

# Public Sector Leadership\*

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## Abstract

We document the importance of leadership on employee effort in the public sector in Denmark. Using hospitalization of leaders, we show the causal impact of leaders on employee effort measured through employee absenteeism in the entire public sector and in the three main sub sectors of health, education and public administration. We identify four aspects of leadership (personal traits; shocks and use of prescription medicine; incentives structures; and, unit organization) and document the correlation with employee absenteeism. We then decompose absenteeism into selection (employee) effects and incentives (unit) effects and we find that the incentives effects explains between 50 pct and 60 pct of the variation in effort. We show important variation in the correlation between the four leadership characteristics and incentives and selection effect across the three main sub sectors. Our result are consistent with the notion that leaders personal characteristics and their actions are crucial in promoting employee effort in the public sector.

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# I Introduction

The public sector constitutes an important part of most economies: The share of labor market working in the public sector varies within OECD countries between 6 and 31 pct (OECD (2021)). Organizing public sector entities to increase quality and quantity of output while reducing cost is high on national and international policy agendas (World Bank (2021)). Reforms of public sector entities focus on improving efficiency and labor effort through streamlining organizational structures highlighting the role of good leadership and improved labor effort. (World Bank (2018)). In this paper we document the impact of leadership characteristics on employee effort for the entire public sector in Denmark.

Leaders of private firms are highly applauded in the public and there is a large research literature documenting their importance. However, we put forward that leadership in the public sector may play at least as important a role in the success of public organizations for at least three reasons: First, labor effort and productivity varies more; second, employee talent varies more; and third, alternative governance mechanisms such as monetary incentives is restricted for both employees and leaders. We support these arguments by documenting that wages structures are more homogeneous and that both employee IQ and employee absenteeism varies more in the public sector.

Measuring leadership, performance and efficiency in the public sector is challenging given that public sector units vary considerably in organizational structure, objectives and outputs across different parts of the public sector. Leadership research often focus on the impact of individual traits - such as drive, personality type, engagement and skills - on both affect who becomes a leader and the success of a given leader. Most of the research relies on qualitative data provided through case studies, interviews, or small-scale surveys (Parry and Proctor-Thomson (2002), Bloom and Van Reenen (2007), Janke et al. (2018)). In the absence of a common metrics to measure the impact of leadership, the economic literature has focused on sub sectors where measurements of input and output are possible either through surveys, randomized experiments or through registers. Within the health sector, Janke et al. (2018) finds little impact of hospital CEOs on survey outcomes in UK<sup>1</sup> Other papers have more indirectly studied leadership through focusing on managerial practices and competitive environment: Bloom et al. (2014, 2015, 2019, 2020) links better managerial practice of hospitals to better health and efficiency outcomes. For the educational sector, Hoxby (2000) shows that increased competition among school leads to higher school productivity. For the administrative sector Rasul and Rogger (2018) show that better management practices in Nigeria improves the efficiency of public sector projects.

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<sup>1</sup>Janke et al. (2018) exploits leaders that move across hospitals to estimate CEO fixed effects on survey outcomes of hospitals output such as capacity, use of hospital beds and on quality of services.

Employee absenteeism is a key theme in organizational studies in the development literature. Chaudhury et al. (2006) documents rates of absenteeism for government doctors at 25 pct. in Peru, 37 pct in Uganda, and 40 pct in Indonesia. The experimental literature has in collaboration with local governments tested various mechanisms such as asking teachers to take a picture of themselves in the classroom (Duflo et al. (2012)) or to install remote biometric monitoring stations in India (Dhaliwal and Hanna (2017)). A special challenge is that the power of such mechanisms are reduced over time (Banerjee et al. (2008), Olken and Pande (2012)).

We take a different approach in this paper. We investigate the impact of leadership on labor efficiency covering all public sector production units in a single country, using employee absenteeism as a common metric of labor effort. Through this we contribute to the literature at three levels: First, we identify a common metric that is correlated with labor productivity and can be measured in all public sector units. Second, we are able to identify and focus the analysis on the role of leadership. Third, we are the first study to analyze the entire public sector in single country and through this be able to compare the role of leadership across different public sector activities.

Using absenteeism as a proxy for effort allow us to measure a proxy for labor effort for all public employees. Linking leadership characteristics and organizational structure at the public sector unit level allow us to investigate a number of important research questions: Is there important variation in employee effort across the public sector units? Are leadership and employee quality correlated with employee absenteeism? Does leaders have causal impact on the level of absenteeism and which leadership characteristics correlates with higher effort through lower absenteeism? What share of absenteeism is due to incentives given to an existing group of employees and what share of absenteeism can be explained by hiring employees with low or high absenteeism? What types of leadership is correlated with attracting more efficient employees? For example are older leaders, female leaders, leaders that use opioids or anti-depressant medicine correlated with lower or higher employee absenteeism? And do such correlations relate to selection or incentives? The answer to such questions are crucial to develop best practices for improving leadership and employee efficiency in the public sector.

We acknowledge, however, that absenteeism is not a complete measure of worker efficiency. Only a part of worker absenteeism is at the discretion of individual employees and it does not measure variation of work effort when employees are at work. Thus, by focusing on registered absenteeism we are at risk of underestimating the impact of leadership on effort.

Our data set covers all (non-military) workplace units in the entire public sector in Denmark from 2010 to 2018, that is an yearly average of 12,802 production units where almost 90 pct of the units are in the three main sectors of health, education and public administration.

For each unit we identify leader(s) from register data on job categories and remuneration. We then send out a survey to all that satisfy our register based leadership definition and ask them if they identify themselves as leaders. Based on a 45 pct response rate, we learn that our register based definition indeed identify the real leaders in our public sector units. However, the survey also reveals that we our register based definition is too broad and include many non-leaders in our leadership sample. This provide a second channel through which we may underestimate the role of leaders.

Our public sector units have a yearly average around 977,669 full and part time employees. To focus our analysis we restrict our employee sample to all full-time employees that work in one and only one public sector unit, which reduces the sample to a yearly average of 270,203 employees. We begin the analysis by documenting the pattern of absenteeism inside the public sector and across sub-sectors. On average, a full-time public sector employee is absent 9.2 days a year, a number that is highest in the health sector and lower within the educational sector and public administration. Across entities we document that there are 8.8 days difference between the average unit level absenteeism for above and below median and the difference between top and bottom 5 pct is 28.0 days.

We then document that absenteeism is important. A rough estimate states that the Danish government could save 790 mill DKK (100 mill EUR) pr year by reducing public sector absenteeism by one day, or equivalently hire almost 3,000 more school teachers (Confederation of Danish Employers (2019)). On the individual level absenteeism is correlated negatively with promotion, positively with job separation, and - in the case of education - teacher absenteeism is negatively correlated with student grades.

We begin our leadership analysis by documenting that leader and employee quality - measured both through remuneration and IQ data - is additive correlated with absenteeism. We then explore the causal impact on leaders on employee absenteeism using leader fixed effects (Bertrand and Schoar (2003)) and leader production unit fixed effects. The latter approach follows Bennedsen et al. (2020) through documenting that when leaders are hospitalized - and thus absent from the workplace - unit effort is reduced through higher employee absenteeism.

Next, exploiting that many employees move between public sector units, we decompose the overall leadership-absenteeism correlation in two broad groups of mechanisms. Leadership characteristics have a direct impact on the type of employees that arrive and exit the unit, the extensive margin. We denote this selection effects. However, leadership also affect the effort level of the current set of employees in a particular entity, the intensive margin. We denote this incentive effects. We separate these two effects by estimating a model of absenteeism as a function of time, individual and public sector unit effects, following the seminal model of Abowd et al. (1999) (henceforth AKM). We aggregate the individual effects to the entity

level and document that the incentive effects explain more than half the variation above and below the median absenteeism level.

Since our model relies on individuals that moves job within the public sector, it is important to document that there is no systematic pattern pre-move in the group of movers. We document this through event studies that provide estimates of the incentive effects that are consistent with the estimates from the AKM model.

Finally, we use the AKM framework to analyze how leadership traits correlate with absenteeism. Individual traits include age, quality and gender. Personal shocks are measured through hospitalization of leaders, and use of two types of prescription drugs (anti-depressant medicine and opioids). On the production unit level we include hierarchical structure, size, turnover and wage dispersion. For example, drug taking, gender, hospitalization and turnover are positively correlated with average unit level absenteeism, whereas leader quality is negatively correlated. We extent this analysis into how these leadership and unit characteristics correlates with the incentive respectively the selection effect. Age, gender, drug-use are all positively correlated with attracting employees with higher absenteeism whereas higher quality leaders attract employees with lower absenteeism. Interestingly, higher quality leaders are positively correlated and age is negatively correlated with incentive effects.

The rest of the paper is organized as follows. In the next section, we present our data and how we constructed our sample, how we define leaders and our measure of absenteeism. We provide a quality check of our leadership definition through survey results. We also report descriptive statistics for public units, leaders and employees. Section III begins by documenting why we believe leadership is important in the public sector and the relevance of absenteeism with respect to career, employee quality and school grades. We then shows the additive correlation between leader and employee quality and employee absenteeism. We continue to provide evidence for a causal relationship between leaders and employee absenteeism through leader fixed and leader-unit fixed effects. In Section V we decompose the variation in absenteeism into incentives and selection effects. Section VI.2 analyzes the correlation between elements of leadership and unit and selection fixed effects. Section VII concludes.

## II Data Construction

### II.1 Data sources

**Public Units.** The administrative data at Statistic Denmark provide us with identifiers for all public organizations. This dataset contain basic information such as subsector within the

public sector (i.e. education, health of public administration), number of employees and location.

**Employee absenteeism.** Statistics Denmark collects absence data for all employees in the central and local governments. Public sector institutions are required to report each spell of absence for all employees in the institution. For each spell, the data contain the employee national identification number (CPR number), the public sector unit where he or she works, start day, end day, and one of four absence categories: “Own sickness”, “Child sickness”, “Work accident” and “Maternity/Paternity-related absence”. In the analysis below, we define absent days as the sum of the “Own sickness” and “Child sickness” not including the two latter categories which are rare events.<sup>2</sup>

Reporting is mandatory for each unit and stated in the law. Statistics Denmark has developed software integrated into the payroll system to facilitate collecting absence information. Thus, the cost for a unit of collecting absence data is considered minimal.

Absence days are not related to vacation days. The number of vacation days in the public sector is determined by a combination of law and centralized negotiation between central and local governments and the public sector trade unions and is not determined at the local level in the individual public sector units. The law establishes the right to five weeks (25 days) of holidays every year that are not recorded in the absence data.

We have data for all public sector employees from 2010 to 2018. In the analysis, we exclude employees with more than 120 days absenteeism in a year. We do this because the focus on the paper is how leadership may induce individuals to deliver more or less effort, not how to deal with long term absenteeism induced by serious illnesses or long term psychiatric issues.

**Integrated Database for Labor Market Research.** We use the matched employer-employee data set for the public sector from the Integrated Database for Labor Market Research (IDA database) at Statistics Denmark. In addition to the employer’s identification number (public sector unit), the IDA data set contains employees’ demographic information such as age, gender, and the employees’ positions in the organization. The position in the firm is based on the Danish occupational code, which again is based on the international standard classification of occupations (ISCO). We have access to this data set for every year in the period 1995 - 2020.

**Prescription Database.** We use the national database that collects all use of prescription medicine for the entire population of Denmark. This database is administered by the government’s health authority (SSI). By linking the prescription data base to the IDA database

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<sup>2</sup>We have done the analysis below with only “Own absence” and with including all four categories. The results are qualitatively the same.

we are able to extract information about the use of anti-depressant drugs and the use of opioids among both leaders and employees in the public sector units.

**National Patient Registry.** Data on hospitalizations of leaders in the public sector is from the National Patient Registry (NPR) at Statistics Denmark. This data set records hospitalization events for all Danish citizens and contains the national identification number (CPR number) and the number of hospitalization days per calendar year. It also contains detailed information about the length of each hospitalization spell and the diagnosis assigned.

**Survey to public leaders.** To verify the quality of our definition of leaders we sent out an online survey to all leaders we identify in our registers. We restrict our sample to units with valid identifier and more than 5 full-time employees in 2020. We define leaders as those whose social code is 131 or 132.

## II.2 Sample construction and summary statistics

**Unit of Analysis.** A public organization has two identifiers. The first is the legal identity and the second is the workplace which we in this analysis denote a public sector unit (PU). A legal entity may contain many public sector units. For example, a given municipality may be a legal entity, where as each school within the municipality is a public sector unit.

Our unit of analysis is the public sector unit (PU), which is the smallest unit where employment, remuneration and absenteeism is recorded. Examples of public sector units include a single school, a single kindergarten, a library, a retirement home, a group of public dentists and assistants in a municipality, an independent administrative section in a hospital, an environmental control office in the municipality, the competition authority, the consumer protection agency and so forth.

Table 1 presents the key figures about our public sector units. We collect information for all public sector units in the period from 2010 to 2018 excluding the military sector where data is not available. In total there are around 17,337 public sector units in the entire country. We exclude units that are located in multiple sectors. This reduce our sample to an average of 12,802 public sector units pr. year. Thus, our analysis is conducted on almost all public sector unit in an entire country.

Measured on number of public sector units, the health sector is by far the largest sector. In our sample, there are around 8,529 health units, 2,302 units in the educational sector and only 630 units in public administration.<sup>3</sup>

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<sup>3</sup>Excluding the units that are located in multiple sectors removes dis-proportionally many units in public administration. We make robustness checks below where we include these units.

**Defining leaders.** The organization of public sector units vary across sectors. Some units have clear leadership with the equivalent of a CEO in a private firms. Others have leaders based on job categories. For instance the leadership in a hospital department both include head nurse, head doctor and sometimes head of administration. Thus, in the absence of a leader identifier in our register data, defining leadership in public sector units is not clear cut.

In this analysis we use job categorization variables provided by Statistic Denmark to identify leaders: First, we define top managers as leaders. However, 67 pct. of the unit years do not have a top manager. Then we proceed to the group of senior managers and pick out those with the highest wage. For each unit we put a cap on the number of leaders, so for every 10 full-time employees we have a maximum of 1 leader and no unit will have more than 10 leaders. That is, units with less than 10 full-time employees have 1 leader, units with 11-20 full-time employees have 2 leaders, units with 21-30 have 3 leaders, etc etc. Finally, public sector units with more than 100 full-time employees have 10 leaders. Table 1 yields the description of number of leaders across public sector units. We have an average number of leaders of 2 and a median of 1, that is more than 50 pct of our public sector units have only one leader as we have defined it.

**Survey based quality leadership identification.** Our leadership identifier is constructed from register data as described above. To obtain insight into how well we define leaders we sent out a survey to individuals, we had defined as leaders according to the algorithm above. The survey was conducted by Statistic Denmark and sent out to 14,750 leaders in the summer of 2022 via email. We received 6,667 answers which equal a response rate of 45 pct. We asked the respondents if they were a leader and if so, what kind of leader allowing for three categories: Leader of other leaders, Leader of employees and Leader without employee responsibility.

We compare our register based definition with the survey answers from the survey in Table 2. In Panel A we observe that, out of the 6,667 register defined leaders that answered our survey, 4,018 answered they are leaders in the summer of 2022. In Panel B we see that our leadership definition is most precise in public administration - where more than 80 pct of our defined leaders answer yes - and least precise in the health sector - where slightly less than 50 pct of the respondents answer yes. From Panel C we notice that almost all of our self-declared leaders either manage other leaders or manage employees. This is reassuring given our focus is on analyzing the importance of leadership on employee absenteeism.

There can be at least three reasons for why 40 pct of our register defined leaders are not leaders today. First, we require that each public sector unit have at least one leader. Second, we force that large units have multiple leaders, and, third those who answered no to being leaders in 2022 may have been leaders in our data years of 2010 to 2018. In the following we

investigate each of these potential bias.

Panel D provides an insight into which part of our register based is most important in identifying leaders. We notice that 86 pct of those with social code 131 (top manager) identify themselves as leaders whereas. For those with social code 132 (manager) it is less than 30 pct. Panel E investigates the social code of those who identified themselves as leaders and we notice the majority have social code 131. This is particular the case in public administration where 95 pct has social code 131. However, in health almost one third of the leaders have social code 132.

Panel F focuses on what type of organizations our register based definition works better in. In the below median sized public units, about 41 pct of our register defined leaders declare themselves as leaders. Among larger public sector units more than 2/3 of our register based leaders identify themselves as leaders. Similarly, in public units with only one identified leader we have less than 50 pct of these identifying themselves as leaders. Contrary to this, in public sector units where we identify multiple leaders, 72 pct identify themselves as leaders.

Finally, we implemented our survey in the summer of 2022 and our register sample covers the period from 2010 to 2018. Thus, in Panel G we take the sample of self identified leaders in 2022 and look at to what extent they are leaders according to our register definition in the period 2010-2018. We notice that in 2/3 of the unit years they are also leaders, which means that most of them have been leaders for a longer period.

To sum up, our novel approach to evaluate the power of our register definition of leaders have provided three important insights. First, our sample of register based leaders over sample the number of real leaders. Thus, it is likely that we underestimate the importance of leadership by having many non-leaders defined as leaders. Second, our definition is weakest in the health sector. Third, our register based definition is most powerful in public units above median size. We take these findings into account in our analysis below.

## **II.2.1 Employees**

Table 1 Panel C states the number of employees in our public sector units. In total the yearly average number of employees in the public sector in Denmark is 977,669. Many of these employees are part time workers and are located in multiple units. To provide a clear analysis of the importance of leadership, we focus in our main analysis on full-time employees that works in one and only one public sector unit. We lose around 200,000 employees from eliminating units that work in several sectors. Another 180,000 employees work in more than one unit and is eliminated. Finally, we know if employees are full time or part time employees. Since our main outcome variable is absenteeism and we do not know the number of hours, part time employees is working, we eliminate all part-time employees. We will in robustness

analysis include other categories of employees.

Our sample, therefore, consists of full-time employees that work in only one public sector unit that belongs to one and only one of the subsectors in the public sector. Thus, our main sample covers a yearly average of 270,203 employees across all sub-sectors and regions. 50 pct of these work at the local government level and the rest on the regional and national government level.<sup>4</sup> The health sector is the largest sub sector with half of the full time employees. After health, follows education with approximately one quarter and public administration with no more than a fifth of the full-time employees. Unit sizes are largest in the public administration with an average of 66 full-time employees per unit and lowest in the health sector with an average of 17 full-time employees per unit.

## **II.2.2 Personal characteristics of leaders and employees.**

### **LEADER CHARACTERISTICS.**

Table 3 documents personal characteristics of the leaders in our sample. Given our definition above we have 237,367 year leader observations or 26,363 leaders per year. More than half of these are in the health sector and only 8 pct are in the public administration sector. Leaders in all sectors are around 50 years old. The average yearly income is 503,110 DKK (approximately 67,572 EUR). Leaders in the health sector are lowest paid and leaders in public administration receive on average the highest income. There are 70 pct women among the leaders in the entire public sector. In the health sector 81 pct of leaders are females, whereas female leaders constitute slightly less than half in the public administration. On average they have been leaders for almost 4 years in all three sub sectors.

The last part of Table 3 provides summary statistics for some of our proxies for shocks to leaders. We will use hospitalization events below to support the notion that public sector leaders have a causal impact on absenteeism. Table 3 shows within each public sector unit there is 0.07 hospitalization days for leaders per year. With an average of 2 leaders per unit, this is equivalent to each public sector leader has on average 0.14 hospitalization days per year. Approximately 8 pct of the leaders take anti depressant drugs and almost 5 pct take opioids in a year. It is interesting to notice that leaders are more likely to use prescription drugs in the health sector where they may have an easier access to them.

Since we are going to exploit variation in leader public units match from leaders that move between different public units, it is relevant to split the leaders in those that move during our sample and those that stay. We observe that more than 45 pct of the leaders move at least once within our data window. There are statistically differences between these two groups

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<sup>4</sup>We exclude the analysis of how the level of government (State, region or local) impact the importance of public sector leaders. We do have the data, but we eliminate the analysis to save space.

the economic differences are relative small.

#### **EMPLOYEE CHARACTERISTICS.**

Table 3 also provides sample statistics for the employees in our sample. We have a total of 2,194,457 employee years in the 9 years of data. The average number of absenteeism days per employee per unit is 9.57 or approximately 5 pct of the contracted yearly work-days. Employee absence is higher in the health sector (10.84 days pr. year) and lower in the educational sector (8.00 days) and public administration (8.14 days).

There is a majority of female employees with approximately 7 out of 10 employees being female. In the health sector is 87 pct., in the education sector it is 64 pct. whereas in public administration it is 50 pct. The average employee wages do also vary significantly across sectors. On average, the yearly wage is 370,200 DKK (approximately 49,712 EUR). The wage is significantly higher in the public administration and lowest in the health sector. The difference between the average wage in these two sectors is more than 20 pct. The preceding numbers highlights the importance for analyzing the role of leadership both across the entire public sector but also within each of the three mains sub-sectors.

Table 3 documents hospitalization events and use of prescription drugs among employees. We notice that hospitalization is a rare event in the sample with hospitalization on happening around 8 pct of the unit years for each employee with no major differences across sectors. On average approximately 8.7 pct of employees takes anti-depressant drugs in a given year and again we notice the frequency is higher in the health sector and lowest in the public administration (unreported). Approximately 4.82 of the employees take opioids and the pattern across sectors is similar to the use of antidepressant drugs (unreported).

Later in this analysis we will divide employees into those who have moved jobs within the public sector, whom we denote movers, and those who have not moved job or have moved job out of the public sector, whom we for simplicity denote non-movers. Table 3 shows that a total of 46 pct. of our employee year sample are categorized as movers, that is they move jobs within our sample. Movers have on average lower age, more likely to be men, lower wages and are on average 0.23 days less absent. There are statistical significant but economically small differences in these numbers across subsections.

### **II.3 Variation in days absent across firms**

Table 4 shows the difference in average days absent for different classifications of public sector units. Our main measure of absenteeism at the unit level is computed by first averaging days absent across all employees in the unit in a given year and then averaging over years.

The average yearly unit level absenteeism across all public sector units is 9.2 days. There is variation across sectors with average absenteeism being 10.1 days in the health sector, 7.8 days in public administration and 7.7 days in the educational sector.

The difference in average days absent between public sector units above and below the median is 8.8, whereas the difference between units in the top and bottom quartile is 14.4 days which is 7.2 pct of the contractual yearly work-days. This difference widens to 28.0 days, corresponding to approximately 14 pct. of annual working days, when we compare units at the top and bottom 5 pct of the distribution.

Furthermore, these differences persist within sectors as the rest of Table 4 documents. In the health sector, the difference between above and below the median unit is 8.6 days but the difference between the 5 pct units with most and least absenteeism is 27.5 days. The similar numbers in the education sector is 6.8 and 21.5 days, whereas they are 8.8 and 33.3 days in the public administration.

To sum up, Table 4 shows that absenteeism is high in the public sector units and there is a very large variation across units. Thus, this motivates that it is important to understand to what extent the choice of leaders are important in explaining this variation in absenteeism.

### **III Leadership and employee absenteeism**

#### **III.1 Leadership as a governance mechanism in the public and in the private sector**

There is a large literature documenting the important role of CEOs in private firms. To motivate our analysis below we highlight that leadership may play at least as important a role in the success of public organizations because the variation in employee effort and talent is higher in the public sector and alternative governance tools such as monetary incentives is more restricted.

To back up this claim, we have compared the distribution of monetary incentives, effort and talent in the public and private sector in Figure 1. We have used the register data for all private and public employees for which we had income, absenteeism and IQ data.

The upper part of the figure compares employees in the public and private sector. To the left we compare the distribution of employee wages in the public and private sector. The wages are registered by Danish Statistic for all employees. We notice that the mean wages in the public and private sector in Denmark is not too different. However, the variation in wages is

much larger in the private sector than in the public. This support the notion that it is harder to use monetary incentives as a governance device within the public sector.

The second figure in the upper part compares the distribution of absenteeism - our proxy for employee effort - between the private and public sector. The absenteeism data is for all public employees and a large and representative selection of employees in private firms (see Bennedsen et al. (2019) for details). We notice that both the average and the variation in absenteeism is higher in the public sector compared to the private sector. This support the notion that the variation in labor effort and productivity is higher across public sector units than across private firms. This provide a larger scope for leadership in the public sector.

The third figure compares the distribution of IQ among male employees in the public and private sector. The IQ data originates from a military test, that all men has to do at age 18 as part of a screening procedure for being able to join the military (see Bennedsen et al. (2023) for details). It is interesting to notice that the IQ distribution for the public sector has a higher average and a larger variance. This is consistent with the notion that the talent distribution in public sector units on average may be broader than in private firms.

The upper part of Figure 1 thus provide suggestive evidence consistent with that in the public sector labor effort and employee talent varies more and that alternative governance mechanisms such as monetary incentives is more restricted. In the lower part of Figure 1 we notice that wages distribution for leaders is also much more narrow in the public than in the private sector. Interesting enough, the IQ of leaders in the public sector is on average higher than the IQ of leaders in private firms. Given this we shall expect leadership to be more important for the outcomes of the public sector units.

### **III.2 The importance of absenteeism as a proxy of employee effort and labor productivity in the public sector**

We address three important premises for using register based absenteeism to analyse the important of leadership in the public sector. First, we argue why absenteeism is a promising proxy for employee effort. Second, we provide evidence that our register based absenteeism records is correlated with real employee absenteeism. Third, we document that registered based absenteeism are correlated with important employee career outcomes and personal traits.

As discussed in the introduction using absenteeism as a proxy for employee effort has a number of advantages: Each individual employee has recorded each absence spell and these records can be aggregated across public sector units. Thus, it is a metric that can be used to compare effort across public sector units and sectors for the entire public sector. We can

link it directly to leadership characteristics in the relevant unit of analysis, i.e. we can link variation in leadership traits, shocks, policy and organization to variation in individual and aggregated absenteeism within the same public sector unit.

We admit that absenteeism measure at most the extensive margin of effort, that employees show up at work. It is important that we measure absenteeism as own sickness and child sickness, so we do not believe it captures work to a from home. Only employees who report sick to the job and then work at home would be working while absent in our data. However, our measure do not measure any intensive margin of effort, the extent to which employees work overtime or slack while being at the workplace. Thus, any result we derive in the following that relates variation in leadership to variation in the extensive margin of effort is expected to underestimate the real effect of leadership on employee effort because it does not include shirking on the job nor that employees may be sick but still show up on the workplace.

Next we provide evidence for that our administrative absenteeism records captures real absenteeism. In Figure 3 we measure the relationship between number of days our public sector employees go to hospital and the recorded absenteeism around this event. The figure provides three insights: First, when employees are hospitalized they do show up as absent in our data. Thus, our administrative absenteeism measure does report real absenteeism. Second, when younger employees go to hospital, they need less days to recover before they are back at work. Again this is what we would expect and thus provide additional evidence for that our measure of absenteeism do reflect real absenteeism. Third, even short hospital stays imply long spells of absenteeism. On average 5 days in hospital implies 25 days absenteeism in our records. This is noteworthy since we will use hospitalization of leaders as part of our empirical strategy to show an causal impact of leadership on employee absenteeism.

Finally, we provide evidence for that recorded absenteeism is economically important. As mentioned in the introduction, the absenteeism rates in key public sector jobs in emerging market countries are very large, sometimes up to 50 pct (World Bank (2018)). In Europe the average absenteeism for public employees are between 3 and 6pct of working time (European Foundation for the Improvement of Living and Working Conditions (2010)). If we include employees with more than 120 days absenteeism, the average number of days would be more than 12 in the Danish public sector. Reducing the average absenteeism with one day is estimated to be the equivalent of 2,800 more employees and to save around 790 mill DKK in less payments for overtime work and temporary appointments. The total effect on the national budget would be 420 mill EUR (Confederation of Danish Employers (2019)).

At the individual level, Table 5 provides strong evidence for absenteeism being correlated with important outcomes. Column (1) shows that absenteeism is correlated negatively with promotion. In specifications controlling for employee and Production Unit controls and

with industry and employee fixed effect, we notice that increased absenteeism is correlated with a smaller likelihood of promotion. In Column (2) we keep the same model but replace promotion with job separation as the endogenous variable. Separation is a measure of employees stop working in the public sector unit either because they are fired or leave voluntarily. Separation is positively correlated with absenteeism and the economic and statistical importance is similar to Column (1). These two results are statistically significant at a 1 pct level and consistent with the notion that leaders find (registered) absenteeism as a signal of employee effort.

In Column (3) and (4) we provide evidence for that absenteeism is correlated negatively with other measures of employee quality. Our first measure is derived from a Mincer style earnings regression (Mincer (1974)). We involve the sum of the years of education attainment, working experience, a quadratic function of working experience, gender and marital status to explain the logarithm of the real wealth of people. Each year we use the Mincer equation to predict the logarithm of the personal real wealth as the measurement of output quality. We notice that more capable employees are less absent. In Column (4) we confirm this using IQ data achieved from Military Session data. This data is described in Section III.1 and covers all male employees who are younger than 50 years old. Again we see a negative correlation statistically significant at the 1 pct level. Thus, Column (3) and (4) are consistent with that high productive workers are less absent.

Finally, in Column (5) and (6) we measure the relation between absenteeism and high school grades. We have collected data for all schools and the grades of all high school students. Column (5) measures the individual grade point average after finishing the secondary school and Column (6) measure the math grades for all students leaving the secondary level. Our explanatory variable is the absenteeism of employees and we clustered standard areas at the public unit level too. We notice that there is a statistically significant (at the 1 pct level) negative correlation between the absenteeism and grades for both grade measures. Compared to the other results in Table 5, this confirms again that absenteeism is negatively correlated with labor productivity.

To sum up, this subsection has provided evidence for that our registered based absenteeism measure real employee absenteeism from work and that absenteeism is a proxy for labor outcomes both at the individual and the public unit level. The measure is not a perfect measure of labor productivity, we have argued that focusing only on registered absenteeism may underestimate the impact of leadership on the efficiency of public sector units.

### **III.3 Leader and employee quality correlation with absenteeism in a setting of assortative matching**

In Table 6 we provide a first look at how absenteeism correlates with leadership. In Panel A we measure leadership and employee quality from a earnings regression (Mincer (1974)), same with what we used in the Column (3) of Table 5. We rank all leaders according to this quality measure and split them into two groups above and below the median quality. For the employees we first derive the mean employee quality at the unit level and then split all units into two groups above and below the median unit employee quality level.

Panel A shows that absenteeism is correlated with both leader and employee quality. The lowest average unit absenteeism is 9.1 days and are in the 30.8 pct of the public units with high quality of both leaders and employees. The highest average unit absenteeism of 10.9 days are in the 28.8 pct of public units with high quality leaders and employees. We also notice that in the 19.2 pct of the units with high quality leaders and low average quality of employees the absenteeism is 9.8 days on average whereas it is higher (10.5 days) in the 21.2 pct units with low quality leaders and high average quality of employees.

We confirm the correlation between leadership quality, employee quality and absenteeism using IQ data from the military draft session in Panel B. This data is only available for men below 50 years and is the result of 70 IQ questions that all men answer around the age of 18. Thus, we only have units with male leaders below 50 years in this panel and since this is biased towards public administration and education, we notice that on average all units have lower absenteeism than in Panel A. Again we group leaders into high and low IQ leaders. We group units into high and low employee IQ units by ranking the average IQ of male employees below 40 years.

Panel B shows a similar pattern that Panel A. Units with high IQ leaders and average high IQ male employees have the lowest average employee absenteeism of 6.4 days pr year. Units with low IQ leaders and low average male employee IQ have highest average employee absenteeism of 8.4 days. Furthermore, units with high IQ leaders and low IQ male employees have lower average absenteeism than units with low IQ leaders and high average male employee IQ.

The results of Table 6 is consistent with the notion that leadership quality is an important factor in explaining the variation in absenteeism across the public sector and the impact of leadership is correlated with employee quality in an a meaningful way. We also notice that the employee absenteeism variation across leadership quality seems to be higher than the variation across employee quality. Leadership and employee quality is not randomly assigned and we notice that there are assortative matching: high quality leaders tend to be in units with high average employee quality and vice versa. Thus, the results in Table

6 are based on correlations. We next turn to providing causal evidence for the impact of leadership on employee absenteeism.

## **IV Causal impact of leadership on employee absenteeism**

In this section we provide evidence for a causal impact of leaders on employee absenteeism, - our proxy for labor productivity. We first do an analysis based on leader fixed effects following Bertrand and Schoar (2003). Then we proceed to derive causal evidence from leader hospitalization event following Bennedsen et al. (2019).

### **IV.1 Causal evidence from leader fixed effect regressions**

We first test the leader fixed effects on employees absenteeism based on Bertrand and Schoar (2003). This approach exploits leaders that move from one unit to another. We notice from Table 3 that around 46 pct of our leaders move at least once within public sector units during our sample window. Given we have on average 7 leaders per year, our leader fixed effect analysis is based on almost 3500 leaders per year. We focus on the highest paid top leaders with longest tenure who move across different production units over time. To make sure the leaders are able to exert a comprehensive influence on employees, we require that the leaders should stay in each unit for at least three years. Then we restrict the sample to the production units for which at least one of the top leaders moves to at least one other public sector unit.

In Panel A of Table 7, we present the results of our analysis on the leader fixed effects in our main sample of full time employees that only work in one public sector units and public sector units that only work in one sub-sector. After adding leader fixed effects, the Adjusted R square increase from 0.203 to 0.227. The F-test statistics of joint significance are large (200.41), thus, the leader fixed effect is statistically significant at any conventional statistical level, rejecting the null hypothesis that top leaders have no fixed effects on employee absenteeism.

We confirm this result using alternative sample of public sector units and employees in Panel B through D. In Panel B we include all public sector units (that is we add public units that stand in multiple sub sectors) and we add all employees (that is we add part time employees and employees with multiple jobs). From Table 1 we notice, that this increase the number of public sector units from 12,802 to 17,337 and the number of employees from 270,203 to 977,669. The F-test for significance of the leader fixed effect is again significant at any conventional statistical level.

In Panel C we construct a sample based on the sample used in Panel A, and add public sector units in multiple sub sectors. Here, we have 14,681 compared to 12,802 units, and 321,354 compared to 270,203 employees. Finally in Panel D, we construct a sample based on the sample used in Panel B, and only keep full-time employees. This decreases the number of public sector units from 17,337 to 15,032 and the number of employees from 977,669 to 333,871. In both cases, our F-test shows that the leader fixed effect is strongly significant.

Thus, Table 7 yields strong evidence for that leaders have an important causal impact on employee absenteeism. The model is based on leader fixed effect and does not as such deliver additional evidence of the magnitude, direction or channel through which leaders impact absenteeism. Furthermore, the model has been criticized for leader moves may not be random and that matching of leaders and public units may be correlated with both observable and un-observable characteristics (see for example Fee et al. (2013)).

For these reasons we proceed to use leader hospitalization events to derive further causal impact from a model where we can apply both leader and public unit fixed effects.

## **IV.2 Causal evidence from leader hospitalization events**

In this section we derive causal impact of leaders on employee absenteeism based on leader hospitalization which was first introduced to study the role of leadership in private firms in Bennedsen et al. (2019). The basic idea of this methodology is that leaders are physically absent from their public sector units when they are hospitalized.

We document the pattern of leaders' absenteeism around the dates that the same leaders are hospitalized in Figure 4. Similar to Figure 3 for all employees, Panel A plot the number of hospitalization days (per year) on the horizontal axis and the registered number of absent days (per year) on the vertical axis. This panel documents that leaders are absent from their public sector unit when hospitalized. The fact that number of absent days are much larger than the number of hospitalization days support the claim that hospitalization provides significant exogenous variation to leaders presenteeism at their workplace.

Panel B documents leader absenteeism in months around a given hospitalization event. We see a sharp increase in absenteeism around the event day and that it takes 2-3 months before the level of absenteeism is back to where it were before the start of the sickness period. We use this insight to confirm the use of event study estimation techniques below.

Finally, Panel C splits hospitalization events into three groups depending on the number of days hospitalized. We notice for all groups, hospitalization generates leader absenteeism. As expected, the longer stay a leader has at the hospital, the more she is absent from work.

The main advantage of basing our causal analysis on leader hospitalization events is that we can choose appropriate counterfactuals. As counterfactual we use leader unit pairs without hospitalization and we can select these pairs from all leader unit pairs (no fixed effects), within the same public unit allowing for change in leadership (unit fixed effect), for the same leader within and across units (leader fixed effects) and, finally and within the same leader-unit match (leader-unit fixed effects). In the latter and most restrictive specification, we compare variation of employee absenteeism between spells where leaders are separated from their production units through hospitalization events and spells where the same leader and the same public unit is matched in normal times. In econometric terms, using leader-unit fixed effects solve the issue of endogenous timing of leader moves and endogenous matching that may challenge other identification strategies such as the leader fixed effect model we applied above.

We analyse the impact of leadership hospitalization events on employee absenteeism in a multivariate setting using yearly data.

Table 8 presents results for standard OLS mean regressions. In all specifications, we include controls for public sector unit characteristics and have year and industry fixed effects. We control the size of the public units and we report the standard errors clustered at the level of PU-leader. In the first five columns we apply our main dataset, that is all public sector units that are located in one and only one industry and we focus on full time employees that have one and only one job.

Column 1 reports the impact of leader hospitalization on employee absent only with public sector controls, year and industry fixed effects. The impact of leader hospitalization on average unit employee absenteeism is positive and statistically significant at any conventional level. The coefficient is economically very large and this motivates why we introduce leader and unit fixed effects.

In Column 2, we introduce unit fixed effect, which allows us to investigate the correlation between leader hospital events and employee absenteeism within a single workplace aggregating hospitalization events for all leaders that work in the unit (that is we introduce unit fixed effects). We show that hospital events are correlated with higher absenteeism, an effect that is statistically significant on a 1 pct level. The coefficient is 1.2 pct. point or approximately one fifth of the effect in Column 1.

In column 3 we do the same analysis but now we replace unit fixed effects with leader fixed effects.<sup>5</sup> Thus, we now exploit variation in the correlation between a leader's hospital events and average unit employee absenteeism for each top leader, independently of which public

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<sup>5</sup>Notice, to introduce leader fixed effects we have to specify one leader in each unit that we can provide fixed effects for. Thus, we specify the top leader as either the one that has the job category 131 (that is top leader) or the highest paid among the leaders with job category 132.

sector unit she works for. The effect of leader hospitalization is very similar to the effect with unit fixed effects, both statistically and economically.

We introduce leader and unit fixed effects in Column 4, where we again use leader effect for a selected top leader within each unit.

Next, we introduce leader-unit fixed effect and look at the entire public sector (Column 4). As discussed in Bennedsen et al. (2019), this is a very restrictive specification that only exploits the impact of leaders hospitalization within the same match of top leader and public sector unit. We see that the effect of hospitalization of leader hospitalization on average unit absenteeism is positive and significant at a 10 pct level. Thus, when a leader is hospitalized average employee absenteeism increases.

In a public financed hospitalization system it is rare to stay more than a few days in hospital, thus most of the hospitalization events are rather short. We do expect the impact on employee absenteeism to be more important for longer hospitalization events (and thus longer leader absenteeism events). We address this in column 5 where we add three dummies for the length of hospitalization events. We observe that events more than 10 days has a significantly larger coefficient and is statistically significant at a 5 pct level.

In Column 6 we again include public sector units that are in more than one industry, and in Column 7 we keep full-time employees without other restrictions on the raw sample, same with Panel C and D in Table 7. Similar to Column 5, events more than 10 days has a significantly positive effect

To sum up, both Table 7 and Table 8 has provided evidence for a causal effect of leaders on unit average employee absenteeism. In Table 7 we followed Bertrand and Schoar (2003) and found that adding leadership fixed effects increase the explanation power of a model of absenteeism and it was robust to both different samples of public units and different employee types. In Table 8 we provided an even more restricted model based on hospitalization events of leaders in public sector units. This allowed us for introducing leader public unit fixed effects. We documented that leader absenteeism (through hospitalization events) cause an increase in average employee absenteeism. The evidence demonstrates that changing managerial supply of effort, resulting from hospitalizations, significantly influences employee effort. That is, leaders in the public sector has a causal impact on employee behaviour in the organizations they lead.

## V Decomposing leadership impact into selection and incentive effects

We now proceed to decompose the overall correlations in two important dimensions. First, we separate two broad groups of mechanisms. Leadership characteristics have a direct impact on the type of employees that arrive and exit the entity, the extensive margin. We denote this selection effects. However, leadership also affects the effort level of the current set of employees in a particular entity, the intensive margin. We denote this incentive effects.

We decompose leaders' impact into selection and incentive effects in three steps: First, we look at a simple mean decomposition. Second, we provide results from an event study. Third, we estimate a model of absenteeism as a function of time, individual and public sector unit effects, following the seminal model of Abowd et al. (1999). Following Finkelstein et al. (2016) and Bennedsen et al. (2019) we aggregate the individual effects to the entity level.

The methodology we apply is based on job movers. Table ?? XX MENGQI CORRECT TABLE LABEL documents the movers across public and private sectors in Denmark (Panel A) and across sectors within the public sector (Panel B). A mover is an employee that across time shows up in at least two different production units within our sample. In Panel A we include the private sector to see how much movement there is within the public and private sectors and how much movement there is across the two sectors. In total we have 90,581 movers within the public sector. It is interesting to see that we have very little movement across the two sectors. Panel B reports that we have 45,538 movers within the health sector, 16,027 movers in the educational sector and 13,398 movers in public administration. It is also clear that there is very little movement across the three sectors.

### Simple mean decomposition

Our first indication of the relative size of the selection and incentive effects is given in Figure ?. XX MENGQI REF In this figure we focus on all movers. On the horizontal axis we measure the difference between average absenteeism between start and end unit for each move. On the vertical axis is the difference between before and after move absence days for the employee. We aggregate moves into 30 bins according to the average net difference between units. If the slope of the figure is 1, we say the change in individual behaviour is the same as the average difference between the units, that is the variation in absenteeism is entirely explained by incentives effects. On the other hand if the curve is horizontal there is no correlation between the differences in the units and the individual around the move. Thus, all variation in absenteeism are explained by selection effects.

In the top figure we exclude the two years where we identify a move. For the entire public sector the slope of the curve is 0.38. However, when we include the two moving years in Panel B, the slope increase to 0.5. Thus, the two figures tell us that both selection and incentives effects are important. In unreported graphs we notice that the slope is marginally steeper in the health sector and significantly lower in the public administration. Thus, incentive effects seem to be more important in the health sector and selection effects are relatively more important in public administration.

## Event study

A fundamental premise for an unbiased estimation using mover analysis is that the decision to move is uncorrelated with individuals absenteeism behaviour.

Our first evidence for this premise is given in Figure ???. We show the distribution of the difference between average absenteeism in the destination unit and the origin unit for each move. We notice that the distribution for the entire public sector is normally distributed around mean 0. Thus, there do not seem to be any systematic pattern in where employees move from and where they move too.

An alternative way of decomposing into unit and individual effects is to use event-study methodology for movers. We present the result of event-studies in Figure ??. We have normalized the average absenteeism in the original public unit to zero and the average absenteeism in the destination public unit to one. We control for time varying and individual characteristics. Thus, we interpret the coefficient in the event-study as the fraction of the difference between origin and destination unit that an individual close before under and after the move, which takes place in year 0.

For the entire public sector we observe that there is almost no change in absenteeism before the move. There is a small change at year 0 but this can be due to we do not identify exact the date of year. The year of the move the mover adapt around 55 pct of the differences between the units and this increase to more than 60 pct in the following years.

Our event study methodology results are consistent with that more than half the measurable impact from leadership to employee absenteeism is due to incentive effects. Thus, good leaders reduce absenteeism both by hiring new people but even more by reducing absenteeism within the unit's group of employees.

## **AKM decomposition**

We next estimate a model of absenteeism as a function of time, individual and public sector unit effects, following the seminal model of Abowd et al. (1999) and applied to employee absenteeism in the private sector in Bennedsen et al 2019.

Table 10 describes the full decomposition from estimating the AKM model. Panel A reports for the entire public sector but leaves out personal controls, which are added in Panel B. MENGQI XX ADD CONTROLS.

For the entire public sector comparing above and below mean absenteeism in Panel A.1, we observe that the difference in absenteeism is 8.28 days. Out of these 4.65 days or 57 pct are due to selection (production unit) effects and 3.63 or 44 pct are due to individual effects. Thus, we observe that for the entire public sector both the intensive margin (ie incentive effects) and the extensive intensive margin (i.e. selection effects) seem to be very important with the incentive effects slightly dominating the selection effects.

When we decompose the difference between top and bottom 25 pct, 10 pct and 5 pct respectively, we observe a slight increase from 56 pct to 62 pct in the share of variation due to incentives.

In Panel B we introduce person controls; however, the results are very similar to the decomposition without personal controls. Thus, we conclude that both the intensive and the extensive margin are important to explain how leaders impact the variation in employee absenteeism.

## **VI Leadership characteristics and channels of absenteeism**

We now investigate the relationship between leadership characteristics and absenteeism. We first do this in simple univariate regression analysis. Then we proceed to analyze the drivers of the incentive and selection effects we identified in the previous section.

### **VI.1 Correlates with total absenteeism**

We classify leadership characteristics into two groups, where the first group include personal traits and shocks to leaders work ability. The leadership literature has identified many traits important for the type of leadership we observe, however, we are restricted to traits we can identify in our register data. We focus on traits such as age, leader quality, gender and shocks

to leaders ability to work. Leadership style may vary across age of leader. Young leaders are creating a reputation where more tenured leaders have established a track record. The literature has argued that female leaders may have a different leadership style than male leaders. We also identify shocks to leaders ability to work thorough hospitalization and use of drugs. We already highlighted the importance of hospitalization spells and we compliment these personal health shocks with the use of prescription drugs. Drugs consumption is a proxy for variation in ability to lead public sector units, both because it may be a result of a personal shock or triggered by personal stress and because the use of drugs directly impacts the behavior of leaders. We focus on the use of opioids and anti-depressant medicine given through prescriptions.

The second group includes proxies for firm structure and corporate policy that provides incentives towards lower or higher absenteeism. First we have firm structure including size and hierarchical structure, measure as MENGQI XXX. Finally, we have proxies for firm policies relevant to employees incentives to reduce absenteeism. Turnover is the sensitivity of absenteeism to separation of employee and unit the following year. Wage increase is the sensitivity between changes in wages and employee absenteeism. We measure wage dispersion both as the standard deviation of wages within the unit and the difference between the top 10 pct and the bottom 10 pct wage earners.

Figure 8 documents the correlation between leadership characteristics and employee absenteeism in univariate regressions. For each variable we run a univariate regressions with controls XX MENGQI PLEASE STATE WHAT WE DO; with or without controls ETC

From the group of leader characteristics we observe that leaders' age is not statistically significantly correlated with absenteeism. Employees with female leaders are on average more absent. This is not surprising since we do not control for industry nor employee composition. Better quality leaders are correlated with significantly lower employee absenteeism (as we noticed in Table 6 too). Leaders that are hospitalized or take prescription drugs are correlated with higher average employee absenteeism.

From the group of public unit characteristics, we observe that unit size is uncorrelated with absenteeism but that the more hierarchical the unit structure is, the higher average unit absenteeism. Units with high employee turnover also have higher absenteeism as have units where employee absenteeism is more correlated with wage increase/wage reduction. Finally we see the correlation between wage dispersion and absenteeism depends on which measure of wage dispersion is used. When we use standard deviation in employee wages, the correlation is highly negative but it is positive (albeit statistically insignificant) when we measure the difference between top and bottom earners in the unit.

In Figure 9 we confirm these correlations between our leadership characteristics and total absenteeism estimated from the predicted values of the AKM model. Given that we esti-

mate one fixed effect by person, the covariates are averaged at the unit-employee pair. We notice that the correlations in Figure 8 and 9 are almost identical, thus confirming the insight above.

## **VI.2 Drivers of incentives (production unit) and selection (individual) effects**

The correlations between leadership characteristics and employee absenteeism identified in Figure 8 and 9, do not highlight if the correlations are generated by incentives or selection effects.

### **VI.2.1 Drivers of selection effects**

The goal of this section is to analyze the correlation between leadership characteristics and selection effects to shed light on which types of public sector leaders are more successful at attracting low-absenteeism employees. Because we include public unit fixed effect in the model, incentive does not drive our results. However, we do not use exogenous variation in individual moves and hence cannot rule out bias in the estimates coming from correlated unobserved characteristics. We present the results of the multivariate analysis in Figure 9.

Among the leadership characteristics in the first group, we see again that female leaders and having more leaders with more female children is positively correlated with attracting individuals with higher absenteeism. In the second group we notice that leaders' hospitalization and use of anti-depressant drugs are both correlated with attracting employees with higher absenteeism. The positive correlation between leaders' use of opioids and employee fixed effects lacks statistical power.

From the third group we observe that a long term absence policy measured as the frequency of separation of workers with a track record of high absenteeism, is correlated with attracting employees with higher absenteeism behaviour. Obvious, this can be explained by public units that attract people with high absenteeism are more likely to introduce a policy for this. The negative correlation between wage dispersion and employee fixed effects is only statistically significant when wage dispersion is measured as the difference in earnings in the top and in the bottom of the distribution. The correlation between bonus hours, bonus rate and employee fixed effects lack statistical power.

We also notice that the units where the sensitivity of absence to labor turnover and wages

and which have a stronger long term absence policy, higher bonus rate and higher wage dispersion also attract employees with higher absenteeism. However, units where the top bottom earners are very far from each other and that have more bonus hours are correlated with attracting employees with lower absenteeism.

This subsection has documented a significant correlation between variation in leadership characteristics and variation in public sector units hiring of employees with different absenteeism behaviour. We find that variation leadership characteristics are systematic correlated with variation personal fixed effects both in the entire public sector and in the three main sub sectors of health, education and public administration.

### **Correlates of personal traits, shocks, policy and organization with unit fixed effects**

We next examine variation in observable leadership characteristics that correlate with the public unit fixed effects. This approach is a cross-sectional regression of firm fixed effects on firm covariates. The covariates are calculated as the average across all sample years for each firm. Again, we include individual effects in the regressions, so our results are not driven by selection. However, we do not use external variation so we cannot rule out that our results are partly explained by omitted - unobservable - variables.

The correlates between incentive effects and leadership characteristics are presented in Figure 10. For the entire public sector we do not see a statistically significant correlation between personal traits such as age, gender and the share of female among leaders children strong correlation to the personal trait group. In the second group we notice again the positive correlation between leadership hospitalization and employee absenteeism but not other significant correlation.

In the incentive group, we notice that higher sensitivity between absenteeism and turn over is correlated with less absenteeism. On the other hand, higher sensitivity between absenteeism and remuneration and wage dispersion in general are correlated with higher absenteeism. However, when wage dispersion is measured as the difference between the top and bottom earners it is weakly negatively correlated with employee absenteeism. From the last group of variable, we notice that larger firm are correlated with less absenteeism as are firms with less hierarchical structures.

Comparing across the three main sectors in the other three panels we notice some interesting differences. In the health sector female leaders, hospitalized leaders and leaders taking anti-stress medicine are all correlated with higher absenteeism. However, leaders taking opioids are weakly correlated with inducing incentives for lower absenteeism. Leadership

policy such as sensitivity of wage increase to absenteeism, long term absenteeism policy and wage dispersion are all correlated with employees being more absent, where as pay differences between top and bottom is correlated with lower absenteeism. Comparing health and educational sectors we notice that female leadership is correlated with lower absenteeism in the educational sector (and in the public administration). Furthermore, use of opioids is correlated with higher public unit fixed effects, that is correlated with inducing more absenteeism.

Finally, in the public administration we in general see less statistically significant correlation between leadership characteristics and unit fixed effects. Female leadership, family death, sensitivity of turnover to absenteeism and firm size are all correlated with less absenteeism. On the other hand a stronger long-term absenteeism policy and a stronger hierarchy is correlated with more absenteeism.

To sum up, this section has provided a number of insights: First, there is a statistically and economically significant correlation between leadership characteristics and employee absenteeism in the public sector. Second, these correlations vary across sectors within the public sector. Third, the aggregate correlation is the sum of incentives and selection effects. Fourth, variation in leadership characteristics are strongly correlated with the hiring of employees with different absenteeism behavior. Fifth, variation in leadership characteristics is also statistically significantly correlated with public unit fixed effects, that is with the incentives effects. Sixth, the correlation between leadership characteristics and employee and unit fixed effects do vary in important ways across different public sectors.<sup>6</sup>

## VII Conclusion

We propose a methodology to measure the impact and role of leaders in the public sector. By relying on a common metric - employee absenteeism - that can be measured for all individuals, in all public sector units and in the entire public sector, we can compare the role of leaders and leadership characteristics across different sub sectors in the public sector.

We document that leaders' absenteeism through hospitalization increase employee absenteeism through own and child sickness. Our methodology allow us to estimate the impact of leaders on their organization using both public unit and employee fixed effects, which is a new contribution for the study of leaders in the public sector. Thus, we prove a causal impact of leadership absenteeism on employee absenteeism in units that do not have too high absenteeism. We conclude that leaders in the public sector have an important impact on the units they lead.

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<sup>6</sup>In unreported results, we confirm the general pattern of correlations between leadership characteristics and individual and unit fixed effects using a post-lasso procedure.

Focusing on movers, we decompose the variation in employee absenteeism into selection and incentive effects. We notice that, the two effects are almost equally important to explain the variation in employee absenteeism above and below median.

Finally, we report strong correlation between variation in leadership characteristics - such as personal traits, shocks and use of prescription drugs, incentive policy and firm organization - and variation in selection and incentive effects both in the entire public sector and across the three main sub sectors of health, education and public administration.

We have focused on registered absenteeism through own sickness and child sickness. However, we do not have data for variation in the attention employees provide while they are on the job. It is plausible that leadership characteristics may have an even larger impact on variation in the attention employees give while they are on work and not report sick. Hence, it would be important in the future to investigate the causal impact on leadership on employees that are not reported sick but may vary in the amount of on the job shirking.

Our methodology allows for a better understanding of how different leadership characteristics may reduce public sector absenteeism. Through this it will be easier to develop best practices for leadership in the public sector.

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## VIII Tables

Table 1: The Sample Size of Production Units and Workers

The table displays the total number of production units in different sectors, total number of workers, average number of workers in each production unit, median number of workers in each production unit and top 5% of average number of workers per unit for the entire public sector and the three largest industries categorized by NACE 1-digit code.

|                                           | Entire public | Health  | Education | Public admin |
|-------------------------------------------|---------------|---------|-----------|--------------|
| <b>Panel A: Production units per year</b> |               |         |           |              |
| Entire sample                             | 17,337        | 10,428  | 3,166     | 1,398        |
| Selected sample                           | 12,802        | 8,529   | 2,302     | 630          |
| <b>Panel B: Leaders per year</b>          |               |         |           |              |
| Number of PUs w/ 1 leader                 | 7,588         | 5,671   | 785       | 283          |
| Number of PUs w/ > 1 leaders              | 5,214         | 2,857   | 1,516     | 347          |
| Mean number per PU                        | 2             | 2       | 3         | 3            |
| Median average per PU                     | 1             | 1       | 2         | 2            |
| Top 5% average leaders                    | 8             | 6       | 9         | 10           |
| <b>Panel C: Employees per year</b>        |               |         |           |              |
| <u>Entire sample</u>                      |               |         |           |              |
| Total                                     | 977,669       | 550,495 | 219,417   | 135,298      |
| Mean number per PU                        | 63            | 51      | 74        | 161          |
| Median average per PU                     | 23            | 20      | 51        | 28           |
| Top 5% average employees                  | 600           | 495     | 412       | 1,873        |
| <u>Selected sample</u>                    |               |         |           |              |
| Total                                     | 270,203       | 143,216 | 63,317    | 41,350       |
| Mean number per PU                        | 21            | 17      | 28        | 66           |
| Median average per PU                     | 8             | 7       | 18        | 14           |
| Top 5% average employees                  | 194           | 162     | 149       | 759          |

Notes: Presented in the table are average values between 2010 -2018

Table 2: Leadership Survey and Administrative data

We report the summary statistics of the public sector survey in Panel A - F. Respondents answered when they started to be a leader in the survey, so that we are able to merge the survey data with the data sample we use in this paper. We check the definition of leaders in the paper, and report in Panel G. Note that if someone was a leader before (i.e. 2010 - 2018) but was not a leader in 2020, we cannot identify him in the historical data. Thus, Panel G underestimates the number of the answer "Yes" and overestimates the number of the answer "No".

Panel A: Respondents defined as leaders

|                      | Frequency | Percent |
|----------------------|-----------|---------|
| Yes, I'm a leader    | 4,018     | 60.27   |
| No, I'm not a leader | 2,649     | 39.73   |
| Total                | 6,667     | 100.00  |

Panel B: Defined as leaders from register and answered survey

|       | Public admin |         | Education |         | Health    |         | Others    |         |
|-------|--------------|---------|-----------|---------|-----------|---------|-----------|---------|
|       | Frequency    | Percent | Frequency | Percent | Frequency | Percent | Frequency | Percent |
| Yes   | 1,071        | 81.32   | 1,116     | 66.31   | 1,568     | 48.23   | 263       | 63.22   |
| No    | 246          | 18.68   | 567       | 33.69   | 1,683     | 51.77   | 153       | 36.78   |
| Total | 1,317        | 100.00  | 1,683     | 100.00  | 3,251     | 100.00  | 416       | 100.00  |
| N     | 6,667        |         |           |         |           |         |           |         |

Panel C: Types of known leaders in the survey

|                                          | Frequency | Percent |
|------------------------------------------|-----------|---------|
| Leader of other leaders                  | 1,556     | 32.81   |
| Manager of employees                     | 2,921     | 61.59   |
| Manager without personnel responsibility | 266       | 5.61    |
| Total                                    | 4,743     | 100.00  |

Panel D: Social code of defined leaders and respondents in the survey

|       | Total | Yes, I'm a leader |         | No, I'm not a leader |         |
|-------|-------|-------------------|---------|----------------------|---------|
|       |       | Frequency         | Percent | Frequency            | Percent |
| 131   | 3,686 | 3,157             | 85.65   | 529                  | 14.35   |
| 132   | 2,981 | 861               | 28.88   | 2,120                | 71.12   |
| Total | 6,667 | 4,018             | 60.27   | 2,649                | 39.73   |

Panel E: Social status code of respondents that answered "Yes, I'm a leader"

|       | Public admin |         | Education |         | Health    |         | Others    |         |
|-------|--------------|---------|-----------|---------|-----------|---------|-----------|---------|
|       | Frequency    | Percent | Frequency | Percent | Frequency | Percent | Frequency | Percent |
| 131   | 1,017        | 94.96   | 916       | 82.08   | 1,072     | 68.37   | 152       | 57.79   |
| 132   | 54           | 5.04    | 200       | 17.92   | 496       | 31.63   | 111       | 42.21   |
| Total | 1,071        | 100.00  | 1,116     | 100.00  | 1,568     | 100.00  | 263       | 100.00  |
| N     | 4,018        |         |           |         |           |         |           |         |

Panel F: Leaders' answers grouped by PU size and single/multiple leaders

|                  | Yes, I'm a leader |         | No, I'm not a leader |         |
|------------------|-------------------|---------|----------------------|---------|
|                  | Frequency         | Percent | Frequency            | Percent |
| Below median     | 917               | 41.387  | 1,299                | 58.62   |
| Above median     | 3,101             | 69.97   | 1,350                | 30.33   |
| Single leader    | 1,652             | 48.45   | 1,758                | 51.55   |
| Multiple leaders | 2,366             | 72.64   | 891                  | 27.36   |
| N                | 6,667             |         |                      |         |

Panel G: Answers of leaders with historical data (2010 - 2018)

|                      | Frequency | Percent |
|----------------------|-----------|---------|
| Yes, I'm a leader    | 10,599    | 63.52   |
| No, I'm not a leader | 6,087     | 36.48   |
| Total                | 16,686    | 100.00  |

Table 3: Personal Characteristics of Leaders and Employees

The table reports average level of leaders' and employees' characteristics, including absent days, age, wage, gender, number of children, hospitalization days, use of anti-depressant drugs and use of opioids. The first four columns report the leaders' characteristics, and the last column reports those of employees. For leaders: Column 1 reports for the whole sample, Column 2 shows for subgroup of movers and Column 3 for non-movers respectively. Column 4 reports the t test of the differences between movers and non-movers. Standard error is shown in parenthesis \*\*\*, \*\*, and \* correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

|                   | Leaders            |                    |                    |                     | Employees          |                    |                    |                    |
|-------------------|--------------------|--------------------|--------------------|---------------------|--------------------|--------------------|--------------------|--------------------|
|                   | Total<br>(1)       | Mover<br>(2)       | Non-mover<br>(3)   | t-test<br>(4)       | Total<br>(5)       | Mover<br>(6)       | Non-mover<br>(7)   | t-test<br>(8)      |
| Absent days       | 6.69<br>(13.92)    | 6.89<br>(14.19)    | 6.53<br>(13.68)    | 0.35***<br>(0.06)   | 9.57<br>(15.95)    | 9.44<br>(15.96)    | 9.67<br>(15.94)    | -0.23***<br>(0.02) |
| Age               | 50.84<br>(8.49)    | 49.72<br>(8.76)    | 51.77<br>(8.14)    | -2.04***<br>(0.03)  | 46.62<br>(10.52)   | 45.28<br>(10.92)   | 47.76<br>(10.03)   | -2.48***<br>(0.01) |
| Wage (K DKK)      | 503.11<br>(195.55) | 496.59<br>(198.89) | 508.59<br>(192.54) | -12.00***<br>(0.81) | 370.20<br>(129.66) | 366.21<br>(131.69) | 373.59<br>(127.82) | -7.37***<br>(0.18) |
| Female            | 0.66<br>(0.47)     | 0.66<br>(0.47)     | 0.65<br>(0.48)     | 0.01***<br>(0.00)   | 0.70<br>(0.46)     | 0.65<br>(0.48)     | 0.74<br>(0.44)     | -0.09***<br>(0.00) |
| No. of children   | 1.94<br>(1.02)     | 1.93<br>(1.03)     | 1.94<br>(1.02)     | -0.01**<br>(0.00)   | 1.73<br>(1.09)     | 1.65<br>(1.11)     | 1.80<br>(1.06)     | -0.14***<br>(0.00) |
| Hospitalization   | 0.07<br>(0.25)     | 0.07<br>(0.26)     | 0.07<br>(0.25)     | 0.00<br>(0.00)      | 0.08<br>(0.27)     | 0.08<br>(0.27)     | 0.08<br>(0.28)     | -0.00*<br>(0.00)   |
| Antidep dosage    | 19.65<br>(103.79)  | 20.70<br>(107.59)  | 18.77<br>(100.48)  | 1.93***<br>(0.43)   | 24.05<br>(119.01)  | 23.44<br>(118.79)  | 24.56<br>(119.20)  | -1.13***<br>(0.16) |
| Antidep use share | 8.25<br>(27.51)    | 8.37<br>(27.70)    | 8.15<br>(27.36)    | 0.22*<br>(0.11)     | 8.73<br>(28.23)    | 8.41<br>(27.76)    | 9.00<br>(28.61)    | -0.58***<br>(0.04) |
| Opioid dosage     | 2.42<br>(30.35)    | 2.59<br>(34.52)    | 2.28<br>(26.36)    | 0.31**<br>(0.13)    | 2.31<br>(31.65)    | 2.03<br>(26.26)    | 2.54<br>(35.58)    | -0.51***<br>(0.04) |
| Opioid use share  | 4.89<br>(21.57)    | 4.96<br>(21.72)    | 4.83<br>(21.44)    | 0.13<br>(0.09)      | 4.82<br>(21.41)    | 4.61<br>(20.97)    | 4.99<br>(21.78)    | -0.38***<br>(0.03) |
| No. of obs.       | 237,367            | 108,350            | 129,017            | 237,367             | 2,194,457          | 1,007,374          | 1,187,083          | 2,194,457          |

Notes: Presented in the table are average values between 2010 -2018

Table 4: Difference in Average Absent Days

This table reports the difference in average absent days of different subgroups for the entire public sector and three major sub-sectors. Each column defines a set of firms R and R' based on percentiles of average absence. The rows report the differences in average days absent overall between the two groups  $y_R - y_{R'}$  for the entire public sector and three major industries. The industry classification is based on NACE 1-digit code.

|                       | Mean | Above/Below<br>Median | Top/Bottom<br>25% | Top/Bottom<br>10% | Top/Bottom<br>5% |
|-----------------------|------|-----------------------|-------------------|-------------------|------------------|
| Entire public sector  | 9.2  | 8.8                   | 14.4              | 21.8              | 28.0             |
| Health                | 10.1 | 8.6                   | 14.2              | 21.5              | 27.5             |
| Education             | 7.7  | 6.8                   | 11.1              | 16.6              | 21.5             |
| Public admin          | 7.8  | 8.8                   | 14.8              | 24.0              | 33.3             |
| Entire private sector | 5.9  | 7.6                   | 12.5              | 19.5              | 26.1             |

Notes: Presented in the table are average values between 2010 - 2018

Table 5: Employees' Days of Absence and Personal Traits

The table reports regression estimates between employees' days of absence and personal traits, including likelihood of promotion, probability in separation of employee and unit, output quality, IQ, general grades and math grades. As the measurement of output quality, we predict the the logarithm of the real wealth by a Mincer style earnings regression (Mincer (1974)). We add industry fixed effects, employee fixed effects, employees' characteristics and public unit controls in regressions. 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.

|                                   | Promotion<br>(1)       | Separation<br>(2)     | Quality<br>(3)         | IQ<br>(4)              | Grades<br>(5)          | Math Grades<br>(6)     |
|-----------------------------------|------------------------|-----------------------|------------------------|------------------------|------------------------|------------------------|
| Absent days <sub><i>t</i>-1</sub> | -0.0002***<br>(0.0000) | 0.0002***<br>(0.0000) |                        |                        |                        |                        |
| Absent days <sub><i>t</i></sub>   |                        |                       | -0.0003***<br>(0.0000) | -0.0154***<br>(0.0028) | -0.0052***<br>(0.0003) | -0.0108***<br>(0.0006) |
| Obs.                              | 1,514,960              | 1,888,219             | 2,118,388              | 157,325                | 226,001                | 177,117                |
| R-squared                         | 0.260                  | 0.355                 | 0.616                  | 0.157                  | 0.192                  | 0.124                  |
| Sample                            | Employees              | Employees             | Employees              | Male empl.             | Employees              | Employees              |
| Industry FE                       | Yes                    | Yes                   | Yes                    | Yes                    | Yes                    | Yes                    |
| Employee char.                    | Yes                    | Yes                   | Yes                    | Yes                    | Yes                    | Yes                    |
| Employee FE                       | Yes                    | Yes                   | No                     | No                     | No                     | No                     |
| PU controls                       | Yes                    | Yes                   | Yes                    | Yes                    | Yes                    | Yes                    |
| No. of PUs                        | 16,438                 | 19,090                | 19,611                 | 8,906                  | 12,701                 | 11,774                 |
| Clustered SE                      | PUs                    | PUs                   | PUs                    | PUs                    | PUs                    | PUs                    |

Table 6: Employee and Leader Absence by Quality or IQ

This table reports average absent days of employees grouped by the output quality of leader and employees (Panel A) and IQ levels of leaders and employees (Panel B). Same with the Table 5, the output quality is measured by Mincer (1974) style earnings equation. Share of units in parentheses shows the percentage of one particular group accounting for all units.

| Panel A: Employee Absence by Quality |              |                                      |                     |
|--------------------------------------|--------------|--------------------------------------|---------------------|
| Employees                            |              | Leaders                              |                     |
|                                      |              | Low quality                          | High quality        |
|                                      | Low quality  | 10.9 days<br>(Share of units: 28.8%) | 9.8 days<br>(19.2%) |
|                                      | High quality | 10.5 days<br>(21.2%)                 | 9.1 days<br>(30.8%) |
| Panel B: Employee Absence by IQ      |              |                                      |                     |
| Employees                            |              | Leaders                              |                     |
|                                      |              | Low IQ                               | High IQ             |
|                                      | Low IQ       | 8.4 days<br>(Share of units: 25.2%)  | 7.7 days<br>(21.4%) |
|                                      | High IQ      | 8.2 days<br>(21.5%)                  | 6.4 days<br>(31.9%) |

Table 7: Leader's Impact on Employee Absence

Based on Bertrand and Schoar (2003), this table examines the impact of the highest leader on employee absence by examining change in adjusted R squared when leader fixed effects are added to the model, and F statistics from joint significance tests on leader fixed effects. Panel A reports the results of our sample, and Panel B, C, D report the results of robustness checks of other samples.

| Panel A: Fixed effects test                            |                   |                             |
|--------------------------------------------------------|-------------------|-----------------------------|
| One highest leader                                     | W/o fixed effects | W/ fixed effects            |
| Observations                                           | 6003              | 6003                        |
| Adjusted $R^2$                                         | 0.203             | 0.227                       |
| F statistics                                           |                   | 200.41 ( $< 0.0000$ , 938)  |
| Panel B: Fixed effects test on raw sample              |                   |                             |
| One highest leader                                     | W/o fixed effects | W/ fixed effects            |
| Observations                                           | 7894              | 7894                        |
| Adjusted $R^2$                                         | 0.299             | 0.397                       |
| F statistics                                           |                   | 137.19 ( $< 0.0000$ , 1121) |
| Panel C: Fixed effects test on multi-industry sample   |                   |                             |
| One highest leader                                     | W/o fixed effects | W/ fixed effects            |
| Observations                                           | 7320              | 7320                        |
| Adjusted $R^2$                                         | 0.245             | 0.274                       |
| F statistics                                           |                   | 492.73 ( $< 0.0000$ , 1142) |
| Panel D: Fixed effects test on full-time worker sample |                   |                             |
| One highest leader                                     | W/o fixed effects | W/ fixed effects            |
| Observations                                           | 7532              | 7532                        |
| Adjusted $R^2$                                         | 0.252             | 0.279                       |
| F statistics                                           |                   | 49.78 ( $< 0.0000$ , 1181)  |

Table 8: The Impact of Leader Hospitalization on Employee Absenteeism

This table examines the impact of leader hospitalization on employee average absence.  $N$  days of hospital stay -  $t$ , is the number of hospitalized days for leader(s) in a given year.  $N$  days of hospital stay -  $t-1$  denotes the number of hospitalized days for leader(s) in a prior year. To address the right skewness, both employee absent days and leader hospitalization days are transformed with  $\log(1+X)$ . Hospitalized days between 1 and 4 is a dummy takes the value of 1 if leaders experienced a hospital stay of 1-4 days in a given year, and zero otherwise. Other two dummy variables, hospitalized days between 5 and 9 and hospitalized days above 10, are defined in the same way. Clustered (PU-leader) standard errors are shown in parentheses. \*\*\*, \*\*, and \* correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

|                                        | (1)                   | (2)                   | (3)                   | (4)                 | (5)                  | (6)                 | (7)                 |
|----------------------------------------|-----------------------|-----------------------|-----------------------|---------------------|----------------------|---------------------|---------------------|
| N days at hospital, $t$                | 0.0625***<br>(0.0038) | 0.0117***<br>(0.0034) | 0.0147***<br>(0.0045) | 0.0083*<br>(0.0049) |                      |                     |                     |
| N days of hospital stay btw 1 and 4    |                       |                       |                       |                     | 0.0097<br>(0.0088)   | 0.0111<br>(0.0098)  | 0.0104<br>(0.0097)  |
| N days of hospital stay btw 5 and 9    |                       |                       |                       |                     | -0.0042<br>(0.0160)  | -0.0192<br>(0.0172) | -0.0179<br>(0.0172) |
| N days of hospital stay at or above 10 |                       |                       |                       |                     | 0.0494**<br>(0.0218) | 0.0401*<br>(0.0242) | 0.0422*<br>(0.0236) |
| Obs.                                   | 104,570               | 104,570               | 104,570               | 104,570             | 104,590              | 110,820             | 113,552             |
| R-squared                              | 0.039                 | 0.514                 | 0.626                 | 0.677               | 0.677                | 0.729               | 0.731               |
| Sample                                 | Entire public         | Entire public         | Entire public         | Entire public       | Entire public        | Multi-industries    | Full-time workers   |
| Year FE                                | Yes                   | Yes                   | Yes                   | Yes                 | Yes                  | Yes                 | Yes                 |
| Industry FE                            | Yes                   | Yes                   | Yes                   | Yes                 | Yes                  | Yes                 | Yes                 |
| PU/CEO FE                              | None                  | PU                    | CEO                   | PU-CEO              | PU-CEO               | PU-CEO              | PU-CEO              |
| PU controls                            | Yes                   | Yes                   | Yes                   | Yes                 | Yes                  | Yes                 | Yes                 |

Table 9: Number of Movers Between Sectors

This table reports size of one-time movers. Panel A captures movers within and across private and public sectors, and Panel B captures movers within and across three major industries and all the other industries within public sector.

Panel A: Movers Between Private and Public Sectors

| Before  | After   |        |
|---------|---------|--------|
|         | Private | Public |
| Private | 85,075  | 7,170  |
| Public  | 5,688   | 90,581 |

Panel B: Movers Within the Public Sector

| Before       | After        |           |        |        |
|--------------|--------------|-----------|--------|--------|
|              | Public admin | Education | Health | Others |
| Public admin | 13,398       | 157       | 169    | 727    |
| Education    | 315          | 16,027    | 2,223  | 447    |
| Health       | 254          | 2,704     | 45,538 | 1,298  |
| Others       | 346          | 840       | 940    | 5,198  |

Notes: Presented in the table are aggregate values across 2010 - 2018

Table 10: Decomposition of Employee Absence

This table reports the decomposition of employee (both movers and nonmovers) annual absence by AKM model. Panel A is based on the estimation without the employee time-varying controls and panel B is based on the estimation including controls for age, wage, occupation and hospitalization. Each column defines a set of production units  $R$  and  $R_0$  based on percentiles of average absence. The first row reports the difference of average absent days overall between the two groups  $y_R - y_{R0}$ ; the second row reports the difference due to incentives  $\gamma_R - \gamma_{R0}$ ; the third row reports the difference due to selection  $\alpha_R - \alpha_{R0}$ ; the fourth and fifth rows report the share and SE of the difference in average absence between two sets of public units that is due to incentives. The last two rows report the share and SE of the difference in average absence between two sets of public units that is due to selection. The standard error of the share is calculated by bootstrap of 50 repetitions.

| Panel A: Entire public Sector Base                |                    |               |               |              |
|---------------------------------------------------|--------------------|---------------|---------------|--------------|
|                                                   | Above/below median | Top/bottom 25 | Top/bottom 10 | Top/bottom 5 |
| Overall                                           | 8.28               | 13.64         | 20.55         | 26.38        |
| Production unit                                   | 4.65               | 7.75          | 12.27         | 16.55        |
| Individual                                        | 3.63               | 5.89          | 8.28          | 9.83         |
| Production unit share                             | 0.56               | 0.57          | 0.60          | 0.63         |
| SE                                                | 0.02               | 0.02          | 0.02          | 0.02         |
| Individual share                                  | 0.44               | 0.43          | 0.40          | 0.37         |
| SE                                                | 0.02               | 0.02          | 0.02          | 0.02         |
| Panel B: Entire public Sector with Person Control |                    |               |               |              |
|                                                   | Above/below median | Top/bottom 25 | Top/bottom 10 | Top/bottom 5 |
| Overall                                           | 8.29               | 13.67         | 20.59         | 26.41        |
| Production unit                                   | 4.40               | 7.32          | 11.54         | 15.82        |
| Individual                                        | 3.89               | 6.35          | 9.05          | 10.59        |
| Production unit share                             | 0.53               | 0.54          | 0.56          | 0.60         |
| SE                                                | 0.02               | 0.02          | 0.02          | 0.02         |
| Individual share                                  | 0.47               | 0.46          | 0.44          | 0.40         |
| SE                                                | 0.02               | 0.02          | 0.02          | 0.02         |

## IX Figures

Figure 1: Absenteeism, Wage, IQ of Public and Private Sectors

This density plot presents the average absent days, annual income and IQ of employees and leaders in public and private sectors.

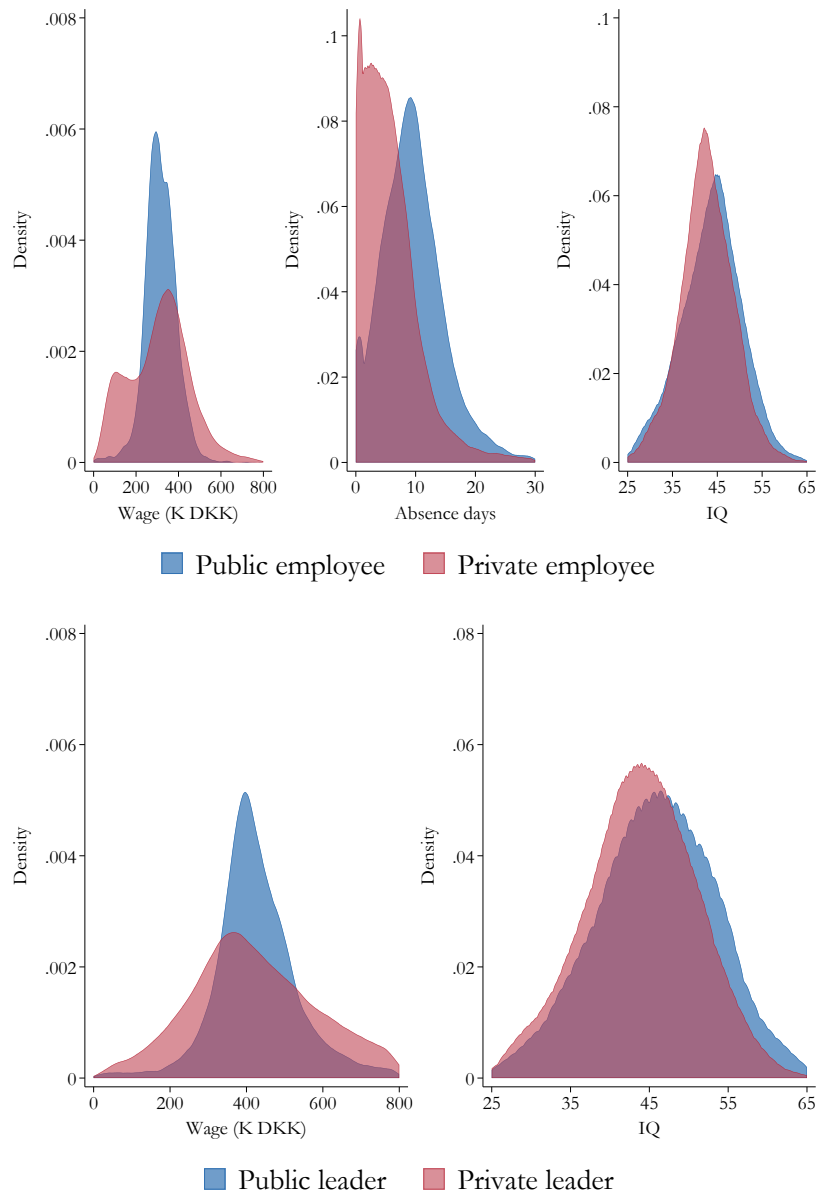


Figure 2: Absenteeism and Output Quality or IQ

This line chart presents the average absent days of employees and leaders for each percentile group as a function of output quality (Panel A) and IQ (Panel B).

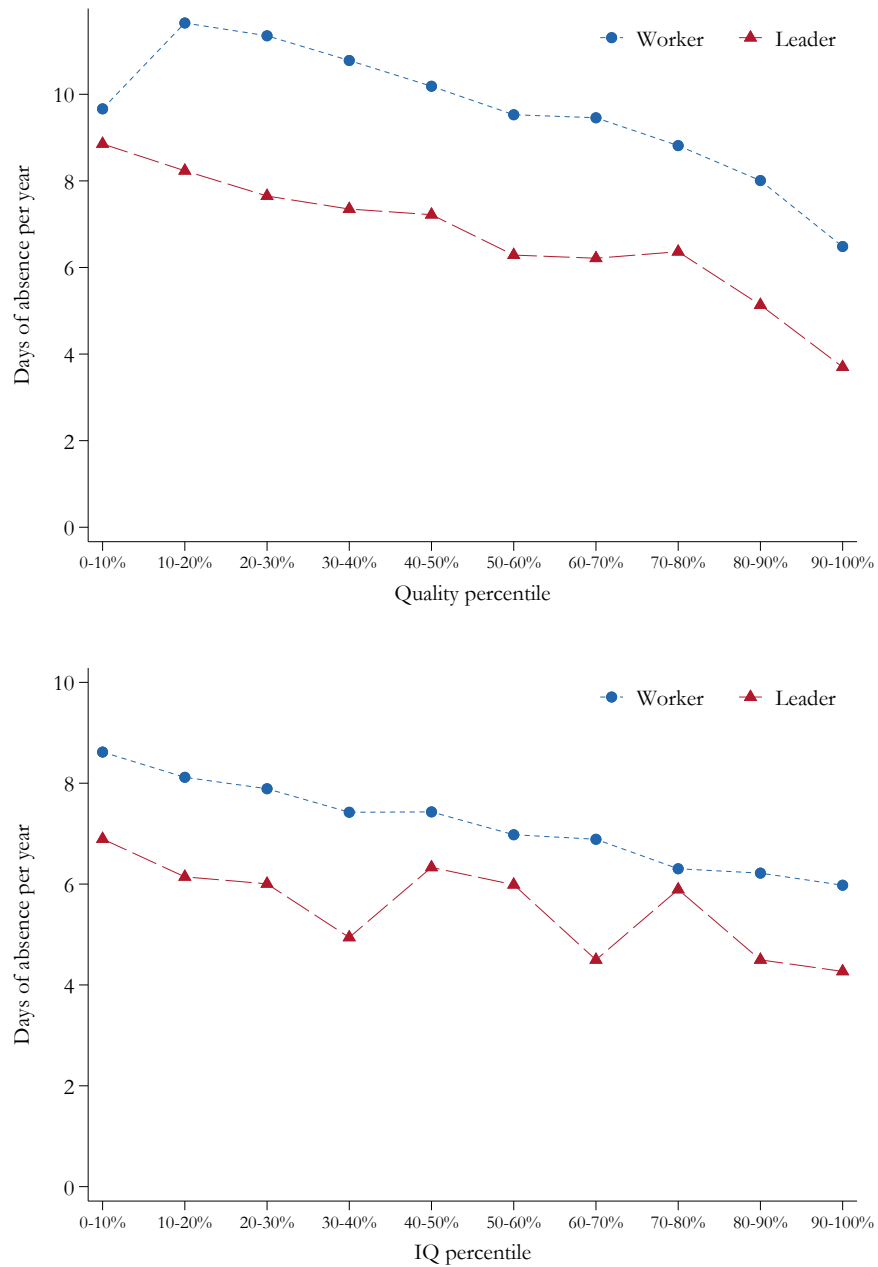


Figure 3: Hospitalization and Absenteeism

This line chart presents the average annual absent days and hospitalized days of all employees (both workers and leaders included) by different age groups, which respectively represent all employees between 20 and 65 years old (solid line), employees between 20 and 45 years old (dash-dot line) and employees between 45 and 60 years old (dash line).

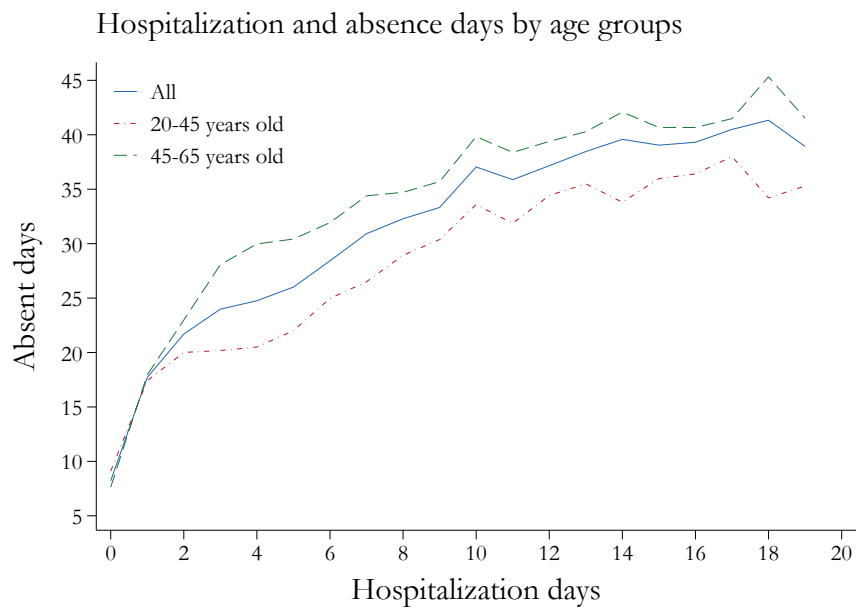
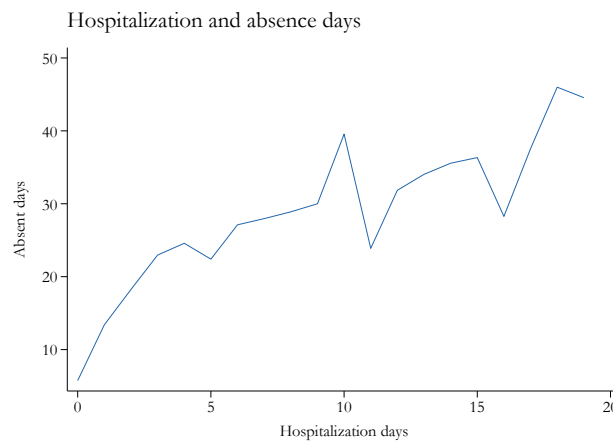


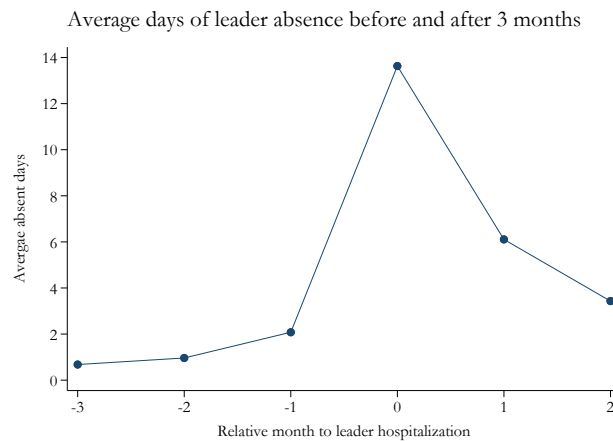
Figure 4: Leader Hospitalization and Leader Absenteeism

Panel A presents in the public sector the average annual absent days of leaders when their annual hospitalization varies. Panel B presents the leaders' average absent days per month (28 days) before and after hospitalization event. On the X-axis, relative month denotes 28-day-windows relative to the leader hospitalization, such that month 0 represents day 1 to day 28 relative to the hospitalization starting day. Panel C shows the absenteeism within different leader hospitalization duration subgroups, which respectively represent duration between 1 to 4 days (blue line), 5 to 9 days (red line), and above 10 days (green line).

Panel A: Leader's hospitalization and absenteeism



Panel B: Absenteeism before and after hospitalization



Panel C: Absenteeism before and after hospitalization by age groups

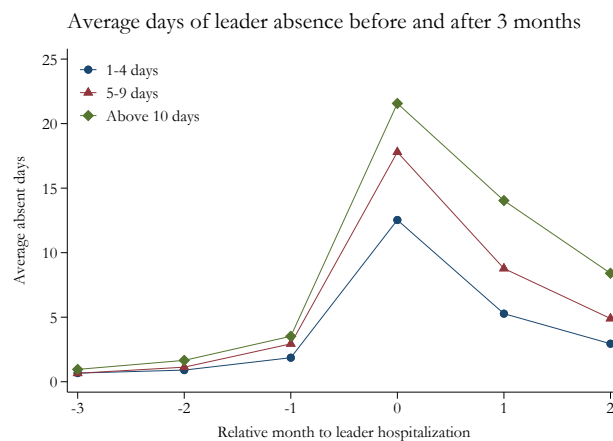


Figure 5: Leader Hospitalization and Employee Absenteeism

This figure presents the employees' average absent days per month (28 days) before and after leader hospitalization event. Red line represents leaders who experienced actual hospitalization, with blue line serving as the counterfactual group in which leaders experienced no hospitalization. On the X-axis, each month denotes a 28-day-window relative to the leader hospitalization starting day, such that relative month 0 represents day 1 to day 28 relative to the hospitalization starting day.

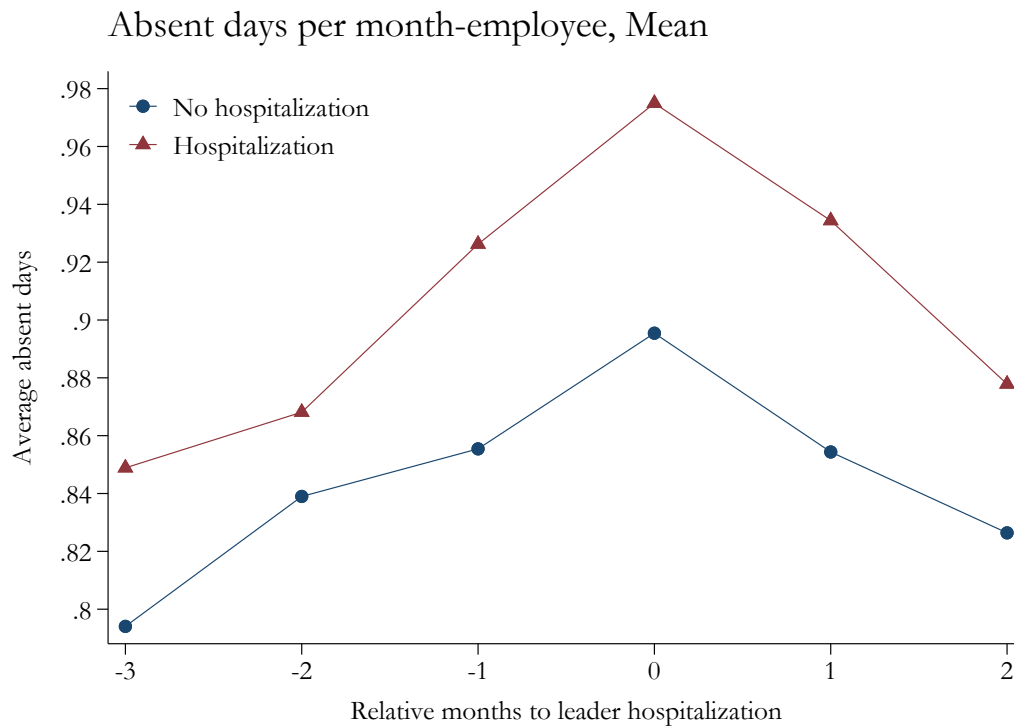


Figure 6: Leader / PU Characteristics and Average Absence

The figure presents multivariate OLS regression results of production unit average annual absence and a set of leader - and PU - level characteristics, using the full public sector sample. All covariates (except dummies) are standardized to normal distribution. Horizontal bars show 90% confidence intervals.

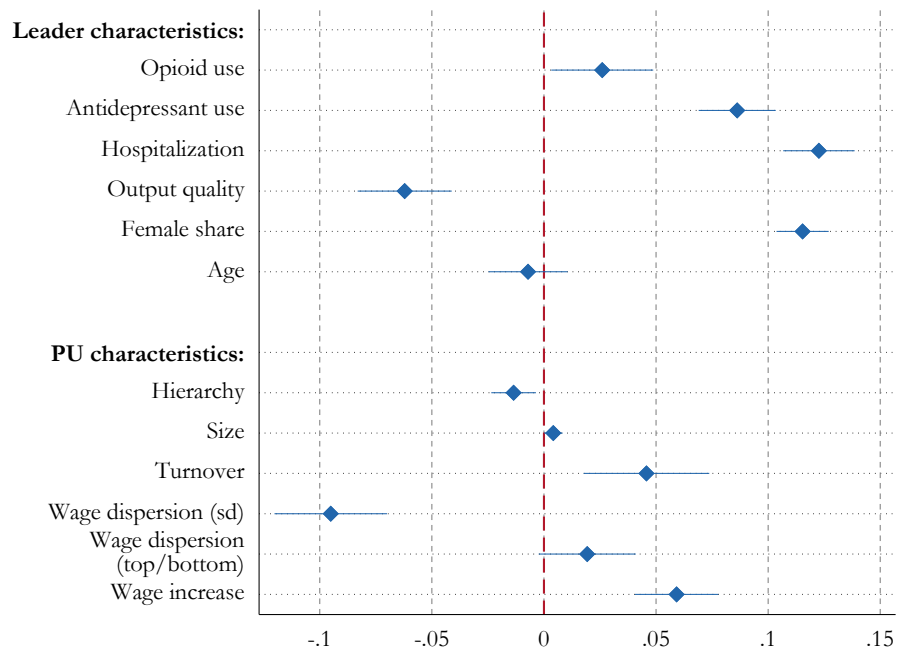


Figure 7: Change in Absent Days

The binscatter plots show the change in annual absent days of once-movers before and after the unit move. For each mover, we calculate the difference in average absence between their origin and destination public units. The x-axis displays the difference of production units the movers move between, and the y-axis shows for movers themselves, the difference of average absent days post-move and pre-move. The line of best fit is obtained from simple OLS regression. Panel A excludes the two moving years of once-movers, while Panel B includes them.

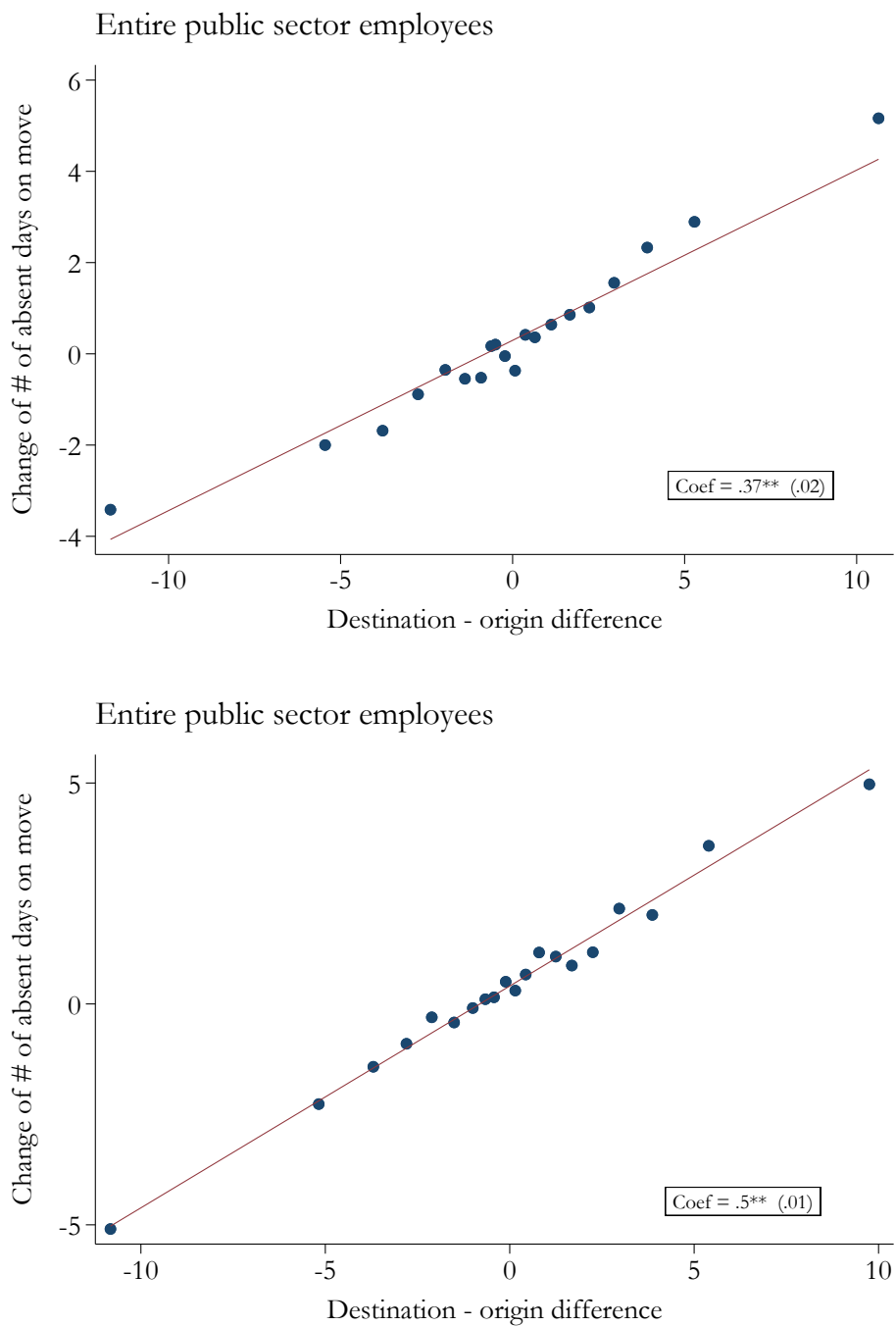


Figure 8: Distribution of Difference in Absent Days among Once-Movers

The histograms show the distribution of difference in terms of mean absence between public units. For each mover, we calculate the difference of average employee absence between their origin and destination. Panel A excludes the two moving years of once-movers, while Panel B includes them.

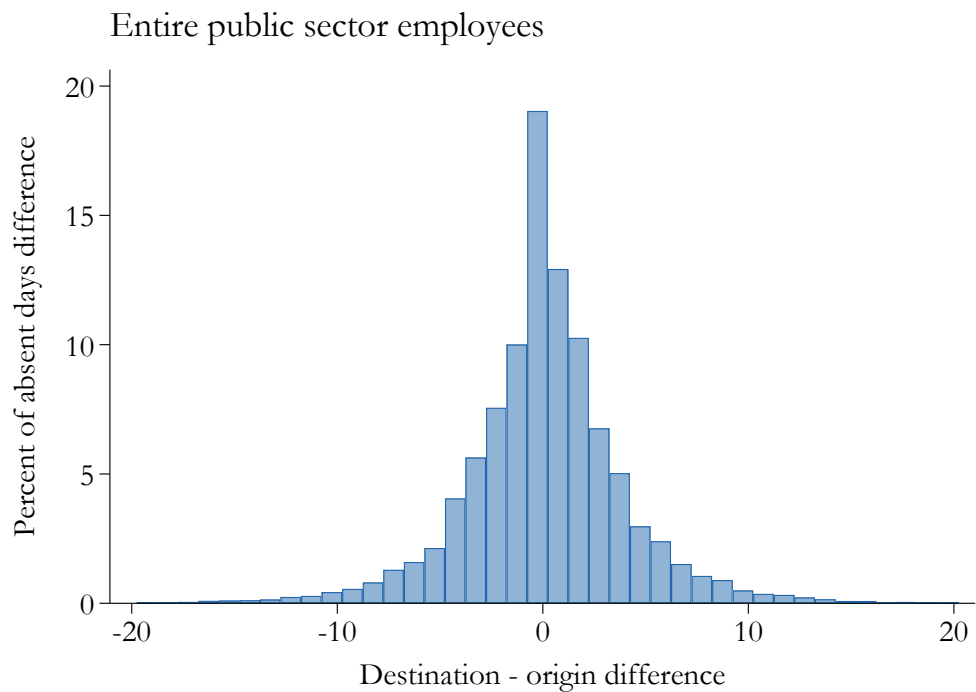
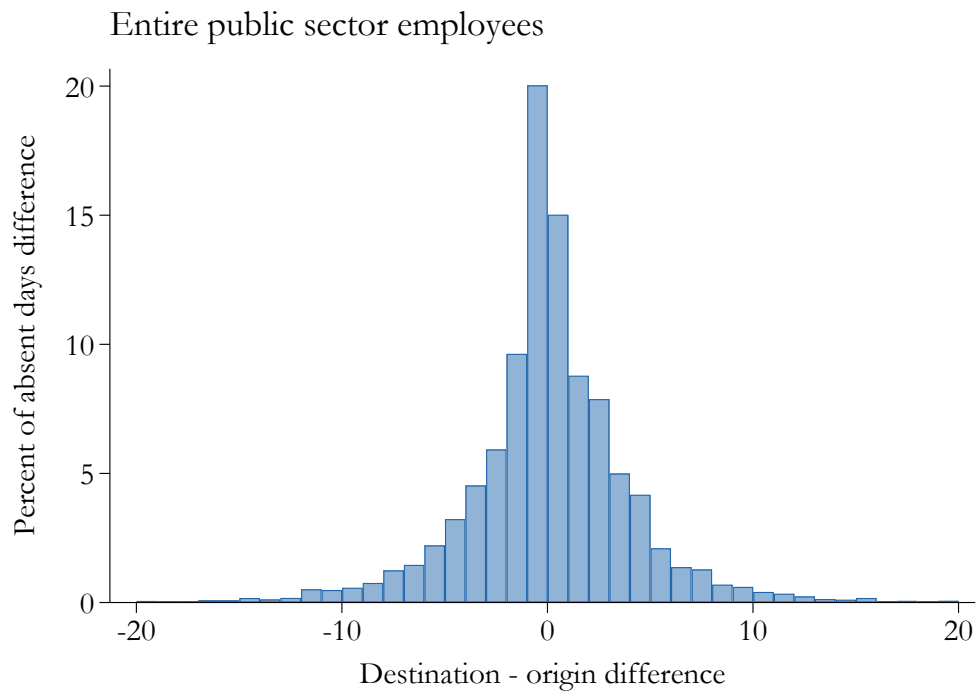


Figure 9: Event Study

This figure shows the fraction of the gap in absenteeism between the origin and destination firms that the employee moves each year, after controlling for individual characteristics and time fixed effects. It corresponds 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.

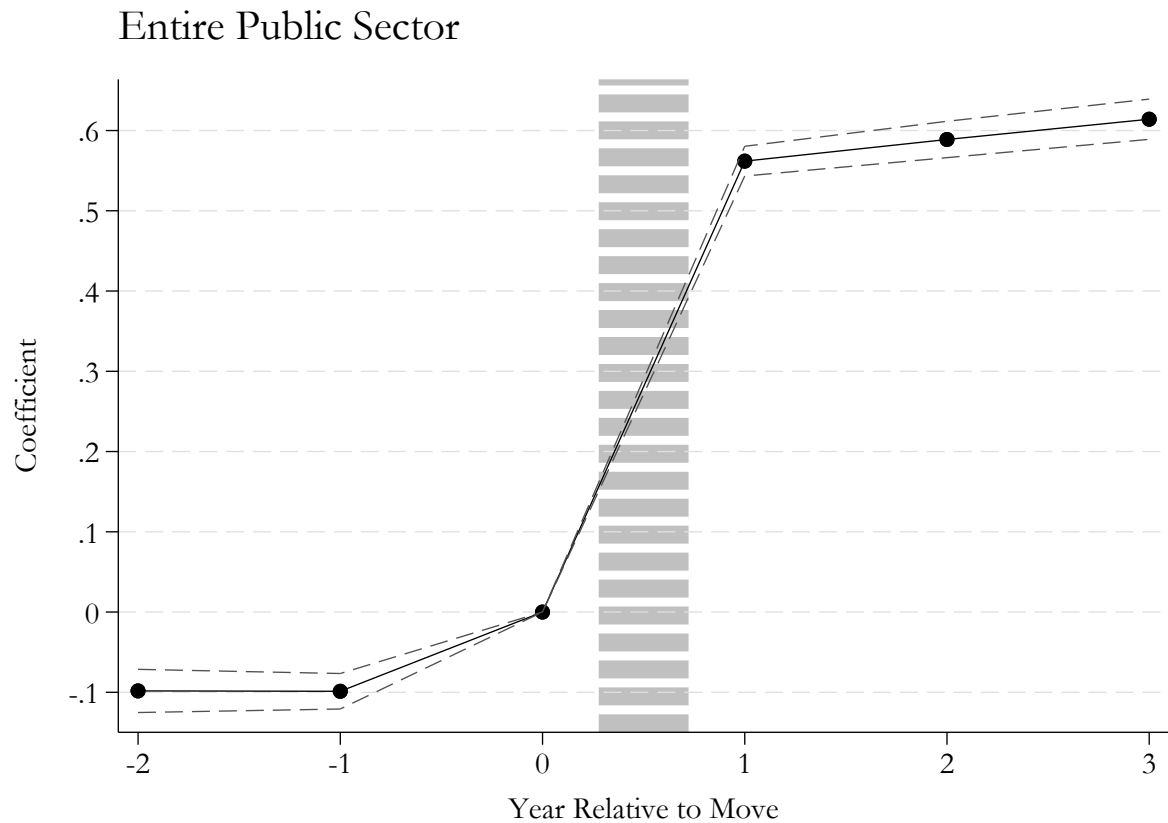


Figure 10: Leader / PU Characteristics and Average Absence - Detrended Total Absence

The figure presents multivariate OLS regression results of production unit average annual absence (estimated by AKM model) and a set of leader - and PU - level characteristics, using the full public sector sample. All covariates (except dummies) are standardized to normal distribution. Horizontal bars show 90% confidence intervals.

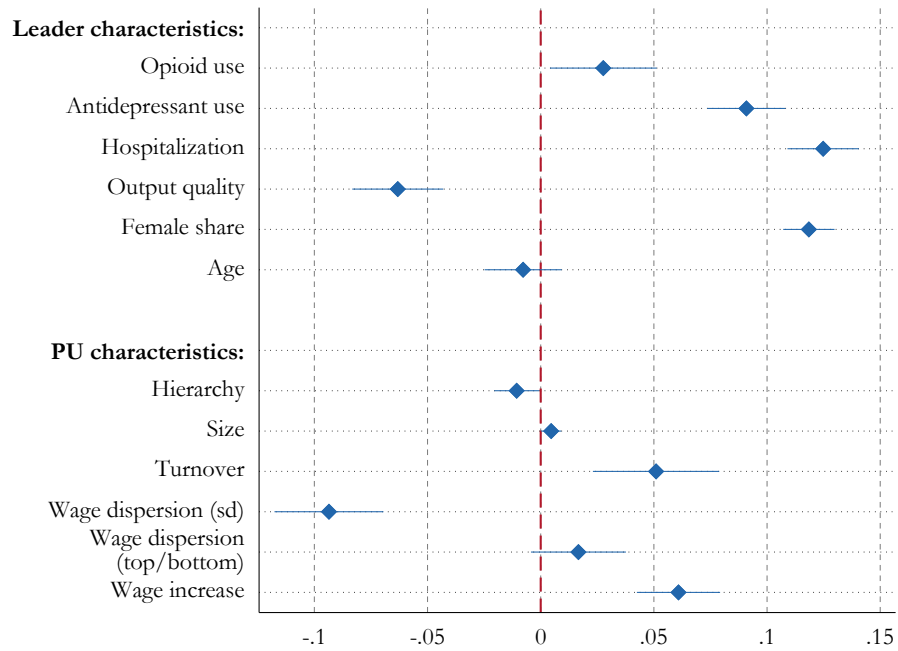


Figure 11: Leader / PU Characteristics and Average Absence - Individual Share

The figure presents multivariate OLS regression results of individual share of absence (estimated by AKM model) and a set of leader - and PU - level characteristics. All covariates (except dummies) have been standardized to have mean zero and standard deviation one. Horizontal bars show 90% confidence intervals. The specifications are the same as of Figure 10.

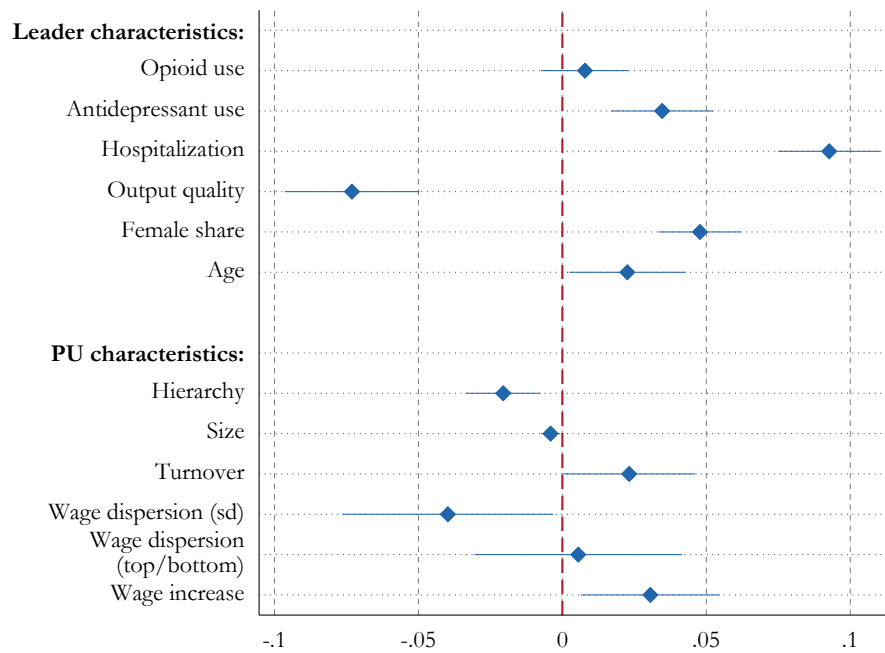


Figure 12: Leader / PU Characteristics and Average Absence - Production Unit Share

The figure presents multivariate OLS regression results of production unit share of absence (estimated by AKM model) and a set of leader - and PU - level characteristics. All covariates (except dummies) have been standardized to have mean zero and standard deviation one. Horizontal bars show 90% confidence intervals. The specifications are the same as of Figure 10.

