = c_{it} + \gamma_j + \mu_t + e_{it}, \tag{3}$$

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

$$\bar{y}_j = \bar{c}_j + \gamma_j + \frac{1}{T}\sum_t \mu_t + \bar{e}_j \tag{4}$$

where $\bar{y}_j$ is computed by the averaging the 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 absent days between groups of firms M and N attributable to incentive explanations is

$$S_{incentives} = \frac{\gamma_M - \gamma_N}{\bar{y}_M - \bar{y}_N} \tag{5}$$

and the share attributable to selection is:

$$S_{selection} = \frac{\bar{c}_M - \bar{c}_N}{\bar{y}_M - \bar{y}_N} \tag{6}$$

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

$$\hat{\gamma}_j = \delta z_j + \psi_j, \tag{7}$$

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

2.5 Event study

Following Finkelstein et al. (2014), 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

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

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:

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

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:

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

The interpretation of θ_τ is the fraction of the gap in absenteeism between origin and destination firm that, after controlling for individual characteristics and time fixed effects, the employee closed after the move.

3 Data and Descriptive Statistics

3.1 Data sources

Survey of employees' absences. Our main data source is the survey of employee absenteeism conducted in Denmark. Statistics Denmark collects absence data for all employees in the central government, local governments, and for a sample of 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. There are a total of 2,600 unique firms from 2007 to 2012 (not all firms are included in every year). Firms report absence spells for each employee. For each spell, the data contains 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" since the reporting of other categories is rare.[9]

Matched employer-employee data. We also use the matched employer-employee dataset from the "Integrated Database for Labour Market Research" (IDA database) at Statistics Denmark. In addition to the employer's identification number (CVR), the IDA dataset contains employee's 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 that is defined based on the international standard classification of occupations (ISCO). We have access to this dataset for every year in the period 1995 - 2013.

Hospitalization data. Data on hospitalizations is from the National Patient Registry (NPR)

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

at Statistics Denmark. This dataset records public hospital interactions of all Danish citizens and contains the individual national identification number and the number of hospitalization days per calendar year.

Firm financial information. Financial data are from *Experian*, which is a private data provider in Denmark. *Experian* provides us with a dataset that covers financial statements for all firms incorporated in Denmark. The data set includes information that firms are required to file with the Ministry of Economics and Business Affairs, including the value of total assets, operating and net income. Even though most of the firms in *Experian* are privately held, external accountants audit firm financial in compliance with Danish corporate law. The *Experian* dataset includes a firm identifier (CVR number) which allow us to link financial to the other datasets.

3.2 Days Absent

In this section we describe the days absent variable from the surveys conducted by Statistics Denmark as well as the relevant regulatory and institutional environment.

First, we present evidence to asses the quality of the days absent variable. In Figure 1a, we plot the number of days absent as a function of hospitalization days. Since these two variables come from different sources (absent days comes from a survey of firms and hospitalization days from administrative data collected from hospitals), it is reassuring to observe the high positive correlation between them. Most employees have zero hospitalization days in a year, however, among those who are hospitalized there is a significant variation in the length of their stay. The effect of hospitalization on days absent is large. For example, employees who spend more than 20 days in hospital are absent 2-3 months.

A different approach to check the validity of the days absent variable is to observe the effect of age on the number of days absent. In Figure 1b we split our sample into young (20 to 45 years old) and old (45 to 65 years old) employees but keep the focus on the relationship between hospitalization days and days absent. As expected, the figure shows that throughout the distribution of hospitalization days, older employees have longer absences relative to younger employees, perhaps due to a longer recovery period.

Second, we show preliminary evidence of a discretionary component in the number of days absent. Figure 1c focuses on the relationship between hospitalization days and days absent for employees in different positions in the firm. To the extent that there is a discretionary component in days absent, we would expect employees with more responsibility to return to work sooner. Throughout the distribution of hospitalization days, employees with senior positions have shorter absences than employees in junior positions. The difference disappears for long hospitalization. This could be because our sample is very limited in this part of the distribution or because incentives play a small role for extremely severe illnesses.

Third, we note that variation in days absent across firms is unlikely to be the result of different firm vacation policies. In Denmark the number of employee 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 adjust this general vacation policy. However these adjustments are negotiated with the unions and not with individual firms.

Fourth, is also unlikely for days absent to vary across firms due to differential reporting. The reimbursement policy of sickness benefits provide firms with incentives to report employees' absences as soon as they start. This is because the firm is required to pay sickness benefits the first 30 days with the Danish government paying only after this initial period. In addition Statistics Denmark developed software that firms can integrate into their payroll system to facilitate reporting.

Finally, we present suggestive evidence that employees' absences matter for the firm. While some studies take this relation as a given (Flabbi & Ichino (2001) state that "workers who are more often and for longer periods absent are less productive for the firm"), this is not necessarily the case. Although absences reduce contemporaneous labor provision, it is possible that employees compensate the lost time by working more efficiently or by working overtime when they return to the workplace.

To perform the analysis we estimate the following model:

$$OROA_{jt} = \gamma_j + \mu_t + \eta absence_{jt} + x_{it}\theta + \zeta_{jt}\delta + e_{ijt} \ , \tag{11}$$

where $OROA_{jt}$ is each firm-year observation of operating return on assets. γ_j is firm fixed effect, μ_t is year fixed effect, and ζ_{jt} are firm controls. The variable $\mathrm{absence_{jt}}$ is the mean days absent over all employees in firm j at time t.

The results are presented in Table A1. Columns 1, 2 and 3 presents results for firms with fewer than 100 employees, more than 100 employees, and above 300 employees, respectively. All columns include firm controls and firm fixed effects. In Columns 2 and 3, the coefficient on average days absent, η, is negative and significant indicating a negative correlation between the average days absent and performance. We do not find a correlation for firms with less than 100 firms. Smaller firms though have noisier data on performance. These results are only preliminary evidence of the effect of days absent on performance, but they are not conclusive as it is difficult to interpret η in a causal way. For example, it could well be that employees decide to take more days off in response to poor firm performance. Since 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 large causal effect of teacher absence on productivity.

3.3 Descriptive Firm and Employee Statistics

Table 1 Column 1 presents summary statistics for the universe of Danish firms and Column 2 reports information for firms in our sample. Column 3 presents differences between these two groups.

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 lower OROA than those in the population and the difference is 2.7 percentage points, which is statistically significant at any conventional level. We find a similar pattern in Net Income to Assets. Given that the Survey of Employees' Absence covers mostly large medium and large firms, it is not surprising that the Table reports significant differences in the natural logarithm of assets and the number of employees between the population and our sample. This Table also reports that firms in our sample are older. In sum, Table 1 documents that firms in our sample are less profitable, larger and older that the average Danish firm.

Table 2 presents summary statistics for the all employees in the population of Danish firms (Column 1) as well as for firms in our sample (Column 2). Column 3 presents differences between these two groups. We report the average over the sample years, from 2007 to 2012. The average wage level for all employees is 306,750 Danish Kroner which is approximately 41,229 EUR.[10] For our sample firms the average wage level is higher, at 425,184 DKR or 57,148 EUR. The average employee age for population of firms is 38.52 years. Workers in our sample are on average 41.3 years old. The difference of 3.3 years is statistically significant on a 5% level. On average, almost 2/3 of the employees are males and there are 5% more female workers in the absence sample. In terms of health outcomes, the average employee in Dernmark is hospitalized for 0.25 days, while employees in our sample of firms is hospitalized only 0.2 days. The Table also reports the average number of absence per year due to "Own Sickness". The average employee is absent 7.6 days a year.

10. The average exchange rate in the period 2007 to 2012 was approximately 7.44 Danish Kroner to one Euro.

3.4 Variation in Days Absent Across Firms

Table 3 shows the difference in average days absent for different classifications of firms. The difference in average days absent between firms above and below the median is 6.3 days while between firms in the top and bottom quartile is 10.4 days. This difference widens to 15 days, corresponding to 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 2 shows. The industry classification is based on 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 there is considerable variation within all industries.[11]

Similar information as in Figure 2 is conveyed in Table 3. The Table 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, while in construction is 6.2 days. The same difference is 10.7 days for public and personal services. The differences in average days absent of firms within industry are even larger (range from 8.8 to 18 days) when we compare the top and bottom quartile and they range from 13.4 to 29.6 days when we compare the top and bottom decile. Overall Figure 2 and Tables 3 show that there is substantial variation in days absent across firms, even within the same industry.

3.5 Movers

Around 19.67% of the 665,661 unique individuals in our sample switch firms during our window. In Figure 4, we plot the difference between average absence in the destination firm and average absence in the origin firm. The figure shows that 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 days absent on average (or any other number of days absent) than the origin firm than to move to a firm that has 1 less days 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 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 suggest that common factors

11. Public and personal services has higher median than the rest as this contains health care and education

at the firm level have a large impact on employee behavior.

Figure 3 shows that changes in absenteeism around a move are symmetric. The figure indicates that the change in absenteeism associated with a move from firm j to firm j' is similar in magnitude but opposite in sign to the changed induced by a move in the opposite direction. As we explained before, this symmetry is reassuring as 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 5-year age bin. Non-movers are displayed with an "×" in Figure 3. By definition, the change in days absent between destination and origin firm for non-movers is zero. The relevant movers to compare the non-movers against 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 these groups experience the same change in absenteeism (zero), suggesting that movers and non-movers are similar.

4 Main results

4.1 Results on Decomposition into individual and firm components

Table 4 shows the contribution of the incentives and selection components in accounting for the difference in average employee absenteeism between different groups of firms. Each column present results for a 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 quartile, top and bottom 10%, and top and bottom 5%.

We estimate 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 while 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 53 percent of this difference is explained by incentives, while the rest is driven by selection. The estimate is quite precise. We find similar results when comparing other groups

(Columns 2-5). Incntive explanations account for 58 percent of the difference between top and bottom quartile (Column 2), 60 percent of the difference between the top and bottom decile (Column 3), and 65 percent of the difference between the top and bottom 5 percent (Column 4). Panel B shows that the results are similar when we also control time-varying employee characteristics, specifically age and hospitalization. The incentive explanations account for 53 to 64 percent.

We repeat this analysis using days absent in spells that start on Monday or Friday or spells that start within two days around a national holiday. This measure is more likely to capture the discretionary component of days absent. Table A2 presents the results. Both the results based on the basic model (Panel A) and the results using employee time-varying controls, show that the firm share ranges from 57 to 70 percent, consistent with our main results in Table 4.

4.2 Event study

An alternative way to present the results is by using the event study methodology described before. We modify Equation (9) so that we estimate one θ for each year from three years before the move to four years after as folows:

The coefficient θ can be interpreted as a normalized change in absenteeism of the mover after controlling for individual characteristics and time fixed effects, with zero indicating that the mover's days absent do not change and 1 indicating that he behaves similarly to the average employee at the destination firm. If for example, absenteeism is purely determined by individual factors θ should not change around the move, while if absenteeism is purely determined by firm factors, we should see θ jumping to 1.

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 slope of the line we discussed in figure 3.

This event study also allows to asses the severity of a potential endogeneity problem described in Section 2. In that section we gave the example of employees with positive shocks to motivation moving to firms with low absenteeism. If motivation changes slowly over time, we should see absent days moving closer to the average in the destination firm even prior to the move. Figure 3 shows that this is not the case.

4.3 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 potential mechanisms that drive the firm component of days absent. We estimate equation (7). Our results in this section are not driven by selection as we have effectively controlled for it in estimating the firm fixed effects.[12] However, we do not have exogenous variation in the firm characteristics and hence cannot rule out bias in the estimates coming from correlated unobserved characteristics.

We first focus on variables related to incentives at the workplace. We investigate the role of debt (Jensen & Meckling (1976) and Jensen (1986)) on improving effort. We also develop firm-level proxies for the sensitivity of wage increases, separations[13], and promotions to days absent. To create such proxies, for each firm we regress the indicator variable wage increase (that takes the value 1 if the employee received a wage increase and 0 otherwise) on employee's days absent. The estimate coefficient is our measure of the strength of the incentives. 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 that managers of firms in competitive industries have strong incentives to reduce slack (e.g. Hart (1983), Schmidt (1997)). Our main measure of product market competition is the HHI. The HHI is a commonly used measure for competition literature and is well grounded in theory (see Tirole (1988), pp. 221-223). We also use the four-firm concentration ratio, which is the sum of market shares of the four largest firms in an industry (Competition9_4).

We furthermore investigate the role of organizational characteristics of the firm. We proxy size by the logarithm of assets and develop a measure to capture how hierarchical the firm is following Caliendo et al. (2015) and Friedrich et al. (2015). The measure is based on the number of different occupational layers represented by workers in a firm. We use workers occupation as reported in the Danish occupational code DISCO (DISCO is a modified version of the ILO international standard classification of occupations). The first layer is the highest level and 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 and blue-collar workers comprise the lowest group. Friedrich et al. (2015) provides detailed information on the construction of the measure.

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

13. We cannot separate whether the employee was fired or departed willingly

Finally, we focus on measures of firm ownership and control. A large body of academic and anecdotal evidence suggest that employee behavior is shaped by the ownership structure of the firm. We first examine how ownership by a private equity firm correlates with the firm fixed effects. 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 which 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 with 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 as these workers might be concerned that 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. It is possible that family owners, due to their long-term horizons, have a comparative advantage at sustaining implicit labor contracts, which might be reciprocated by workers with cooperative behavior (Sraer & Thesmar (2007), Ellul et al. (2014)). It could also be that their large ownership stakes motivates family owners to monitor more or be tougher with labor (Mueller & Philippon (2011)), leading to higher effort provision. To identify family firms we use the information on family trees of managers and board members and we identify family ties among them. Using these ties, we define firms as family controlled if 1) two board members are related with the CEO by blood or marriage or 2) any three board members are related (even if none of them is a CEO).[14]Finally, we investigate single owned firms as the concentrated ownership could lead to greater monitoring.

Figure 5 presents the results. Each row represents a different variable. The points are coefficients from separate OLS regressions. All covariates have been standardized to have mean zero and standard deviation one, thus the coefficients report the relationship between a one standard deviation change in the covariate and the respective outcome. All regressions except with those using competition as covariate include industry fixed effects. Horizontal bars show 90 percent confidence intervals.

14. Although our definition of family firms is based on family control, the family control highly correlates with family ownership in the firm.

Figure 5 shows that firms with higher of incentives in terms of promotions, wage increases or separations have lower firm effects. Competition, size and hierarchy do not seem to relate with days absent. Finally family control and concentrated ownership are associated with statistically significant lower firm effects.

Figure 6 shows the results of a post-Lasso estimation including all covariates. The Lasso procedure leads to non-zero coefficient for two measures of incentives, one measure of competition, one measure of hierarchy, and the family firm indicator. Out of these covariates only the family firm indicator and the competition indicator are significant.

One potential (and trivial) explanation for our results is that firms have specific policies to address absenteeism (such as a high sensitivity of "punishments" to days absent) and that these policies explain a large fraction of the variation in firm fixed effects that we find. However, our results in the Lasso estimation does support this theory. Note that the incentive variables in terms of promotions, wage increases and separations measure the direct rewards and punishment for absenteeism. Although our Lasso procedure keeps two of these incentives variables, they are not significant. Indeed, even after controlling for the reward and punishment of absenteeism, we still find that competition and family firm status are important in explaining absences.

4.4 Variation between Managers and non-Managerial Employees

In the previous sections we show that firm effects explain a large part of the variation of days absent across firms. Furthermore these firm effects correlate with incentives, as well as ownership and control on the firm. In this section we study whether the effect of policies/environment is different for employees at different levels of the organization. .

In Table 5 we repeat the analysis of Section 4.1 separately for managers (Panel A) and for non-managerial employees (Panel B). Focusing on Panel A, Column (1) decomposes the difference in average absence of managers between above-median and below median firms. The overall difference is 4.49 days. We find that 58.6 percent of the difference in average absence is due to firms, while 41 percent of the difference is due to the effect of manager characteristics. The estimate is quite precise. Columns (2)-(5) present different partitions of firms and show that the results on firm share remain similar. Firm factors account for 65 percent of the difference in managers' days absent between top and bottom quartile (Column (2)), 63 percent of the difference between the top and bottom decile(Column (3)), and 80 percent of the difference between the top and bottom 5 percent(Column (4)).

Panel B presents the same analysis for non-managerial employees. We also observe that firm effects account for a substantial part of the variation in non-managerial employees days absent across firms, but overall the firm shares are lower compared to the firm shares for managers. The firm share ranges from 51 to 68 percent.

Overall, Table 5 presents a similar picture to our main results: firm effects account for a large part of the variation in days absent across firms, and this holds both for managers and non-managerial employees.

We also repeat the covariate analysis for managers and non-managerial employees and report the results in Figure 7 and Figure 8. We observe that for managers the estimated firm fixed effect relate negatively to competition, while competition does not correlate with the non-managerial employees firm effects. This is consistent with theoretical models that product market competition gives incentives to managers to reduce slack. Furthermore we find that although incentives in terms of promotion, separation and wage increases correlate with firm effects for non-managerial employees, the effect is muted for managers. Finally, the effect if family firm status and concentrated ownership seems to be different for managers and non-managerial employees. In a recent paper Bandiera et al. (2013) study differences in CEO behavior in family and non-family firms and find that family CEOs record 8% fewer working hours relative to professional CEOs. Figure 7 and Figure 8 show that our results are not inconsistent with theirs since the negative correlation of family status with the estimated firm effects is driven by non-managerial employees.

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 a large fraction of the variation is explained by policies/environment (e.g., incentives, corporate culture) of the firm that affects all its employees. A lower fraction, although still considerable, is attributed to selection of employees. We also find suggestive evidence that the firm policis/environment that matter are strong incentives and family control.

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Figure 1a: Hospitalization and Absence Days

This figure presents the average absence days per year for different days of hospitalization that year.

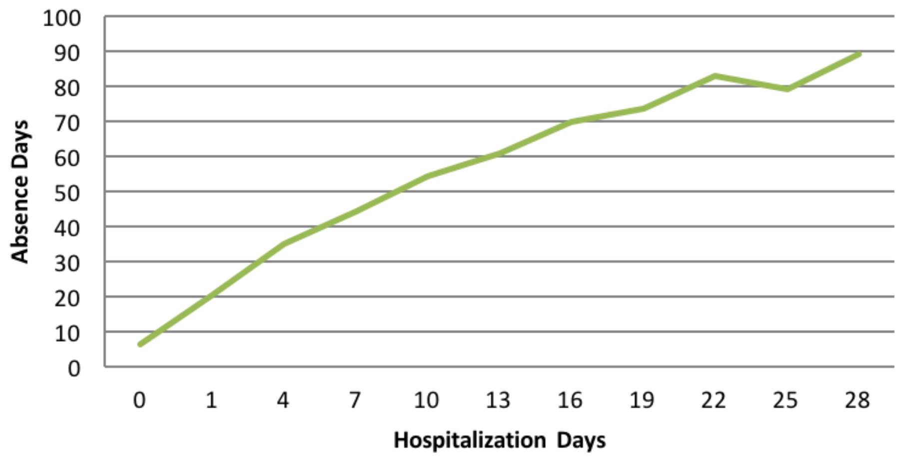

Figure 1b: Hospitalization and Absence Days by Age Groups

This figure presents the average absence days per year for different days of hospitalization that year for employees 20 to 45 years old (full line)and employees 45 to 65 years old (dashed line).

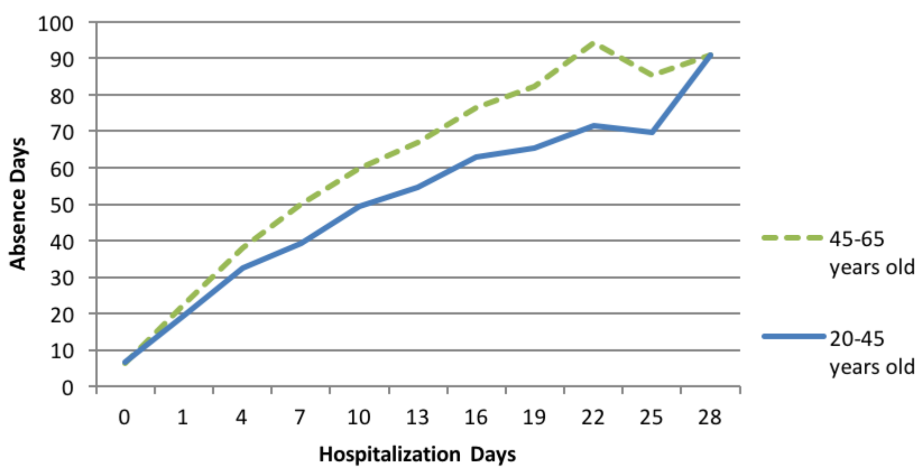

Figure 1c: Hospitalization and Absence Days by Position in Organization

This figure presents the average absence days per year for different days of hospitalization that year for employees with high position in the organization (dashed line) and intermediate and low position in the organization (full line).

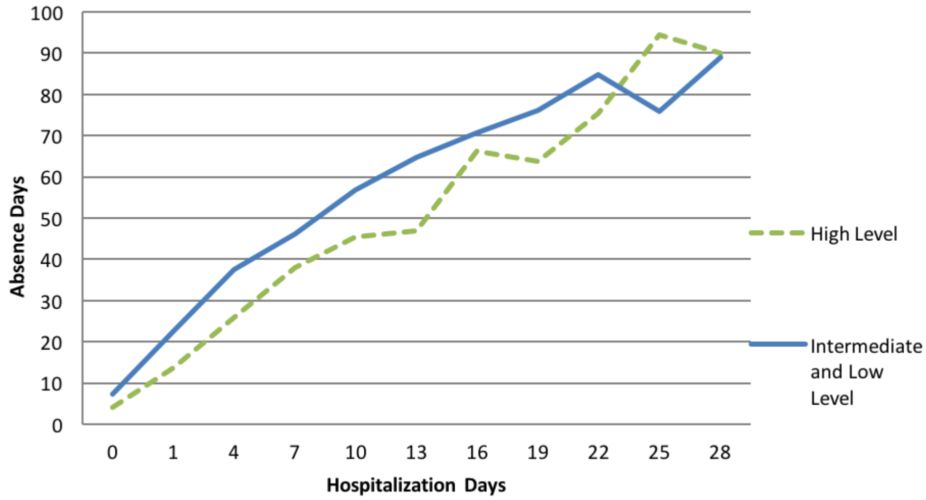

Figure 2: Distribution if Days Absent by Industry

This figure presents boxplots of days absent for the different industries. Industries are classified based on NACE 1 digit classification. Each boxplot presents the minimum, first quartile, median, third quartile, and maximum of days absent for each industry.

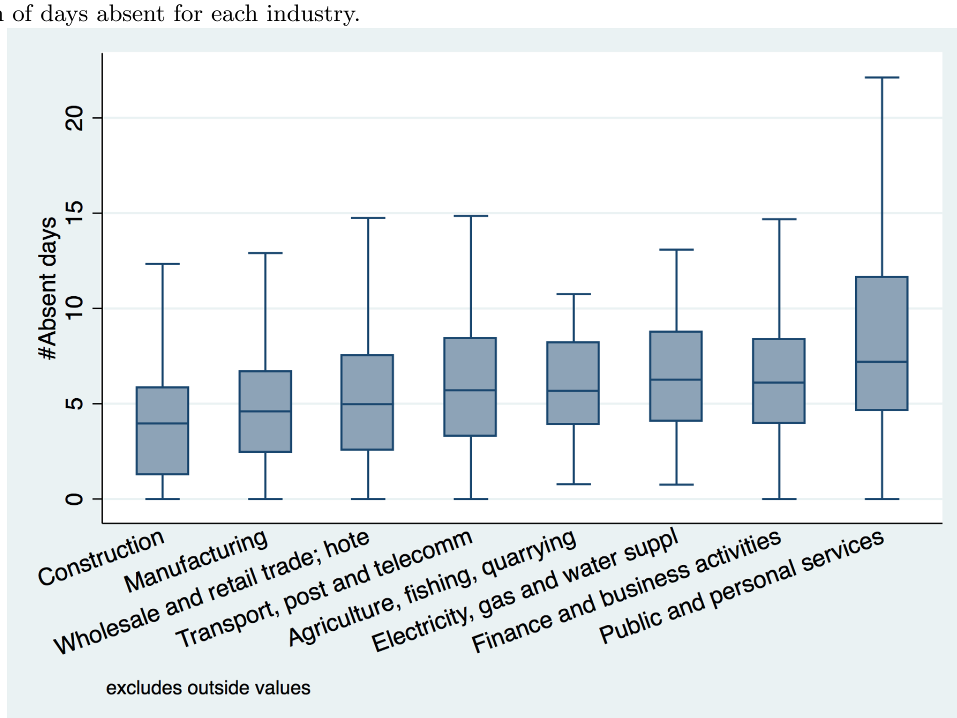

Figure 3: Change in Days Absent By Size of Move

Figure shows the change in absence days 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 we the X marker on the graph.

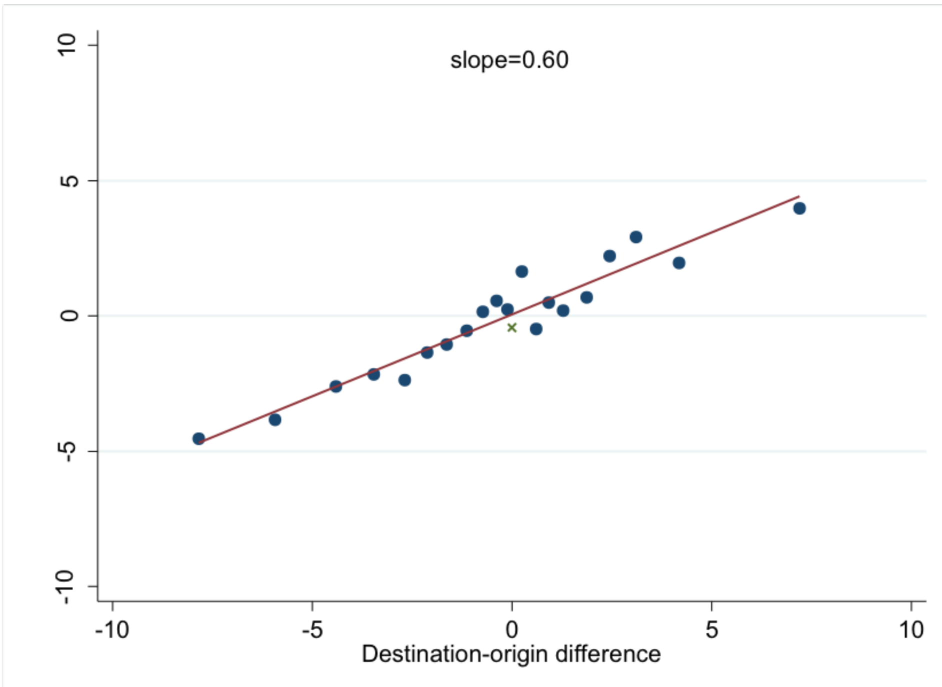

Figure 4: Distribution of difference in average absence between destination firm and origin firm

This figure presents distribution of difference in average absent days 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.

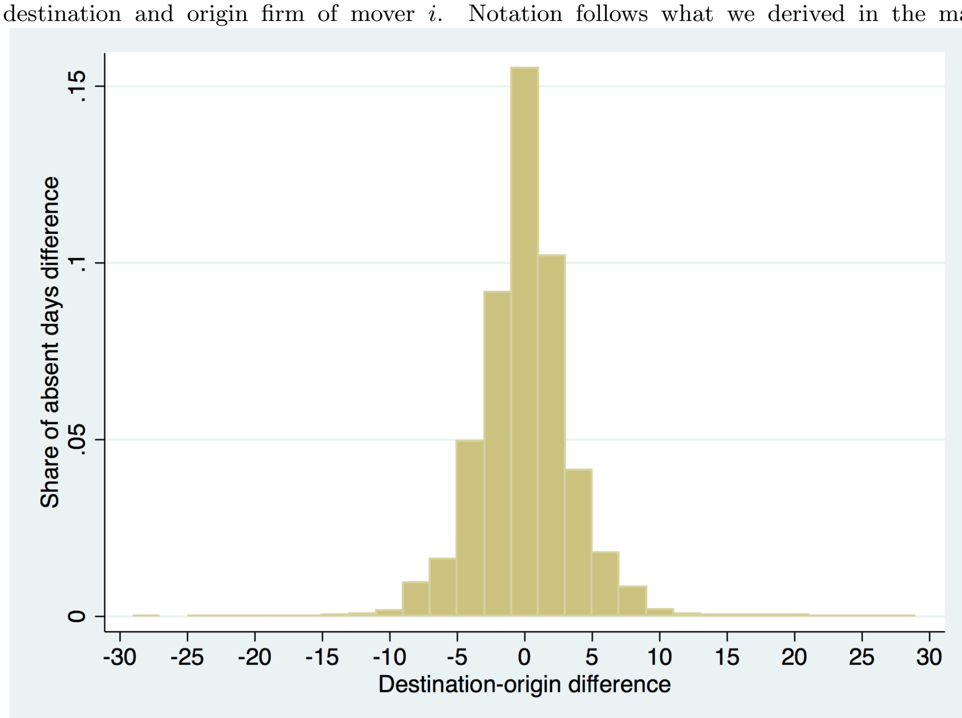

Figure 5: Firm Characteristics that Correlate with Average Firm Effects

The Figure presents bivariate OLS regressions results of firm fixed effects on a set of firm and industry level characteristics. All covariates have been standardized to have mean zero and standard deviation one. All regressions except with those using competition as covariate include industry fixed effects. Horizontal bars show 90 percent confidence intervals.

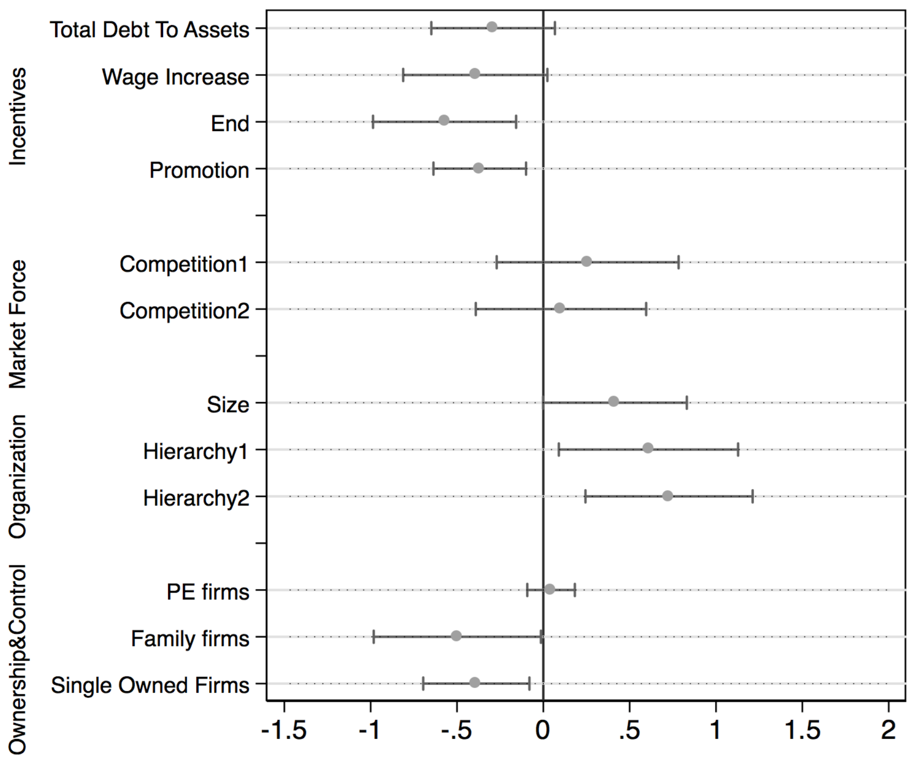

Figure 6: Firm Characteristics that Correlate with Average Firm Effects selected by Lasso

The Figure presents multivariate OLS regression results of firm fixed effects on a set of firm and industry level characteristics selected through Lasso. All covariates have been standardized to have mean zero and standard deviation one. Horizontal bars show 90 percent confidence intervals.

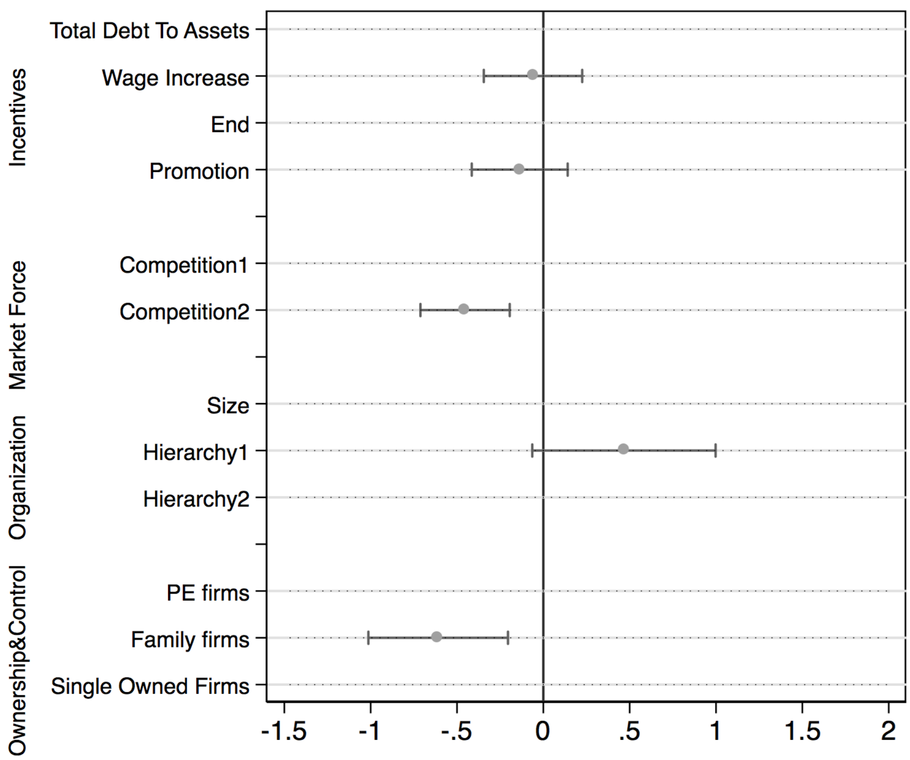

Figure 7: Firm Characteristics that Correlate with Average Firm Effects. Analysis based on Managers

The Figure presents bivariate OLS regressions results of firm fixed effects (based on the managers sample) on a set of firm and industry level characteristics. All covariates have been standardized to have mean zero and standard deviation one. All regressions except with those using competition as covariate include industry fixed effects. Horizontal bars show 90 percent confidence intervals.

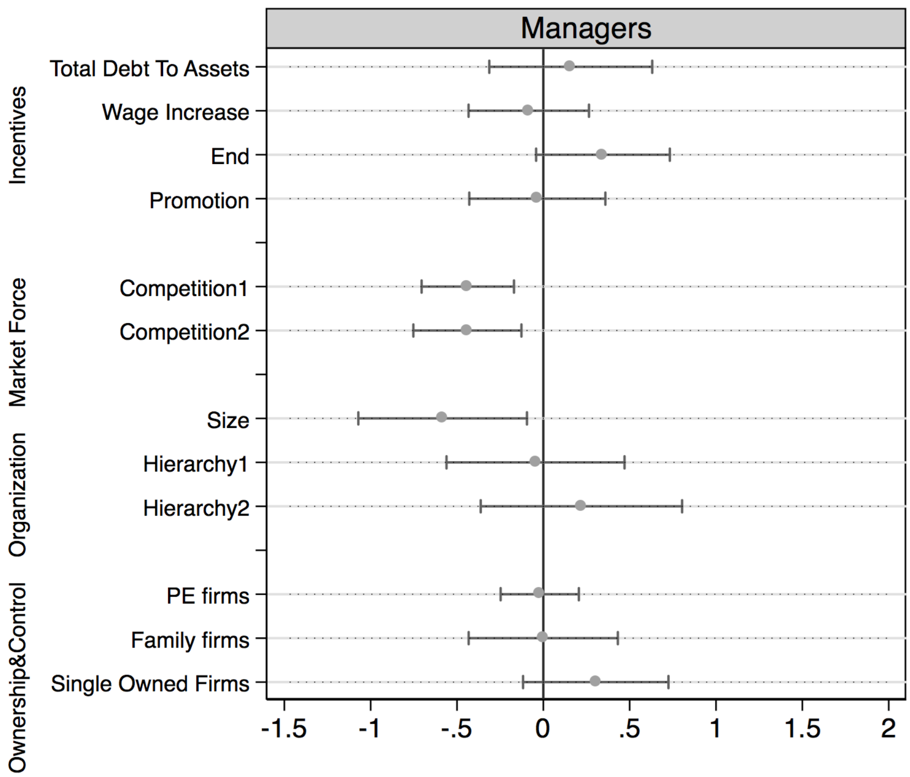

Figure 8: Firm Characteristics that Correlate with Average Firm Effects. Analysis based on non-Managerial Employees

The Figure presents bivariate OLS regressions results of firm fixed effects (based on the non-managerial employees sample)on a set of firm and industry level characteristics. All covariates have been standardized to have mean zero and standard deviation one. All regressions except with those using competition as covariate include industry fixed effects. Horizontal bars show 90 percent confidence intervals.

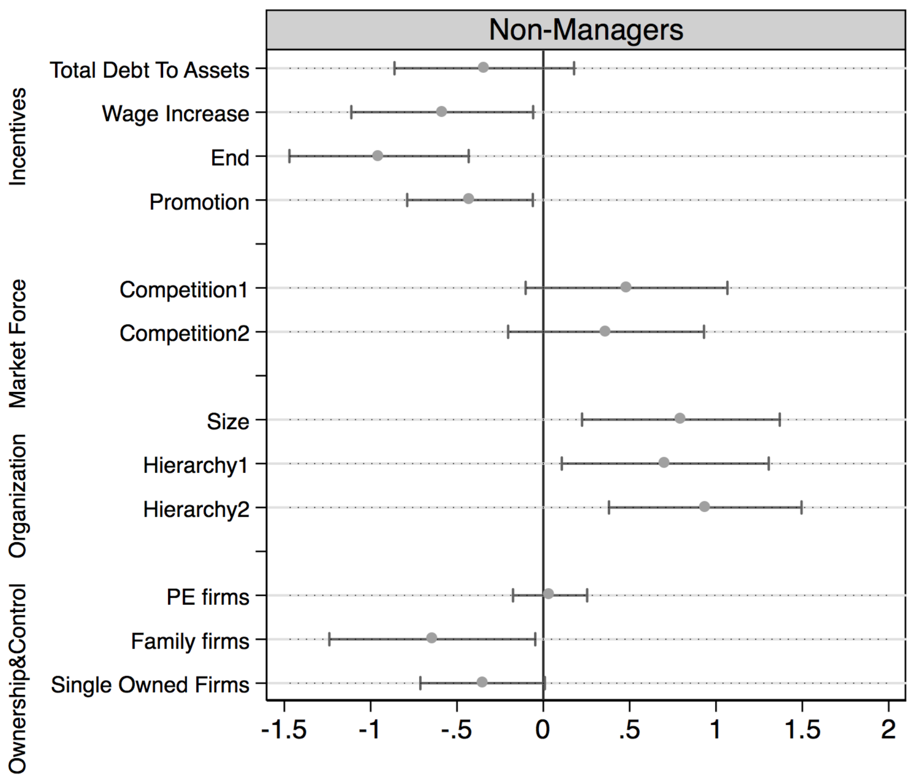

Figure 9: Event Study

Figure shows the coefficient $\hat{\lambda}_{r(i,t)}$ estimated from Equation (9) in Appendix C. The dashed lines are upper and lower bounds at the 95% confidence interval. Appendix C contains details on the graph construction.

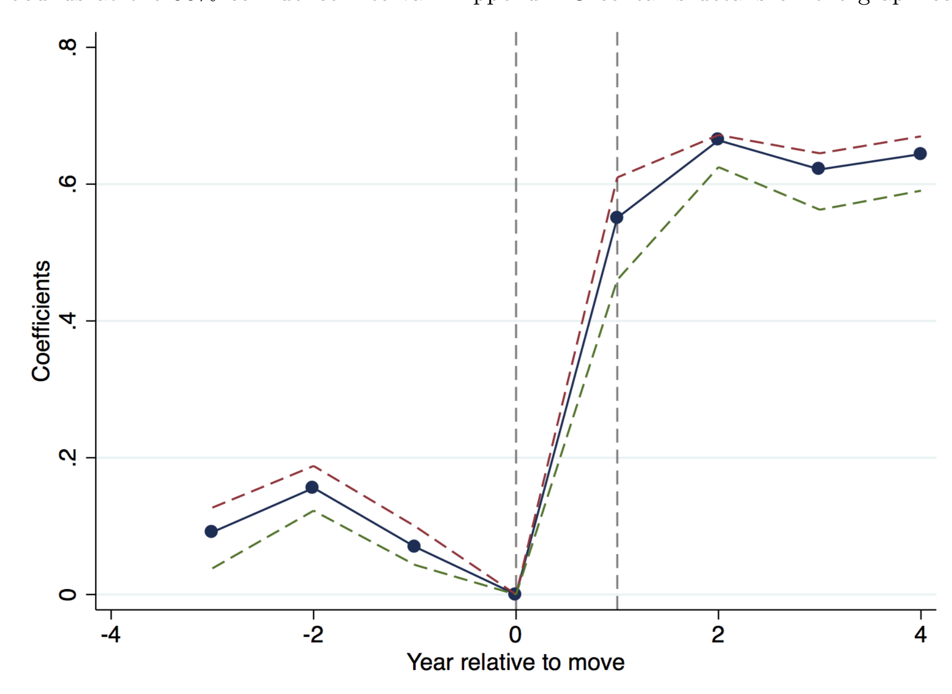

Table 1: Summary statistics for family vs non-family firms

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 (columns 2). Column 3 presents differences.

	All	All -sample firms	Diff All vs Sample
OROA	0.0757	0.0599	-0.0267***
	(0.0007)	(0.0025)	(0.0026)
	[257,397]	[7,678]	[257,397]
Net Income/assets	0.0433	0.0349	-0.0087***
	(0.0005)	(0.0022)	(0.0023)
	[257,392]	[7,673]	[257,392]
Assets	51.8463	364.1203	321.9191***
	(0.8400)	(9.7585)	(9.7870)
	[257,432]	[7,713]	[257,432]
Ln(Assets)	2.8465	4.9601	2.1789***
	(0.0082)	(0.0340)	(0.0349)
	[257,431]	[7,712]	[257,431]
No. of employees	38.5082	179.0560	145.0036***
	(0.3553)	(3.5823)	(3.5965)
	[257,636]	[7,917]	[257,636]
Firm age	22.9027	35.0215	12.5025***
	(0.1416)	(0.5679)	(0.5860)
	[256,356]	[7,867]	[256,356]

Table 2

This table presents employee characteristics for all limited liability firms in Denmark during 2007-2012 (column 1) as well as for firm characteristics for our sample firms (columns 2). Column 3 presents differences.

	All	All -sample firms	Diff All vs Sample
Employee wage	306,750	425,184	147,087***
	(3143.6150)	(8458.332)	(8864.1990)
Employee age	38.5200	41.1428	3.2780***
	(.1747)	(.2802)	(.3381)
Male	0.6625	0.6207	-0.0523***
	(.0041)	(.0089)	(.0100)
Hospitalization Days	0.2512	0.2095	-.0520***
	(.0017)	(.0038)	(.0042)
Sickness Absence	.	7.6321	.
	.	(.3042)	.
No. of Children	1.3843	1.2647	-.1488***
	(.0093)	(.0170)	(.0200)

TABLE 3

	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
All	6.295	10.372	15.696	20.08
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

Table 4: Decomposition of employee absence

The dependent variable is annual number of absent days. 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 and hospitalization. The adjusted R-squared from estimated equation is 0.488. 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 firms $\gamma_R - \gamma_{R'}$; the third row reports the difference due to employees $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two set of firms that is due to firm $S_{firm}(R; R')$. The last row reports the share of the difference in average absence between two set of firms that is due to employees $S_{employee}(R; R')$. Standard error of the share is calculated by bootstrap of 50 repetitions.

Panel A: base				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
Overall	6.2948	10.3718	15.6956	20.0801
Due to firm	3.3922	6.0216	9.4964	13.1734
Due to individual	2.9026	4.3502	6.1992	6.9067
Share of difference				
Due to firm	0.5389	0.5806	0.6050	0.6560
	(0.0614)	(0.0524)	(0.0765)	(0.0951)
Due to person	0.4611	0.4194	0.3950	0.3440

Panel B: person control				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
Overall	6.2881	10.3535	15.6565	20.0462
Due to firm	3.3613	5.9583	9.4164	12.9796
Due to individual	2.9268	4.3952	6.2401	7.0666
Share of difference				
Due to firm	0.5345	0.5755	0.6014	0.6475
	(0.0582)	(0.0507)	(0.0791)	(0.0978)
Due to person	0.4655	0.4245	0.3986	0.3525

Table 5: Decomposition of absence of managers and non-managers

The dependent variable is annual number of absent days. The sample is movers and non-movers. Both Panels are based on estimation of equation (1) which includes controls for age and hospitalization. Panel A is based on managers while 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 firms $\gamma_R - \gamma_{R'}$; the third row reports the difference due to employees $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two set of firms that is due to firm $S_{firm}(R; R')$. The last row reports the share of the difference in average absence between two set of firms that is due to employees $S_{employee}(R; R')$. Standard error of the share is calculated by bootstrap of 50 repetitions.

Panel A: managers				
	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
Overall	4.4991	7.4119	11.0616	14.3781
Due to firm	2.6365	4.8521	7.0343	11.5621
Due to individual	1.8626	2.5598	4.0273	2.816
Share of difference				
Due to firm	0.5860	0.6546	0.6359	0.8041
	(0.1066)	(0.0955)	(0.0911)	(0.1274)
Due to person	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)
Difference in absence				
Overall	6.8551	11.3225	17.1227	22.1998
Due to firm	3.5217	6.2083	10.6866	15.1222
Due to individual	3.3334	5.1142	6.4361	7.0776
Share of difference				
Due to firm	0.5137	0.5483	0.6241	0.6812
	(0.0582)	(0.0507)	(0.0791)	(0.0978)
Due to person	0.4863	0.4517	0.3759	0.3188

Appendix A Additional Analysis and Robustness Tables

Table A1: Employee Absence and Firm Performance

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 firm fixed effect, μ_t is year fixed effect, and ζ_{jt} are firm controls. $\mathrm{Absence_{jt}}$, is the mean absence days 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 in Column 3 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. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Dependent Variable: OROA	< 100 employees	100 > employees	300 > employees
Absence	0.0000	-0.0008**	-0.0011*
	(0.0007)	(0.0004)	(0.0006)
Firm Age	-0.0079***	-0.0079***	-0.0065***
	(0.0030)	(0.0015)	(0.0020)
Assets	0.0004	-0.0000	-0.0000
	(0.0029)	(0.0000)	(0.0000)
Constant	0.3120***	0.3740***	0.3228***
	(0.0935)	(0.0586)	(0.0815)
Observations	3,499	4,078	1,932
R-squared	0.8058	0.7127	0.7035
Year FE	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
No.firms	1,652	1,236	550

Table A2: Decomposition of employee absence on Monday, Friday and around holiday

The dependent variable is the annual number of absent days 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 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 absent days overall between the two set of firms $y_R - y_{R'}$; the second row reports the difference due to firms $\gamma_R - \gamma_{R'}$; the third row reports the difference due to employees $\alpha_R - \alpha_{R'}$; the fourth row reports the share of the difference in average absence between two set of firms that is due to firm $S_{firm}(R; R')$. The last row reports the share of the difference in average absence between two set of firms that is due to employees $S_{employee}(R; R')$. Standard error of the share is calculated by bootstrap of 50 repetitions.

Panel A: base

	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
Overall	3.0089	4.965	7.5295	9.7189
Due to firm	1.7393	3.0919	5.0956	6.8686
Due to individual	1.2696	1.8731	2.4339	2.8503
Share of difference				
Due to firm	0.5781	0.6227	0.6768	0.7067
	(0.0571)	(0.0544)	(0.0672)	(0.0928)
Due to person	0.4219	0.3773	0.3232	0.2933

Panel B: person control

	Above/below Median	Top/bottom 25%	Top/bottom 10%	Top/bottom 5%
	(1)	(2)	(3)	(4)
Difference in absence				
Overall	3.0023	4.9497	7.4964	9.6809
Due to firm	1.7279	3.0922	5.0937	6.8265
Due to individual	1.2744	1.8575	2.4027	2.8544
Share of difference				
Due to firm	0.5755	0.6247	0.6795	0.7052
	(0.0563)	(0.0535)	(0.0702)	(0.0978)
Due to person	0.4245	0.3753	0.3205	0.2948

Appendix B

Table B1: Definitions of variables

Variable	Definition
Firm Level Variables	
Family	An indicator variable that takes the value 1 if the firm is a family 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.
Employee Level Variables	
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 Children	The number of living children the employee has. 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 degree. The variable is constructed based on information on 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.
Legacy Employees	An indicator variable that takes the value 1 if the employee is a legacy employee. We define legacy employees as employees that have family members who are current or past employees in the firm. We require that their family members were employees at the firm for at least 3 years.
Family20pc	Is a dummy variable that takes the value 1 if the firm has at least 20 percent family ownership.