Workforce Adjustment in Frictional Markets: Evidence from Unexpected Separations

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Resumen

Este estudio tiene como objetivo entender cómo las empresas ajustan su fuerza laboral ante separaciones imprevistas en un contexto de mercados laborales con fricciones. Utilizando datos de la Seguridad Social de Uruguay para el período 1997–2022, la investigación utiliza muertes imprevistas de trabajadores para estimar efectos causales. La estrategia empírica se basa en un análisis de estudio de eventos, en el cual los grupos de control se seleccionan mediante Propensity Score Matching. Los resultados son consistentes con la existencia de fricciones en el mercado laboral, donde los ajustes se realizan tanto en el margen extensivo (contrataciones) como en el margen intensivo (empleados existentes). Se encuentran resultados heterogéneos según la posición vacante, en línea con la literatura sobre capital humano. Se realizan diversas especificaciones de robustez, que confirman los resultados obtenidos.

Palabras clave: Mercado laboral con fricciones, Capital humano; Uruguay; Ajuste de empleo; Separación de puesto de trabajo

Abstract

This study aims to understand how firms adjust their workforce in response to unexpected separations in a context of frictional labor markets. Using Social Security data from Uruguay from 1997 to 2022, this research exploits unexpected worker deaths to estimate causal effects. The empirical strategy relies on an event study analysis where controls are selected through Propensity Score Matching. Results are consistent with frictional labor markets, where adjustments are made on the extensive (hiring) and intensive (incumbent) margins. Heterogeneous results are found according to the position of the deceased, in line with human capital literature. Several robustness specifications are performed, confirming the results.

Keywords: Frictional labor markets; Human capital; Uruguay; Employment adjustment; Worker Separations.

Contents

1 Introduction

The strategies firms employ to cope with unexpected workforce separations are central to understanding labor market frictions. This paper provides a causal analysis of this, by leveraging the exogenous shock of worker deaths to identify how firms adjust to sudden vacancies.

Some theoretical labor market models assume frictionless adjustments, where vacancies can be filled instantly and at no cost. In such models, firms would simply replace a worker with another, and the vacancy would not result in any disruption. However, empirical evidence suggests that labor markets are far from frictionless, with search and matching costs, skill mismatches, and informational asymmetries playing critical roles (Pissarides, 2000; Manning, 2011). These frictions affect not only how firms hire but also how wages are determined and how tasks are distributed within organizations.

This study builds on a growing body of literature that examines how firms adapt to workforce disruptions. Jäger and Heining (2022) analyze the impact of unexpected worker deaths on firms in Germany. They find that although a hiring response is triggered, there are also changes for incumbent workers. Using this information they quantify high replacement costs for firms, with differences depending on worker characteristics related to human capital.

In addition to studies on worker deaths, research has explored other forms of workforce disruptions. Brenøe et al. (2025) and Brenøe et al. (2024) find through analyzing parental leaves that the anticipation aspect mitigates this, something reinforced by the work from Ginja et al. (2022), where unanticipated changes on parental leaves indeed trigger negative responses.

While previous research provides valuable insights, most of the evidence comes from developed economies with relatively thick labor markets and advanced institutional frameworks. Little is known about how firms in developing countries, such as Uruguay, respond to similar disruptions. Uruguay's labor market presents unique characteristics, including strong formal employment protections, high unionization rates, and collective bargaining mechanisms.

This study seeks to fill this gap by examining how firms in Uruguay adjust their workforce in response to unexpected separations. The analysis uses matched employer-employee data from Uruguay's social security records, covering the period from 1997 to 2022. The identification strategy uses the exogeneity of worker deaths, ensuring that the observed separations are not influenced by firm-driven decisions or voluntary quits. This allows for a detailed causal examination of firm-level responses and individual-level impacts, including changes in employment, wages and firm survival.

The main findings confirm that the Uruguayan labor market shows significant frictions, as firms turn to internal reorganization, including increasing salaries, rather than relying solely on hiring new workers as an adjustment mechanism. The total number of employees increases by around 5% after treatment, which accounts for less than one extra worker. Both the total wage bill and the average salaries increase, aligned with the rent-sharing mechanism explored by Jäger and Heining (2022).

Heterogeneous results are found depending on the position of the deceased within the firm. This includes higher probabilities of closing for firms with deceased bosses which are mitigated by higher salary increases.

The following sections are organized as follows: Section 2 discusses the related literature, Section 3 moves onto the theoretical framework of the study, Section 4 presents the research question, hypothesis and empirical strategy. Finally, Section 5 discusses the main results and Section 6 concludes. An appendix can be found relating to the main figures and results and a second appendix includes all additional tables.

2 Background

The most relevant previous research related to this study has been done by Jäger and Heining (2022). It estimates the causal effects of workers exits by leveraging a quasi-experimental design based on workers deaths and then uses this information in a structural model to calculate implied replacement costs of workers. The main causal findings include an increase in both incumbent wages and their employment at the same firm as well as additional hiring. These results do not align with a frictionless labor market framework in which workers are perfect substitutes and therefore there should only be additional hiring. With this in mind, Jäger and Heining (2022) move on to estimating a structural model where they find high replacement costs and marginal costs of hiring that increase with the hiring rate. This relates back to the adjustments seen in other areas besides hiring. Moreover, their results are heterogeneous according to the specific human capital of workers, providing evidence that human capital can raise rent sharing between the firm and the worker. Besides the fact that this investigation heavily relies on a similar empirical strategy, this paper is relevant as it discusses and shows evidence of how firms are affected by a worker's exit and how this relates both to the human capital and replacement costs literature.

As the seminal paper from Becker (1962) proposes, human capital can be thought of as having a general and a specific component. The first one is broadly useful as it increases productivity at any firm. On the other hand, firm-specific human capital raises the productivity of the worker at the current firm only. This implies that the worker will be the one bearing the costs of training for the general component while firm-specific human capital costs would be shared. The human capital literature relates to the question this study aims to answer, as it seeks to better understand, among other things, the role of human capital in wages and why the end of an employment spell can have negative long-lasting effects on workers' wages. Amarante et al. (2014) explore the worker's perspective and find that for high-tenured displaced workers in Uruguay, their wage losses are around 48% on the first quarter after the event, compared to pre-displacement, 8% a year later and still persistent after 5 years, accounting for around 3%.

The human capital framework is expanded by Lazear (2009), proposing a skill-weights model. The general idea is that the skills needed can be generally applicable in any firm but that the way in which they are combined (the weights assigned to each skill) is specific. For the author, this is a better approximation to the available empirical evidence, as workers in thicker labor markets will be less impacted by a change of firm while wage loss will be greater for workers who are part of thinner labor markets. Although this framework is developed with supply-side in mind, from a demand perspective, the exit of a worker with a high level of specific training can also have a negative impact. This aligns with the findings from Jäger and Heining (2022) since the cost of replacing workers is higher if the lost skills are more idiosyncratic, therefore increasing the incumbent wage premium as the importance to retain those workers raises.

Another extension, based on Lazear (2009) is done by Deming and Silliman (2024), where the importance of higher-order skills is highlighted. These skills are defined as capacities that guide workers into making choices, applying knowledge and interacting with others. This includes social skills useful for teamwork as well as decision-making. The authors argue that this type of human capital is generally overlooked but is actually very important and that the firm-specificity component is aligned with what Lazear (2009) proposes. Taking this into consideration means understanding that if a worker exits a firm, this will change the dynamics inside it. A worker who has an essential role in communicating different teams or in making decisions will not be easily replaced.

Studies on large supply-shocks can help understand these heterogeneities present in different replacement situations. Dicarlo (2022) leverages a labor reform in Switzerland to study this as a negative supply shock at the Italian border. The study finds negative effects both in terms of productivity and wage for high-skill intensive firms, attributed to imperfect substitutability of replacement workers. On the other hand, low-skill intensive firms suffer less and easily replace workers, even providing opportunities for disadvantaged workers. This example aligns closely with the findings from Jäger and Heining (2022) and with the broader literature on specific human capital previously discussed.

A different way to study how firms adapt to worker's exits is to look at parental leaves. Brenøe et al. (2024) look at the Danish case and their findings show that firms adapt well to the shock in employment supply. The compensation is done both through the extensive and intensive margins, with new employees and higher hours and retention rates for incumbents in the same occupation. This is again evidence of the importance of specific human capital since workers from different occupations do not experience significant effects. Moreover, firms with no other employees in the same occupation actually experience negative impacts (lower total wage bill and hours and fewer hires), which the authors discuss as a consequence of not being able to exploit the intensive margin. A similar approach is taken to study maternity leave on Austrian firms and the results are analogous (Brenøe et al., 2025).

Both studies mentioned explain these results in light of the anticipation effect. Firms adapt well to the shock in labor supply because they have enough time to plan the replacement accordingly. This conclusion is reinforced by a similar study that looks at a parental reform. Ginja et al. (2022) take advantage of a Swedish reform from 1989 that suddenly expanded parental leave for an additional three months. Workers who were already on leave could request it and employers had to grant it. This setting is therefore different because it lacks the anticipation component, replacing it with a short-notice of a shock in labor supply. In this case, researchers find an increase on the total wage bill, which had remained unchanged for the other studies. Moreover, Ginja et al. (2022) find that the responses on the extensive and intensive margins vary depending on the conditions of the labor market. For firms in thick external labor markets, their strategy relies predominantly on hiring, while on thin labor markets they increase incumbent hours. This shows the importance of the anticipation of the shock as well as the impact of different combinations of human capital on replacement strategies.

The use of deaths as source of exogenous variation has been exploited in other studies besides Jäger and Heining (2022). Fietz and Schmeißer (2024) use worker deaths to study the effect of sudden changes in racial peer composition on retention of incumbent workers, for the case of Brazil. They find that a decrease in the share of non-white coworkers negatively affects the retention of non-white incumbents. These results are heterogeneous depending on the occupation and tenure of groups. A different study for the Brazilian labor market examines hiring decisions and replacement wages after a worker death, focusing instead on gender inequality (Britto et al., 2022). Besides the identification strategy, these investigations show the impact a worker exit can have on the remaining coworkers and how the process of replacement changes according to the characteristics of the position and of who will occupy it.

Moreover, Azoulay et al. (2010) use the quasi-experimental variation to study the impact on the deceased's co-authorship networks. They find that a collaborator of a deceased academic superstar experience a lasting decline in their publication rates of between 5 and 10%. This suggests that the superstar was an irreplaceable source of ideas which relates to several points raised before. The positions occupied by the deceased are comparable to those of managers, allowing to make the link between this and the negative effects of manager's exits previously discussed. This also relates to the soft-skill and collaboration points raised by Deming and Silliman (2024).

On a similar note, Lee et al. (2020) and Kuang et al. (2022) use deaths as an exogenous variation to study different impacts on CEOs and firms. The first one investigates the link between founder CEOs and innovation and finds that when (due to a sudden death) a firm transitions from a founder to a professional CEO, in the new setting the firm is less innovative. One interesting finding is that in this new setting the firms also lost their most innovative employees, relating back to the idea of the importance of collaboration. Kuang et al. (2022) looks at an indirect effect through grief. The death of a colleague generates a pessimistic effect on management forecasts from CEOs. This is relevant as it studies the emotional response and its effects on the firm, something that could also be behind some results that will be discussed later.

The points raised by the reviewed literature motivate this study's aim to to examine the firm's perspective on a match separation, as part of a larger question of understanding how frictional labor markets affect the matching process in the Uruguayan case.

3 Theoretical Framework

Contrary to the classical labor market model where adjustments are predicted to be instantaneous and frictionless, real-world labor markets are characterized by frictions that make adjustments non-automatic, costly, and time-consuming (Pissarides, 2000). These frictions are best characterized in the framework of the search and matching model and are empirically validated by micro-data studies as discussed in the previous section.

In search and matching models, the interaction between firms and workers results in equilibrium outcomes for job vacancies, employment, and wages. The process of job creation is inherently costly for both sides. Firms face uncertainty when offering a position, and workers incur an opportunity cost by accepting an offer and foregoing potentially better jobs. Due to these frictions, monopolistic rents result from job creation (i.e., when positions are filled) (Manning, 2011). Wages depend on how these rents are split, which is mediated by the worker's outside option, job productivity, and the bargaining power of each party.

The labor market tightness (the ratio of vacancies to unemployed workers) dictates this dynamic. Higher tightness benefits workers, strengthening their bargaining position and leading to higher wages; a slack market gives firms greater leverage, resulting in lower wages. This mechanism implies that the cost of adjustment is intrinsically linked to external labor market conditions, something that has also been tested at the micro-level.

An important source of friction, particularly in the context of this study, is the imperfect substitutability of workers, linked to different levels of human capital. As discussed, the human capital framework proposed by Becker (1962) distinguishes between general and specific human capital. The skill-weights approach proposed by Lazear (2009), expands this, arguing that the specificity is not based on the skills themselves but rather on the particular way of combining them according to the needs of the firm. This idiosyncratic combination is what makes it harder to find a new match both from the worker's perspective (find other firms that will need skills combined in the same way) as well as from the firm's perspective (find workers that already have mastered the skill combination).

Imperfect substitutability makes replacement costly. The fact that firms respond to an exit by adjusting incumbent worker compensation rather than relying on hiring provides evidence of this. In this context, several models have been developed to try to quantify such costs. Jäger and Heining (2022) build on a wage posting model proposed by Kline et al. (2019) and find that rather than having constant hiring costs, which would be consistent with a frictionless labor market, hiring costs are convex. This means that they increase with additional hiring. As a consequence, the incumbent wage premium is a function of the marginal hiring costs. It is important to note that they attribute the consideration of incumbent salaries to their higher estimates, compared to previous results. Their estimates of marginal replacement cost is on the order of magnitude of about two annual salaries of a deceased worker, compared to approaches using only explicit costs declared by firms, which are closer to one month of a worker's pay.

The rise in incumbent salaries is explained by the fact that the match between a firm and a worker generates a rent that is divided according to the bargaining power of each agent. This power increases for employees in the context of a coworker's unexpected exit, as they become more valuable to the firm. This allows them to capture a bigger portion of the rent, increasing their salaries.

Moreover, Lazear (2009) framework predicts that wage loss is greater for workers in thinner labor markets because it is harder to find a new firm with closely matching skill weights. Jäger and Heining (2022) confirm this, finding that replacement costs are roughly twice as large in thin labor markets compared to thick ones. This is explained by the change in wages required to retain an additional worker is substantially larger in thin markets, showing how market thickness mitigates the friction of imperfect substitutability.

4 Empirical Strategy

4.1 Research Question and Hypothesis

This study aims to understand how firms reorganize their workforce following unexpected job separations in frictional labor markets. Specifically, it examines how firms adjust employment levels, average wages, total wage bill, as well as the likelihood of closure after the unanticipated loss of a worker. In addition, the study explores how incumbent workers are affected by these shocks, tracing their subsequent employment paths within or outside the affected firms. By leveraging worker deaths as a source of exogenous shocks, the analysis quantifies the impact of an unexpected vacancy on various firm-level outcomes, providing insights into the strategies firms may use to overcome such disruptions. The motivation, as discussed earlier, stems from the literature on frictional labor markets.

The first hypothesis is that following an unexpected worker separation, overall employment at the firm level is expected to increase, but not on a one-to-one replacement basis. On average, treated firms adjust to the shock both by hiring new workers and through internal reorganization. Because workers are not perfectly substitutable and firms face uncertainty when hiring new employees, they tend to respond by reallocating tasks and increasing incumbent workers' hours rather than fully replacing the lost worker immediately.

The second hypothesis is that the salaries of incumbent workers will increase in response to the shock. After the unexpected separation, remaining employees become more valuable to the firm, as the cost of replacing an additional worker would be even higher. This effect is expected to be stronger in the selected sample, firms with fewer than 50 employees, where workforce flexibility is limited and each worker plays a more critical role in production.

The third hypothesis is that the effects of an unexpected separation will be heterogeneous, depending on the nature of the position left vacant. In particular, when the deceased worker held a hierarchical position, the negative effects on the firm are expected to be larger, as firms will face greater difficulties filling the gap. This is consistent with the literature on specific human capital, which highlights the higher replacement costs and organizational disruptions associated with such roles. Consequently, under the chosen definition of bosses, the likelihood of firm closure is expected to increase, given the central role these positions play in coordination and decision-making.

4.2 Empirical Strategy

4.2.1 Sample Selection

The study uses matched employer-employee data from the Uruguayan social security (BPS) between 1997 and 2022, which covers all formal employment for the country in the period [1]. The data from the employees includes information on monthly wages, weekly worked hours and monthly days worked [2]. Information on the type of contract (daily, monthly, etc) as well as the functional link (employee, boss, owner, among others) is present as well. It also includes information on when an employment spell starts and ends and the reason for it. Finally, from the employees side sex and date of birth are also included[3]. Besides an individual identifier the records also have a firm identifier that allows to group employees by firm. The only firm variable used that is not derived from individual results is sector.

At baseline, all firms need to have over 5 and under 50 employees to be able to study the shock properly and firms from the public and construction sector are excluded due to their particular dynamics. An important note is the definition used for someone to be counted as part of the firm. The person needs to either be an employee (monthly or daily worker) or a boss. Bosses are defined as those declared as directors, owners or managers who work in the company. This definition essentially excludes board members with no activity and follows the approach used by Ceni et al. (2025) for this database. Moreover, they need to have worked in the company for at least 3 months for daily workers, they need to have an average 3-month mobile salary equal or higher to the national minimum wage to be considered part of the firm.

Firms report to social security different reasons for ending an employment spell. Among the possible reasons, there is a category stating the spell ended due to the death of the employee; this is used to identify treated firms. Since this study is aiming to understand how the exit of an employee affects both the firm as a whole and the employees' coworkers, this identification strategy provides a clear exogenous shock. Looking at employment spells that end because the employee quit could include endogeneity on the reasons for the decision as well as a leaving notice from the employee or even a suspicion from the firm, which could make the company take action (such as increasing salaries of other important employees or redistributing tasks). A similar scenario could happen if the cases considered were when the employee

[1] Formal work accounts for 70% of total employment at the beginning of the period, reaches a minimum of 59% in 2004 and then raises again, reaching 88% in 2022 (Perazzo, 2001; Carrasco et al., 2018)

[2] Based on information on hours worked per week and days worked per month we construct monthly hours. For those with missing information only on days, we assume a full month was worked. For those with information on days worked but not on hours, we assume an 8-hour workday. Finally, for those without information on any, we use the average of days or hours worked on the same firm by other employees.

[3] A shortcoming from this database is that information on occupation within the firm is not available.

was fired. Therefore to ensure exogeneity as well as a clear event, employee's unexpected deaths are considered.

For the treated sample only employees under 60 years old are considered, with only one full time position (over 120 hours per month in only one firm). The person needs to either be an employee (monthly or daily worker) or a boss. For both bosses and employees they need to have a positive salary and a tenure of at least 6 months.

Since the event needs to be unexpected, the sample should not include those who experienced a long sickness spell. In the Uruguayan Social Security regime, doctors can justify paid sick leave for up to 90 days, after which they need to go through a board of doctors from the Social Security Agency (Amarante and Dean, 2017). Therefore we take 90 days as the threshold from which a sickness spell is considered long. Information for those covered by social security due to illness is not available for the whole period. As a proxy, a salary ratio is created, relying on the fact that health benefits don't fully cover the employees salary when absent. The ratio is defined as the average salary on the semester before death over the average salary on the 6 months previous to that, meaning months 7 to one year before the event. Only employees whose salary did not drop more than 30% between the two semesters (ratio > 0.7) are included in the sample. A robustness exercise is performed for the years with the full health information available. Moreover, only employees under 60 years old are considered, with only one full time position (over 120 hours per month). The person needs to either be an employee (monthly or daily worker) or a boss with a salary and must have tenure of at least 6 months. Finally, firms with two deceased workers within the treatment window are excluded.

To construct the control group, a one-to-one propensity score matching is performed at a baseline point defined as 6 months before death, following a similar strategy to Jäger and Heining (2022). Worker-firm pairs are selected from firms that did not experience a death but had lagged characteristics similar to those in the treatment group in the semester previous to the event. The PSM considers both employee and firm characteristics to find a similar non-deceased employee in a similar firm at the same month and year. The PSM includes employees age, tenure group, whether it is a daily worker, sector, percentage of females in the firm and both person and company percentiles[4]. Both variables are calculated in terms of the whole population of firms that have over 5 and under 50 employees and are not from the public or construction sector and those considered employed in a firm are selected in the same way as in the treatment group. The employees are assigned to a percentile based on their salary 3-month mobile mean and compared to all other employees in all the firms for the same month and year. Company deciles are

[4]The tenure groups are up to 3 years, between 3 and 7 years and over 7 years

based on the average firm salary. In both cases the sample is more concentrated on the higher part of the distribution. Because of this, the dummies included are 20%, 40%, 50%, 60%, 65%, 70%, 75% 80%, 85%, 90% and 95% for person percentiles and 20%, 40%, 60%, 70%, 80%, 80.5%, 90%, 92.5%, 95% and 97.5% for company ones[5]. Finally, the regression also includes exact matching for month, year, sex and whether the person is or not a boss, as this is a very important variable for the analysis. Treated firms can be controls outside of the treating period, defined as 2 years before and 5 years after treatment[6].

To summarize, the treatment unit is the firm and the identification strategy is the unexpected death of an employee.

Table 1 shows general firm characteristics for the treated sample, the full pool of potential control firms and the selected control sample. Similar employee-level characteristics are presented in Table 2. To test mean differences, t-tests are performed and p-values are reported. Although in both tables these tests are significant for several variables, looking closely the differences do not seem economically significant. As these descriptive tables show, after applying the selection criteria, there are 2200 treated firms, each one paired with a selected control.

Table 1: Firm-level Descriptives

Controls	Potential Treated	Controls	P-value	
Total Employees	12.61	14.97	14.43	0.076
Percent Female	38.53	31.36	28.53	0.000***
Number of Workers	5.74	12.07	11.60	0.083
Number of Bosses	0.48	1.20	1.13	0.018*
Number of Daily Workers	0.82	3.48	3.26	0.255
N	5908375	2200	2200	

Table 2: Individual-level statistics

	Incumbent Control	Incumbent Treated	t-test Incumbent	Deceased Control	Deceased Treated	t-test Deceased
Mean Age	39.32	39.22	0.403	44.37	44.8	0.218
Mean Monthly Earnings	33538.54	34816.05	0.000***	43575.77	43039.59	0.847
Mean Tenure (years)	5.84	6.06	0.000***	6.99	7.08	0.705
Mean Monthly Hours	163.38	162.19	0.001***	176.67	173.78	0.000***
Percent Female	30.1	33.24	0.000***	18.09	18.09	1.000
N	25885	27061		2200	2200	

4.2.2 Empirical Approach

Two separate sets of results are estimated: Firm-level outcomes and incumbent worker outcomes.

[5] In both cases this means for instance, up to 20%, between 20% and up to 40%, etc.

[6] A probit exercise performed with treated as the dependent variable can be found in Table A.1

Firm-level outcomes. Following Jäger and Heining (2022), the equation to estimate firm-level outcomes is the following:

$$y_{jt} = \alpha + \gamma_j + \sum_{t=-4}^{10} \beta_t \times \mathbf{1}(\text{period}_t) + \sum_{t=-4}^{10} \beta_{\text{Treated},t} \times \mathbf{1}(\text{period}_t) \times \text{Treated}_j + \varepsilon_{jt} \tag{1}$$

The dependent variable y_{jt} denotes the outcome for firm j in semester t, which includes several variables discussed later. The equation includes an intercept α as well as firm-level fixed effects γ_j to capture time-invariant characteristics of each firm. The term $\sum_{t=-4}^{10} \beta_t \times \mathbf{1}(\text{period}_t)$ represents the coefficients for each period from $t = -4$ to $t = 10$, where the indicator function $\mathbf{1}(\text{period}_t)$ is 1 if period t applies and 0 otherwise. The treatment effect is captured by the interaction term $\sum_{t=-4}^{10} \beta_{\text{Treated},t} \times \mathbf{1}(\text{period}_t) \times \text{Treated}_j$, which represents the effect of a worker death on firms in the treatment group across different periods. Here, Treated_j is an indicator variable for whether firm j is in the treatment group. Finally, ε_{jt} is the error term capturing unobserved factors affecting the outcome.

In this specification, standard errors are clustered by firm. The coefficient of interest is $\beta_{\text{Treated},t}$. The key identification assumption is the exogeneity of workers' deaths. Since worker-firm pairs are matched at baseline on observables, these are not included on the equation. Considering this and to strengthen the estimation strategy, two periods are excluded from the regressions ($t = -1, -2$). This is due to the fact that in some particular cases we will have a small number of observations and this approach makes sure that outliers on the periods before the event are not compromising the sample and the estimation without having to delete them.

The outcome variables estimated are the following[7].

- *Log number of employees*: logarithm of the total number of employees at the firm for the semester.
- *Log average salary*: logarithm of the average of the monthly wages for all employees at the firm for that semester.
- *Log total wage bill*: sum of all salaries paid by the firm on the semester.
- *Log number of new employees*: logarithm of the total count of employees that entered the firm that month, considering they passed the 3 month mark.
- L*og average salary of new employees*: average salary of employees who enter the firm (after the three month period).

[7] In both the firm and individual level outcomes the deceased and the individual matched worker in the control firm are excluded, except for the specification for Retention Rate (Deceased) which only considers them.

- *Company exists*: dummy variable equal to 1 if the company is still reporting information to Social Security for any month of that semester.

Incumbent worker outcomes. Incumbent workers are defined as those who were working at the firm baseline, $t = -1$. Similarly to firm-level outcomes, the main equation used in the analysis is:

$$y_{ijt} = \alpha + \gamma_{ij} + \sum_{t=-4}^{10} \beta_t \times \mathbf{1}(\text{period}_t) + \sum_{t=-4}^{10} \beta_{\text{Treated}t} \times 1(\text{period}_t) \times \text{Treated}_{ij} + \varepsilon_{ijt} \tag{2}$$

The equation is analogous to the firm-level one described above. Standard errors are clustered at the firm level. For incumbent worker outcomes, the model is estimated as a weighted regression, with each observation weighted by the inverse of the total number of incumbent workers at a firm in the death month. This ensures that all worker deaths have equal weight in the analysis, allowing for direct comparison of treatment effects across different specifications. A key difference from the firm-level outcomes is that these results are estimated for coworkers of the deceased at baseline, to study how the exit of a coworker affects them. Once again, the identification assumption is that worker deaths are exogenous.

The outcome variables for incumbent coworkers are the following.

- *Retention rate*: dummy variable equal to 1 if information for that worker was reported by the firm to Social Security for any month in that semester.

- *Log monthly wage*: logarithm of the individual average salaries received by the worker for that semester.

- *Monthly worked hours*: the average number of monthly worked hours by each worker at the firm every month in that semester.

- *Monthly worked days*: the average number of monthly worked days by each worker at the firm every month in that semester.

5 Results

5.1 Main Results

This section will present the results following the strategy previously described. Once again, the analysis looks at how the end of an employment spell has effects on a firm and individual level. To do so, it is important to see whether the event defined implies a shock in employment to the firm. Figure 1 shows the employment of the deceased (both treated and control) for each period. The event occurs at $t = 0$ and all coefficients are with respect to the mean of the omitted periods (-2 and -1). The dependent variable is binary, equal to 1 if the individual is employed at the same company as they were at $t = -1$. Immediately after the event we can see that employment significantly falls in the treated firms compared to the control ones. However, this fall in employment is estimated at -0.89 (p value 0.000) which shows that in that period some of the matched employees in the control group also leave their positions. If the matched employees at the treated firms were still present there, the drop would be equal to 1.

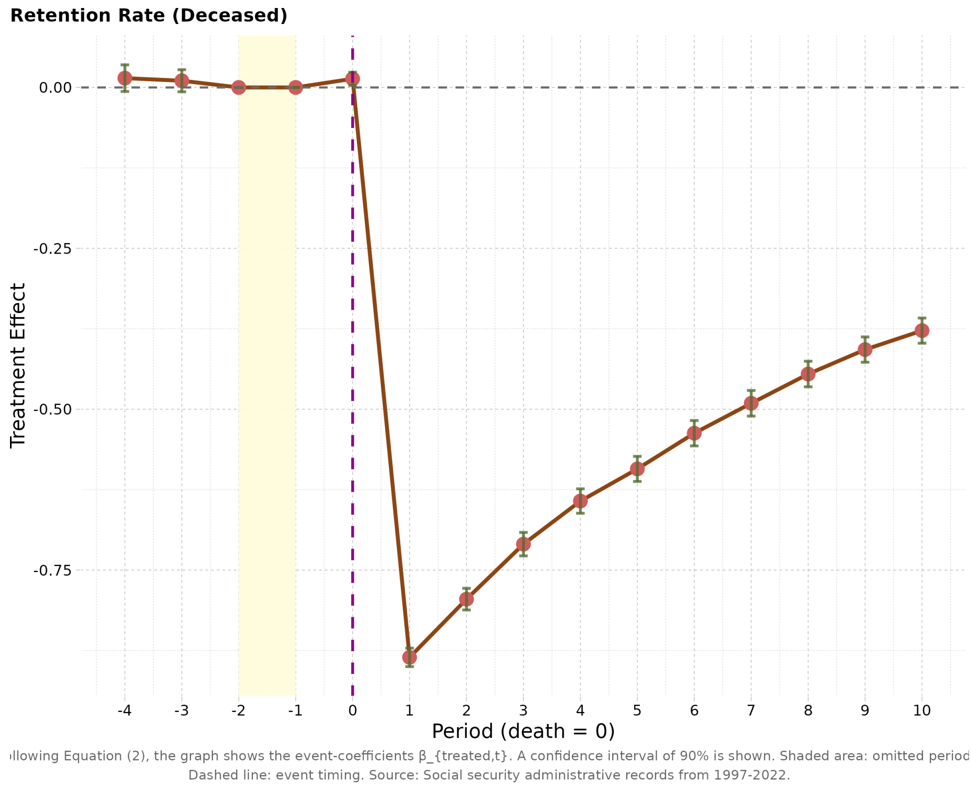
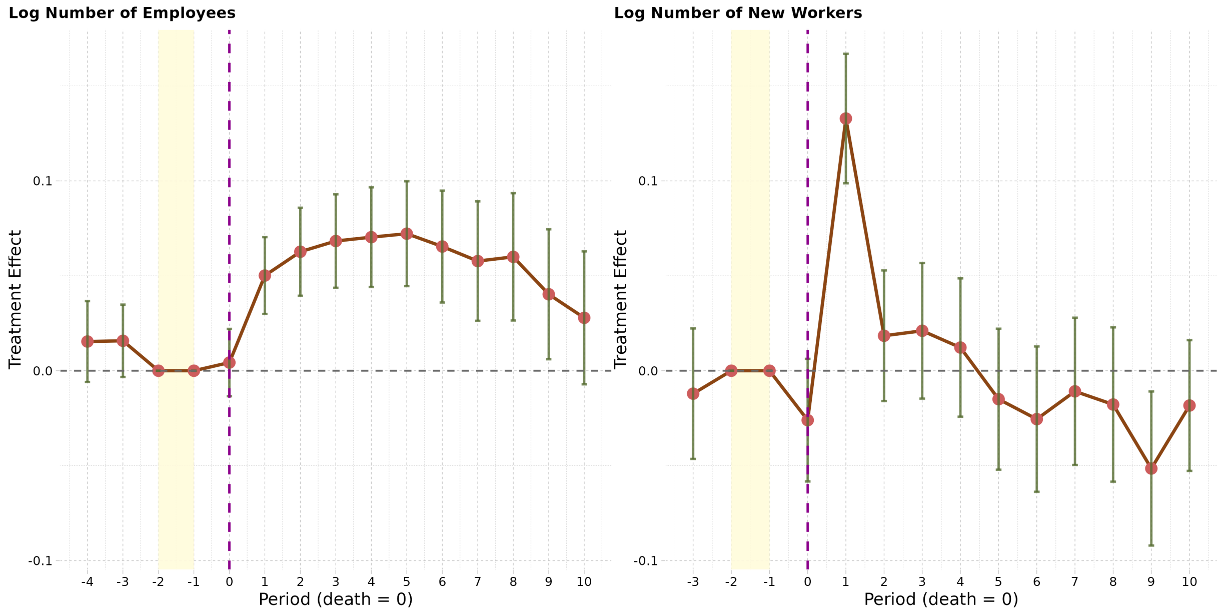


Figure 1: Employment of Deceased at Firm

Analyzing the results in terms of the firm, Figure 2 shows the estimations for the total number of employees and the number of new workers of the firm.[8] Both panels of Figure 2 show a sharp increase

[8]The right panel starts at $t = -3$ because the variable represents a change (new workers) so the first period is omitted as all workers would be considered new.

following treatment. In particular, for the first period after treatment, the number employees at the treated firms increases by approximately 5.01% (p-value 0.000) with respect to the control group. This increase is sustained over time meaning that after treatment, these firms are consistently larger than their control counterparts. However, compared to the baseline period, the increase represents 0.64 workers more, meaning that not all firms increase their number of workers.

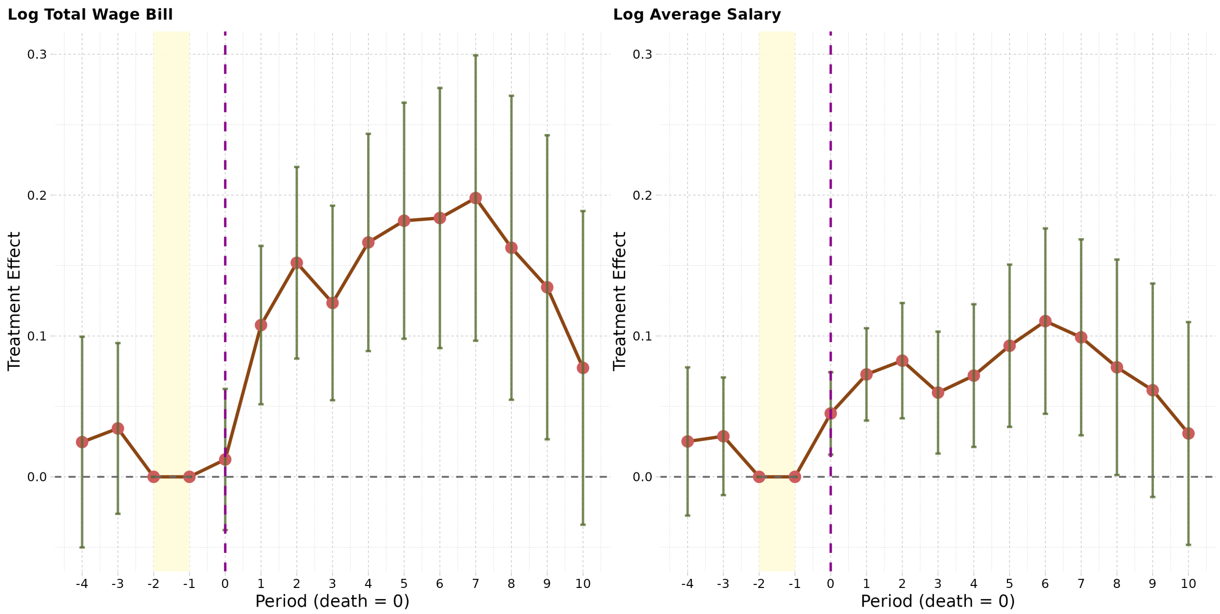


Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Number of Employees: reference = 2.527; Log Number of New Workers: reference = 0.652 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 2: Main Outcomes: Firm Level - Log Employees and New Workers

The right panel of Figure 2 shows a sharp increase in the number of new employees treated firms have, raising 13.28% (p-value 0.000). This means a change in hiring patterns can be seen 6 months after treatment. This is expected considering our setting. However, it is important to notice two aspects. The first one is that looking at the baseline mean, the reported percentage represents an increase of approximately 0.27 new workers. In other words, not all treated firms hire workers. Looking at both panels together, it seems like on average firms substitute workers with two-thirds of another worker, 40% of those are new workers and the rest of the substitution is explained by other changes in the total number of workers that is different to the pattern controls have. This pattern is stable at least until two and a half years after the event. The second aspect is that the sharp increase only lasts for one period, so the firms that do hire do it immediately. These patterns are consistent with the results previously found, where the adjustment firms make is not only on the extensive margin (Jäger and Heining, 2022; Ginja et al., 2022).

Turning now to Figure 3, two firm-level wage outcomes are shown. The left panel represents the total amount of salaries paid by the firm (excluding the salary of the deceased). The total wage bill increases across the analyzed period. For $t = 1$, the estimation shows a 10.77% (p-value 0.002) increase compared to the control group.[9] The right-hand panel of Figure 3 shows that the average salary of the treated firms also increases 7.27% (p-value 0.000). Looking at Figures 2 and 3 together, a possibility could be that the new workers are getting higher salaries compared to the incumbent ones. However, this is not true. There is no significant effect of an increase on the salary of new workers on the treated firms, as shown in Table B.7. Therefore, the increases in both the average salaries and the total amount that the firm pays is driven by incumbent workers.



Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Total Wage Bill: reference = 12.573; Log Average Salary: reference = 10.177 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 3: Main Outcomes: Firm Level - Log Total and Average Salary

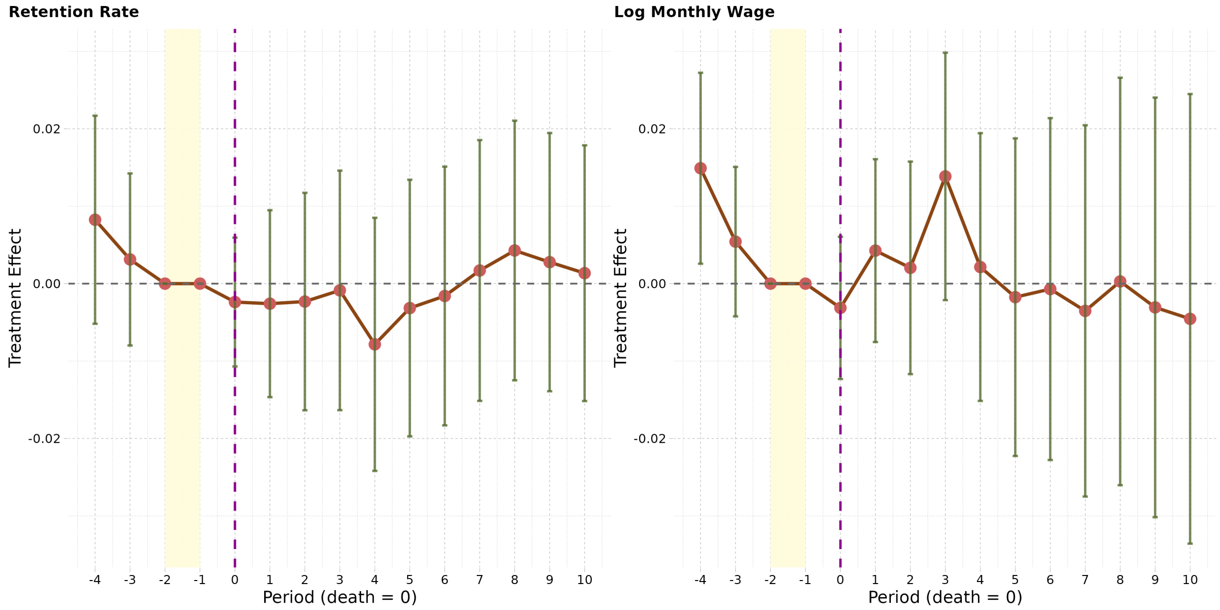
The first set of incumbent-level outcomes is shown in Figure 4, where outcomes are presented in an individual-level. The left panel shows the retention rate, defined for the workers present in the firm at baseline, with the dependent variable equal to 1 if the worker is present in that semester. Even though the graph shows lower point estimates for retention rate after treatment, these are not significant. Something similar happens in the incumbent monthly wages, where the pattern of the point estimates shows an increase (similar to what was discussed in Figure 3), but none of the coefficients are statistically significant.[10] These results are not contradictory to the ones shown in Figure 3: significant increases on the average but not at the individual level point at a high salary increase to only a few employees.

Figure 5 shows estimations on how the monthly days and hours worked by incumbent workers evolve.[11] In administrative data, firms will report a change in the number of days worked rather than

[9]This represents around 33,000 Uruguayan constant pesos (2010 level).

[10]It is important to note that the first period ($t = -4$ is statistically significant, which compromises the identification strategy. However, these individual-level outcomes are never significant in the analysis.)

[11]The pre-trends for Monthly Worked Hours should not be significant. However, besides the drop found at $t = 0$, the results are not relevant to the analysis.



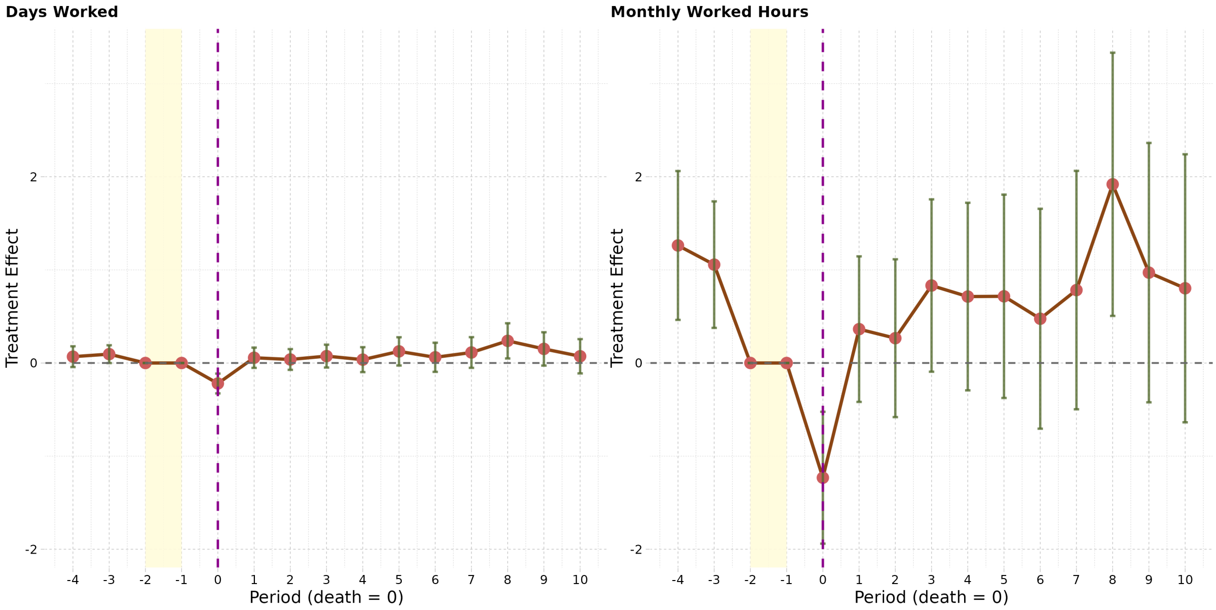
Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Retention Rate: reference = 0.921; Log Monthly Wage: reference = 10.219 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 4: Main Outcomes: Incumbent - Retention Rate and Salary

the number of weekly hours. Since monthly worked hours are calculated based on weekly hours and total days, the drop in 1.23 hours (p-value 0.004) we see on the left panel likely comes from the -0.22 days the employees on the treated firms work, compared to the controls (p-value 0.000). It is also important to note that the effect for the incumbent's days and hours worked is at $t = 0$, meaning (for those treated) that it is in the same period as the death of their coworker is experienced. A possible explanation is therefore less time worked due to the emotional shock experienced by the coworkers in the treated firms, something we could call a "sadness effect". These findings are aligned to what is discussed by Kuang et al. (2022), on the negative effects grief can have.

5.2 Heterogeneities by position of deceased

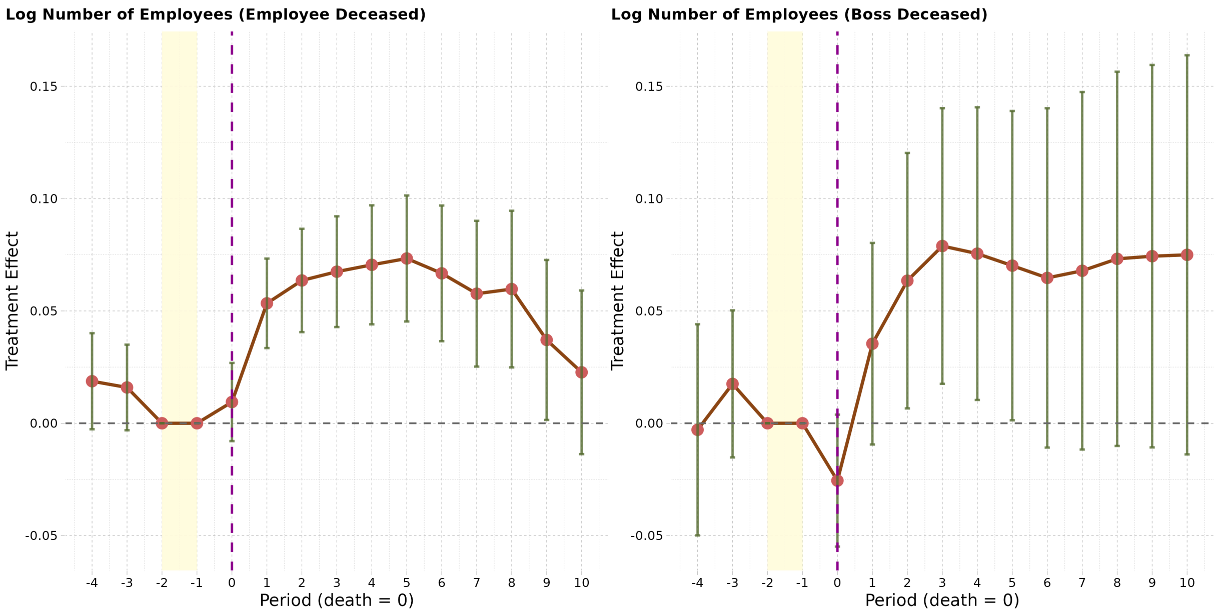
To understand better how the nature of the vacant position could have different effects, the next set of results shows a subset of the outcome variables, separated for when the deceased was an employee or a boss. These different estimations explore possible differential effects based on human capital. If a deceased worker is a boss, the level of human capital specificity can be assumed to be high and therefore harder for the firm to replace. Figure 6 shows firms with a deceased employee on the left panel and a deceased boss on the right panel. The number of employees at treated firms with deceased employees see an increase of 5.34% (p-value 0.000) for the first period after the event. This effect increases slightly until period 5 and continues to be significant until 4 years after. For firms where the deceased was a boss, the point estimations are also positive, and significant between the second and fourth semesters



Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Days Worked: reference = 27.368; Monthly Worked Hours: reference = 163.402 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 5: Main outcomes: incumbent - days and hours

after treatment, but, since this group of firms is smaller, the confidence intervals are wider. In particular, on $t = 2$, the number of employees increases by 6.35% (p-value 0.067) and point-estimates show this is stable for up to 5 years after the event.

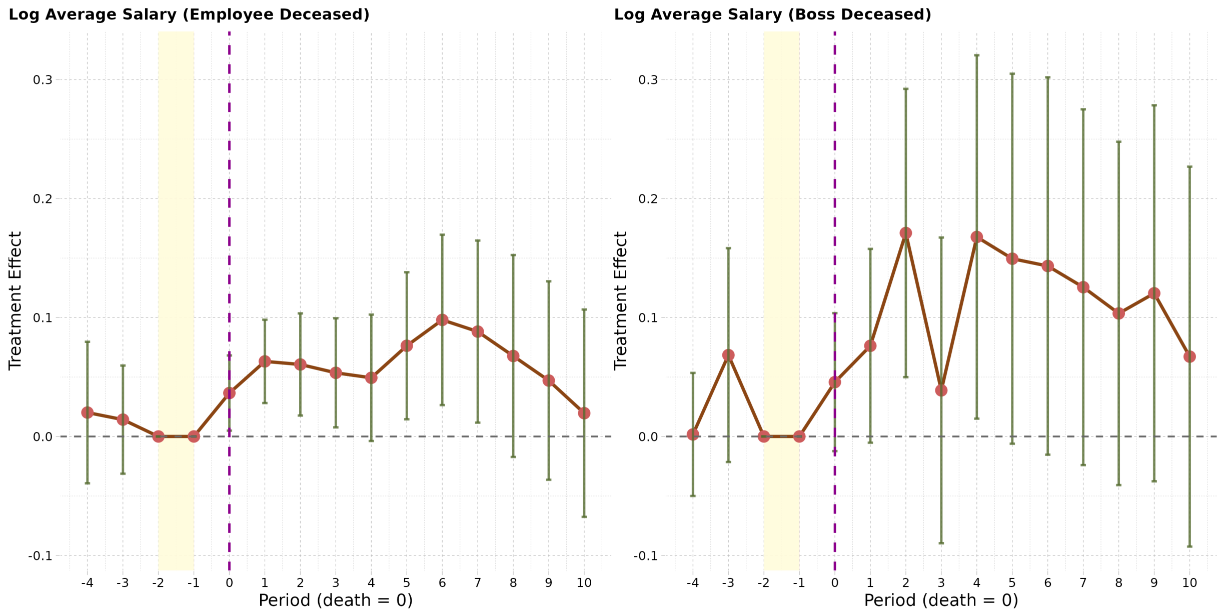


Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Number of Employees (Employee Deceased): reference = 2.583; Log Number of Employees (Boss Deceased): reference = 2.054 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 6: Firm-level Heterogeneities by Position: Log Employees

Turning now to the average salary results on Figure 7, the employees of a firm with a vacant position left from another employee see an average salary increase for several semesters after treatment. The first semester after treatment their salaries are 6.31% higher than the control firms (p-value 0.003). The effect continues to be positive, reaching its maximum six semesters after treatment, with a 9.8% (p-value 0.025) increase in average salary for the treated firms. Looking at the right panel, once again the point estimates are higher but the confidence intervals are wider. Either way, the group of firms where the position from a boss is left vacant, experiences an increase in their salaries compared to control firms. On the second semester after treatment, these firms have average salaries which are 17.1% higher (p-value 0.021).

If we analyze this information together, it seems like some treated firms are hiring employees to replace the deceased worker while also increasing the overall salaries. What is interesting to note is that, as mentioned, looking at the effect of treatment on the salaries of new hires, the increase in the company's average salary does not seem to be explained by new hires' salaries, suggesting that the salaries of the incumbents are being increased. Since, as mentioned, the substitution is not 1-1, this could point to a redistribution of the deceased tasks to coworkers.

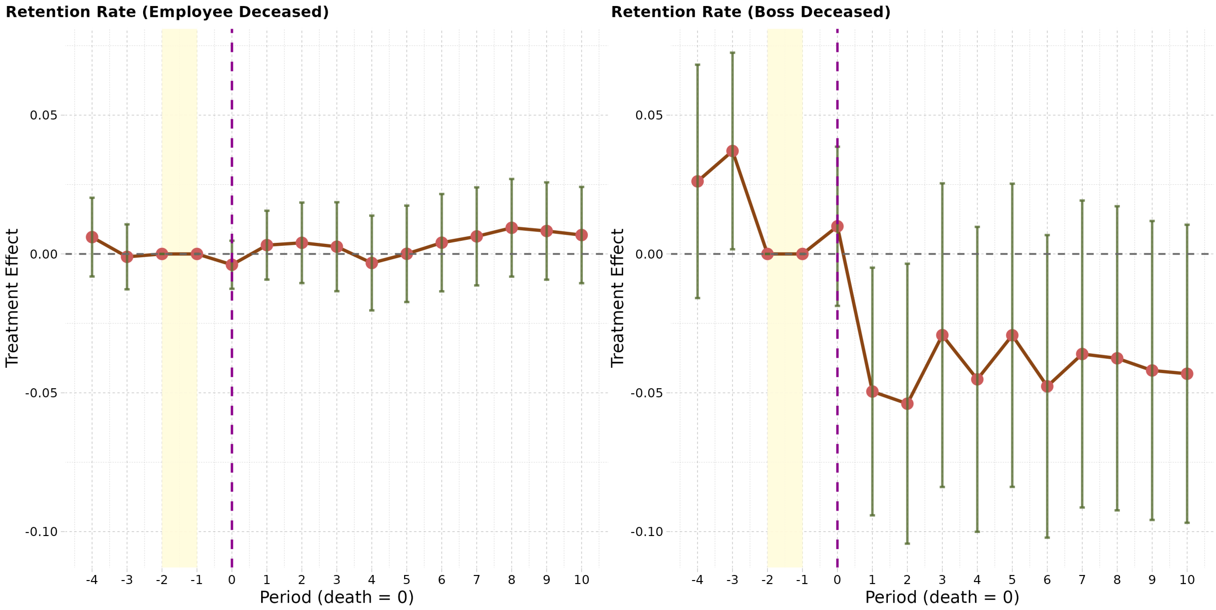


Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Average Salary (Employee Deceased): reference = 10.195; Log Average Salary (Boss Deceased): reference = 10.026 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 7: Firm-level Heterogeneities by Position: Average Salary

Moving on to incumbent outcomes, Figure 8 shows two graphs for retention rates. The left panel shows no statistically significant changes for companies with an employee position left vacant. The right panel however shows that retention rates, i.e. the probability of incumbent employees remaining at the firm, decreases significantly. In particular, the first semester after treatment the probability is 4.95 percentage points lower (p-value 0.068).

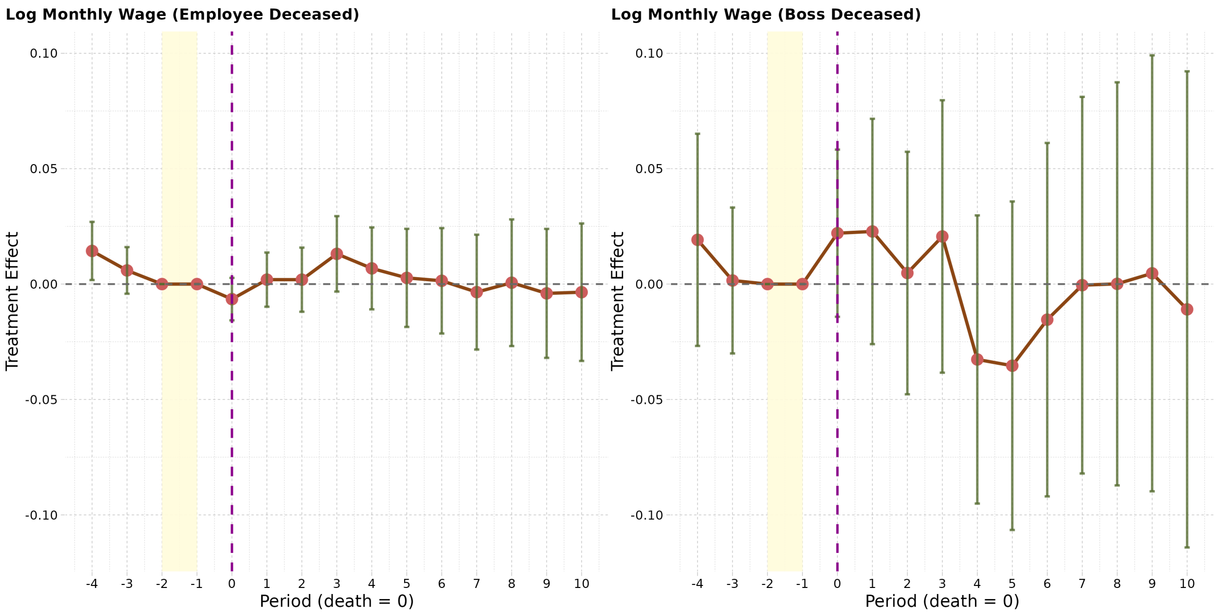
Figure 9 shows that monthly wages for incumbents do not have statistically significant changes for the treated for any of the cases. Once again it is important to remember this could be a matter of power



Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Retention Rate (Employee Deceased): reference = 0.922; Retention Rate (Boss Deceased): reference = 0.914 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 8: Incumbent-level Heterogeneities by Position: Retention Rate

due to the number of observations available.



Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Log Monthly Wage (Employee Deceased): reference = 10.262; Log Monthly Wage (Boss Deceased): reference = 9.888 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 9: Incumbent-level Heterogeneities by Position: Monthly Salary

To understand if the results could be explained by treated firms closing, Figure 10 shows an event-study analysis on the probability of survival of the firm. As previously defined, the outcome variable is based on having active employees which are being reported as such by the firm to Social Security. There is indeed a significant lower probability of staying open for treated firms, with a drop of 2.5% (p-value 0.053). This effect is fully explained by the companies in which the deceased is the boss. For these firms, the probability of being open drops 17 percentage points (p-value 0.000). Since these firms are relatively small in their number of employees, this raises the question of whether this is explained by the death of the only present boss or if there are actually several but the firm still does not manage to recover.

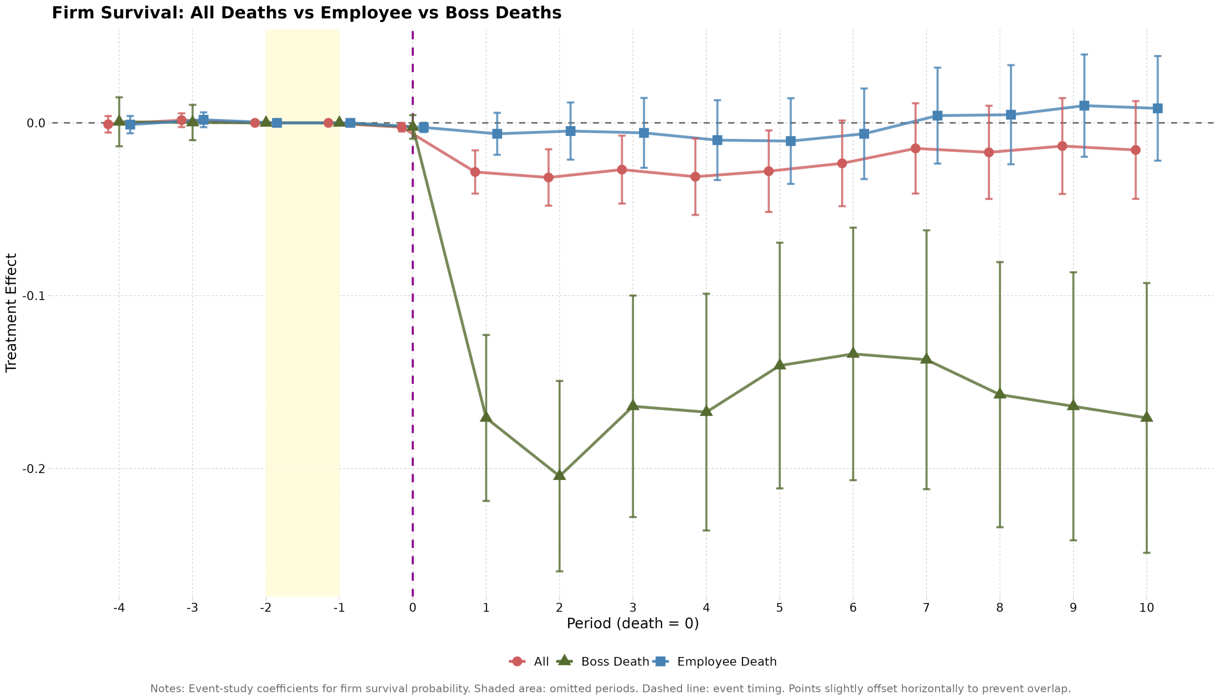


Figure 10: Firm survival by Deceased Position

5.3 Heterogeneities by Number of Bosses when Boss Deceased

The following set of results analyzes the heterogeneity of having one versus several bosses at baseline, for the cases in which the deceased was occupying a paid managerial position. To better understand these results, Table 3 shows some firm-level statistics for both groups.[12] The number of employees is naturally higher in firms with more than one boss.

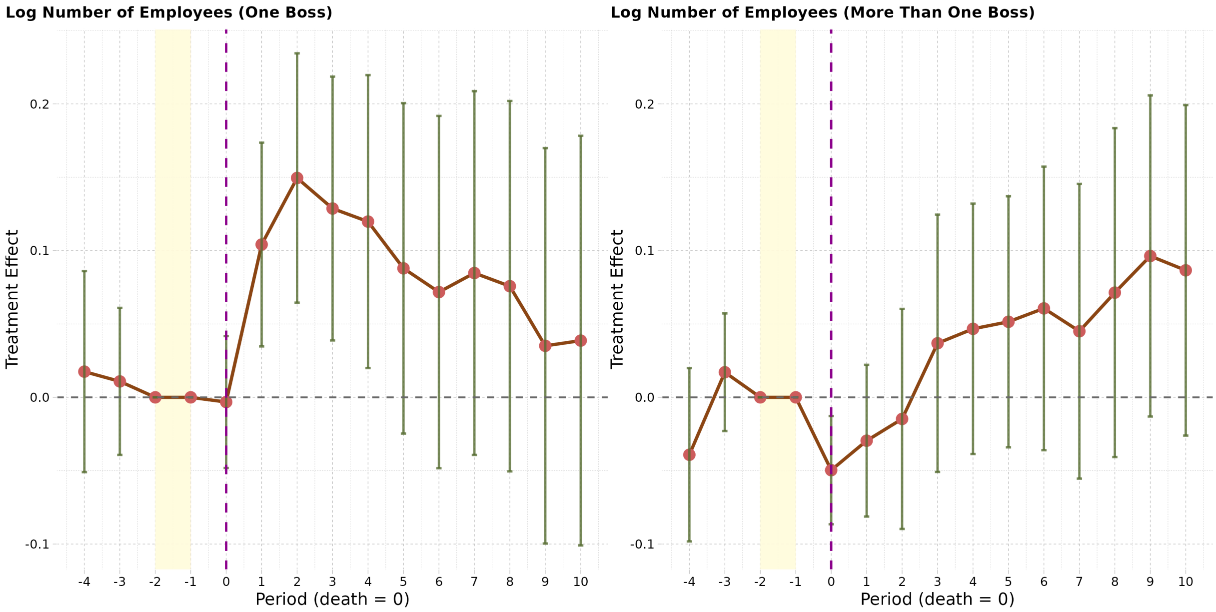
Table 3: Firm-level Descriptives

	One Boss	More than one
Total Employees	8.11	10.59
Percent Female	37.79	31.12
Number of Workers	6.08	6.68
Number of Bosses	1.00	2.86
Number of Daily Workers	1.26	1.11
N	145	152

Looking at Figure 11 the adjustment on the number of employees is only statistically significant for

[12] The number of bosses for firms with one boss is not equal to 1 because we are defining bosses as those with remuneration, some firms only have owners.

firms with only one boss at baseline. During the first semester after treatment, there is a 10.41% increase in the number of employees for treated firms (p-value 0.014), and the increase in the variable remains significant up until four semesters post treatment. The results on the number of employees for the right panel (more than one boss) are not statistically significant.

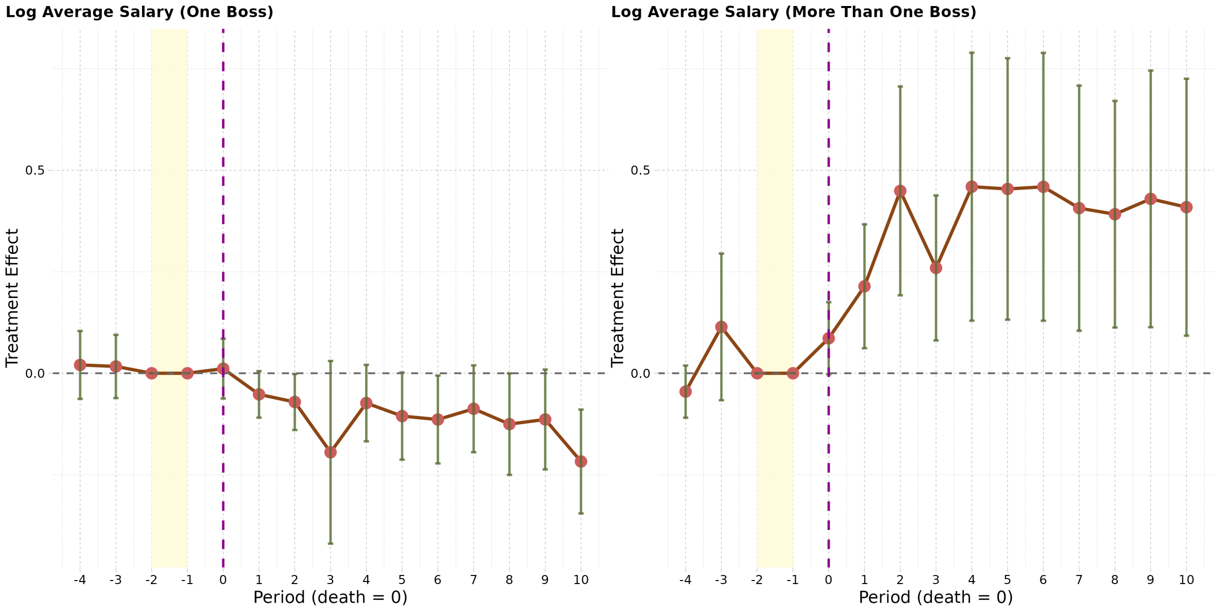


Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Number of Employees (One Boss): reference = 2.013; Log Number of Employees (More Than One Boss): reference = 2.069 Shaded area: omitted periods. Dashed line: event timing.
Source: Social security administrative records from 1997-2022.

Figure 11: Firm-level heterogeneities when boss deceased: Employees

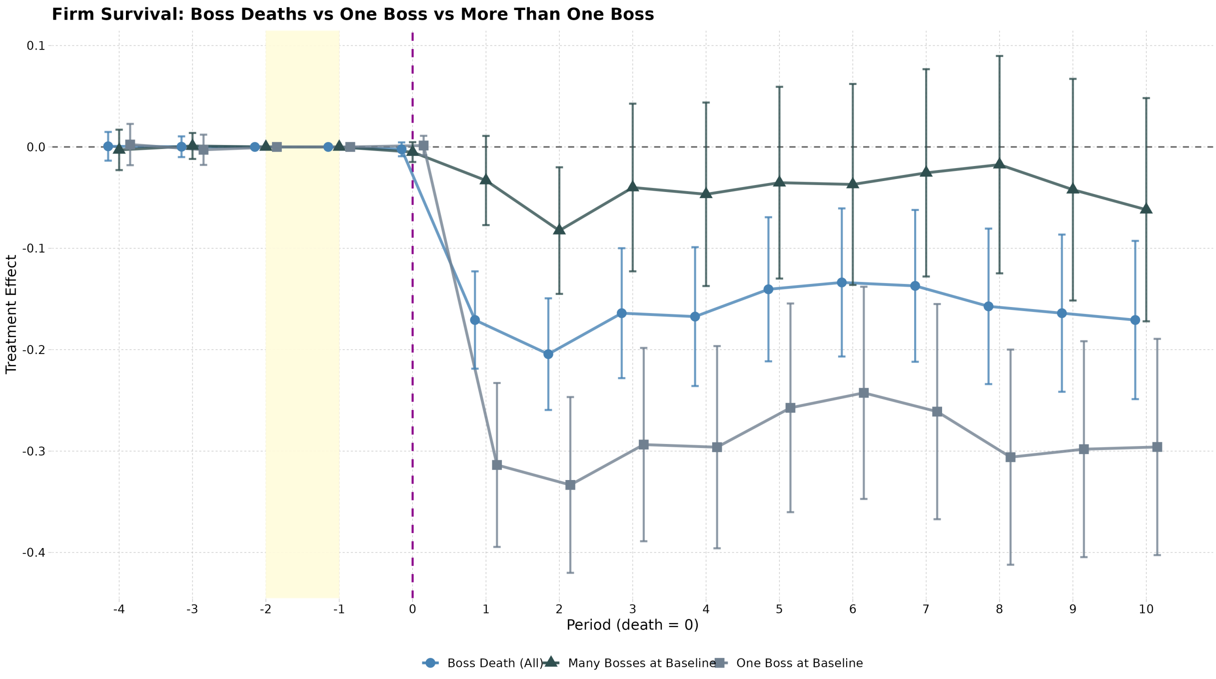
On the other hand, the average salaries (Figure 12) show a significant increase for firms with more than one boss. The first semester after treatment, average salaries increase by 21.41% (p-value 0.022) and for most of the analyzed period the increase is closer to 50%. A way to look at this is that for firms with only one boss the probability of recovering from the shock (i.e. staying open) is much lower and the point estimates of the salaries even show a possible decrease, pointing to a poorer performance from these firms. On the other hand the firms from the right-hand panel have to make substantial salary adjustments to adjust after the shock.

Finally, Figure 13, shows the results for firm survival split by the number of baseline bosses, for the case where the boss was deceased. The negative trend is present in all specifications but the effect is much greater when the company only had one boss. For the second semester after treatment, which is the first significant semester for all three results, the probability of a treated firm with a boss deceased being open falls 33.3 percentage points (p-value 0.000) compared to the control firms. For those firms that only had one boss at baseline, this number is even greater, -36 percentage points (p-value 0.000) while for the firms with many bosses this is the only statistically significant period with a point estimate of -8.3 percentage points (p-value 0.011).



Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Average Salary (One Boss): reference = 10.128; Log Average Salary (More Than One Boss): reference = 9.988 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 12: Firm-level heterogeneities when boss deceased: Salary

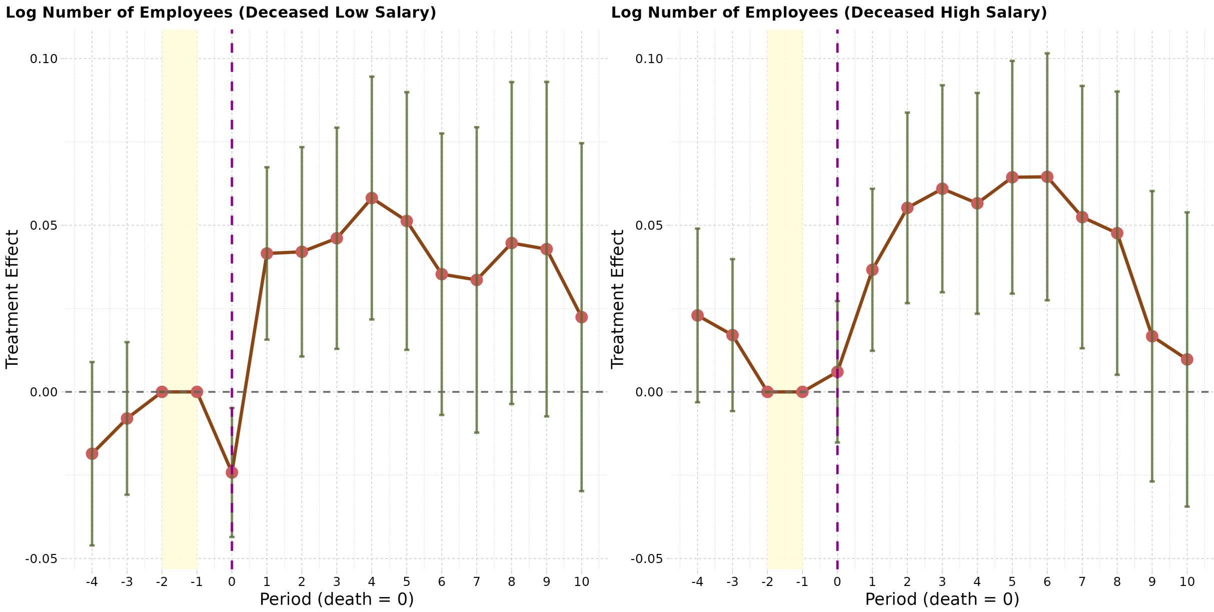


Notes: Event-study coefficients for firm survival probability. Shaded area: omitted periods. Dashed line: event timing. Points slightly offset horizontally to prevent overlap.

Figure 13: Company survival by deceased position

5.4 Heterogeneities by Salary of Deceased

These final heterogeneous results split the firms by those in which the deceased earned a salary above or below the median in their own company, at baseline. This is again a way to see how human capital may trigger different responses from firms. The left panel of Figure 14 shows the results for the number of employees for firms where the position vacant was left by an employee with a low salary.[13] The number of employees increases more for those deceased who left a high-salary position, with point estimates of around 0.6 until the fourth year after the event. However, these are only slightly higher to what the left panel shows.

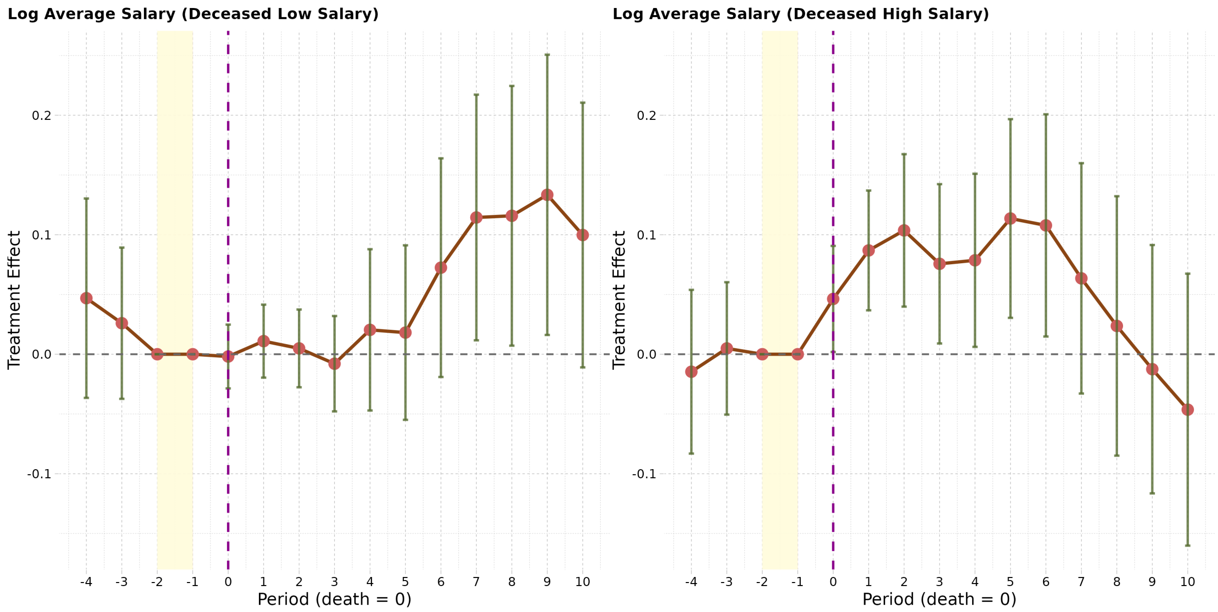


Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Number of Employees (Deceased Low Salary): reference = 2.478; Log Number of Employees (Deceased High Salary): reference = 2.565 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure 14: Firm-level Heterogeneities by Relative Salary: Number of Employees

Turning now to Figure 15, there seems to be bigger differences between the two sub-samples. In particular, for those firms where the deceased left a high-salary position within the firm, their coworkers see an immediate increase in their average salaries of around 10%. These results are consistent with previous studies discussed and can be understood as an attempt for the firms to retain the remaining workers in the context where there is a higher loss of specific human capital.

[13]Employee is used as a general term, both groups include employees and bosses.



Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Average Salary (Deceased Low Salary): reference = 10.157; Log Average Salary (Deceased High Salary): reference = 10.193 Shaded area: omitted periods. Dashed line: event timing.
Source: Social security administrative records from 1997-2022.

Figure 15: Firm-level Heterogeneities by Relative Salary: Average Salary

5.5 Robustness checks

Four different robust specifications are performed for the two main specifications (number of employees and average salary). First, results for a balanced sample are presented on Figure A.7. The balanced sample is defined as firm pairs of treated and control units that are present for the whole period analyzed (two years before to five years after). It is important to note that in light of the results (many firms close) and the number of years the sample is available, this subsample is heavily reduced compared to the original data.[14] The left panel of Figure A.7 shows a very similar pattern to the results discussed previously, particularly on the left panel of Figure 2. Although the confidence intervals are wider, the number of employees is still significantly higher for treated firms until 3 years after the event. However, the magnitude of the effects is smaller. Similarly, on the right panel the average salary shows consistent results with those from Figure 3.

The second set of robust results is performed for a subsample with firms with less than 30 employees.[15] This sample is selected to ensure that results are not only driven by bigger firms.[16] Figure A.8 shows the results for the main specifications. As with the balanced sample, there is an increase in both the number of employees and the average salaries of the treated firms, consistent with previously discussed

[14]The balanced sample has 1584 unique firms including both treated and controls.

[15]Since the number of employees is part of the PSM, this does not guarantee that the treated and control firms will have equal values in this variable. Therefore, with the same initial treated sample restricted to firms with 30 employees or less, another PSM is performed to find control firms who strictly have 30 employees or less.

[16]Descriptive information for the sample can be found in Tables B.1 and B.2.

results. The estimates are also relatively smaller in magnitude.

Figure A.9 shows the same specifications but for a sample constructed using the information available on sickness spells. As previously mentioned, this information is only available partially (2005 to 2015 and 2018 to 2022) which is why the main sample uses a salary ratio as a proxy. The criteria considered is that the deceased cannot have more than 90 sick days on its last semester at the firm. It is important to note that although this sample is reduced, the number of treated firms is still high, suggesting that the ratio criteria is conservative and that if information on sick leave was available for the whole period, some sample power issues could be mitigated.[17] The results are consistent with those previously discussed, with an increase after treatment for both variables.

Finally, to test the importance of the threshold for the salary ratio, a sample considering only those deceased with a ratio of above 0.9 is constructed.[18] As a reminder, the original threshold considered is 0.7 and this measures the variation of the total salary in the semester before death over the total salary on the previous semester. Figure A.10 shows that the general patterns of both panels are very similar to the main results, validating the strategy used.

[17]Descriptive information for the sample can be found in Tables B.3 and B.4.
[18]Descriptive information for the sample can be found in Tables B.5 and B.6.

6 Conclusions

This study investigated how a sudden worker exit in a firm affects both the firm's general outcomes as well as individual coworker outcomes. To ensure a causal setting, unexpected deaths are used as a source of exogenous variation. The main findings show an increase in both the number of workers and on the average salaries paid by the firm. These results are consistent with a frictional labor market in which firms are not able to find perfect substitutes to hire and therefore their decisions include internal changes to adapt to the worker's exit.

Results also show heterogeneous outcomes depending on the nature of the position left vacant. Positions associated with higher human capital, such as those of bosses or those with higher relative salaries within the firm, implied higher replacement costs. This is aligned with the reviewed literature on specific human capital. The position of the deceased also proves to be a very relevant factor in the probability of the firm closing. In particular, firms with multiple bosses survive by making large salary adjustments (intensive margin), while firms with a single boss try to hire (extensive margin) but often fail and close. Several robustness exercises are performed, which confirm the findings.

A natural next step is to estimate replacement costs, as done so by other investigations discussed. Moreover, from a policy perspective it would be interesting to find the heterogeneity of these results for different labor markets, as market thickness has been shown to be important in the context of this research.

With more information on sickness data from Social Security and with occupational information within the firm, the results estimated here could be improved. Additional information on firm productivity could be explored to understand the impacts of an exit in those terms.

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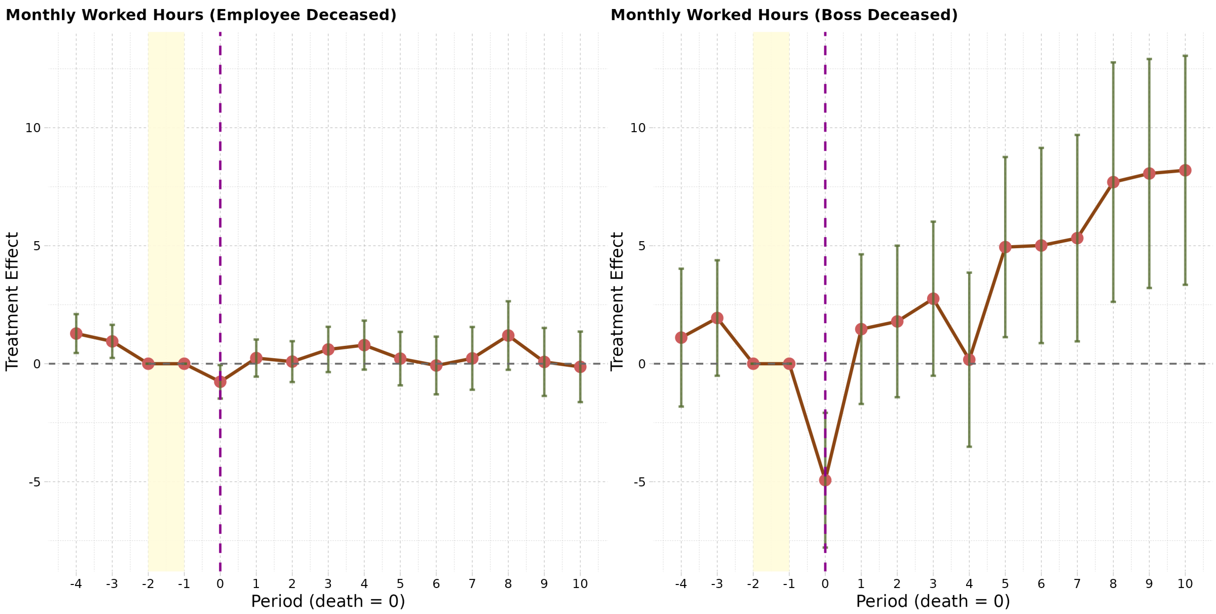
A Appendix

A.1 Additional Figures

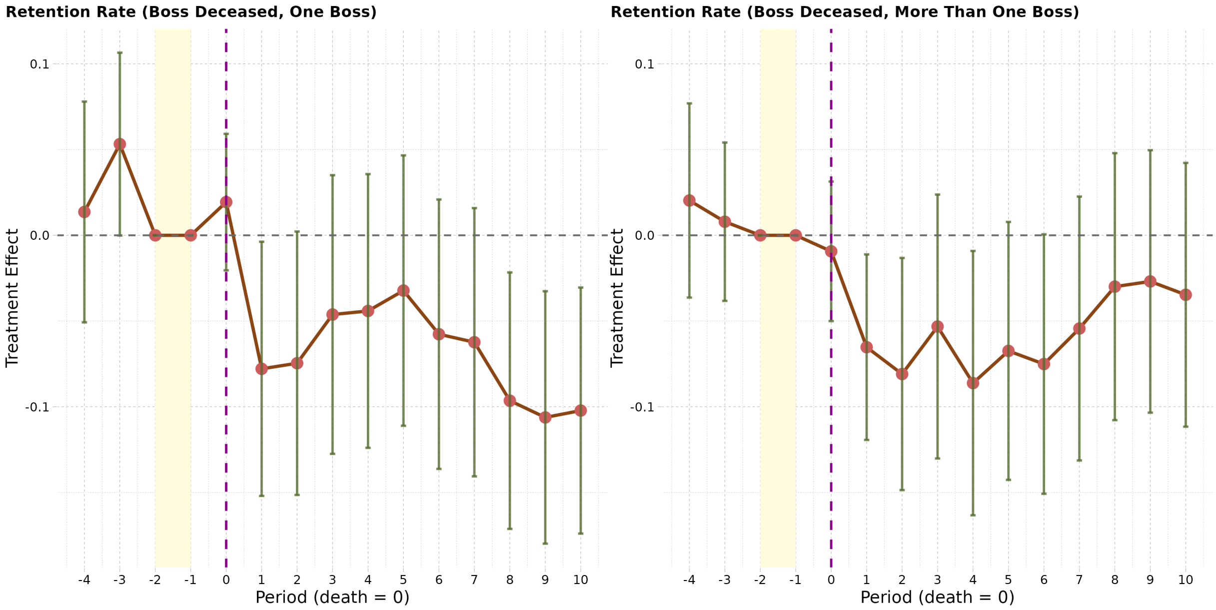
Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Days Worked (Employee Deceased): reference = 27.365; Days Worked (Boss Deceased): reference = 27.391 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.1: Incumbent-level heterogeneities by position of deceased: days worked



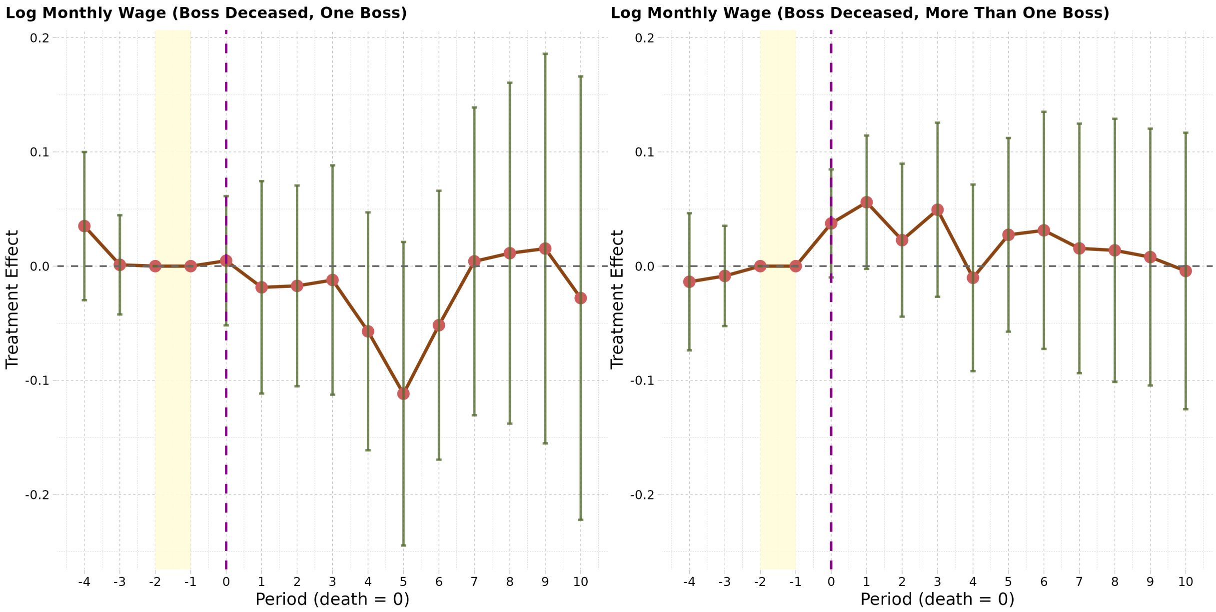
Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Monthly Worked Hours (Employee Deceased): reference = 163.924; Monthly Worked Hours (Boss Deceased): reference = 159.126 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.2: Incumbent-level heterogeneities by position of deceased: hours worked



Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Retention Rate (Boss Deceased, One Boss): reference = 0.921; Retention Rate (Boss Deceased, More Than One Boss): reference = 0.921 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.3: Incumbent-level heterogeneities when boss deceased: retention rate

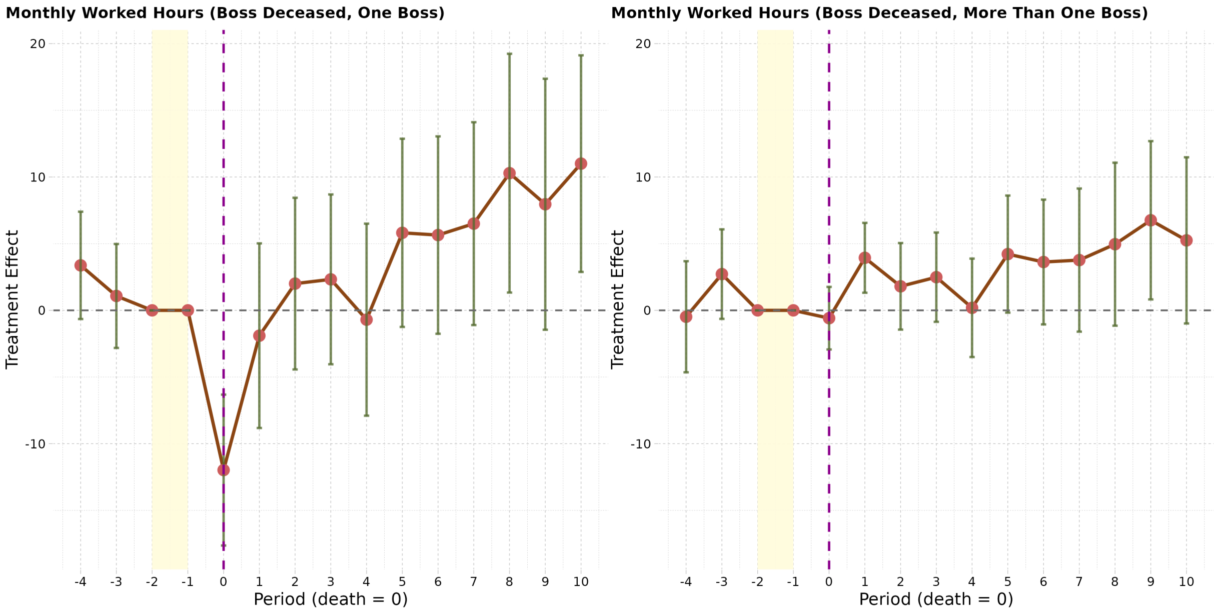


Following Equation (2), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Monthly Wage (Boss Deceased, One Boss): reference = 10.219; Log Monthly Wage (Boss Deceased, More Than One Boss): reference = 10.219 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.4: Incumbent-level heterogeneities when boss deceased: salary

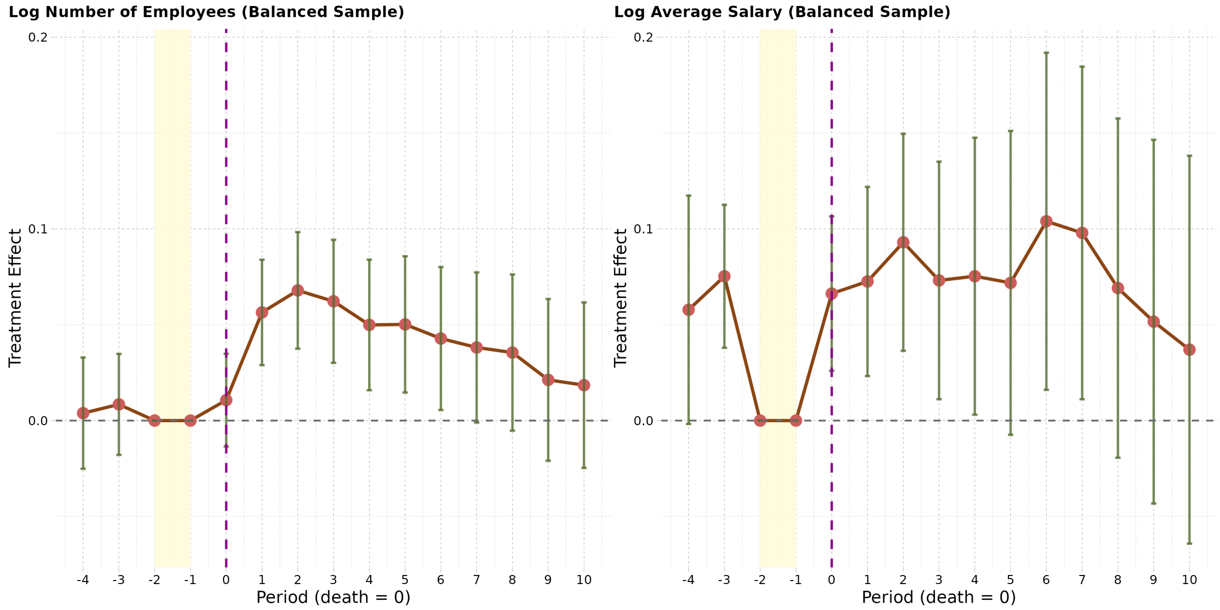
Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Days Worked (Boss Deceased, One Boss): reference = 27.368; Days Worked (Boss Deceased, More Than One Boss): reference = 27.368 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.5: Incumbent-level heterogeneities when boss deceased: days worked



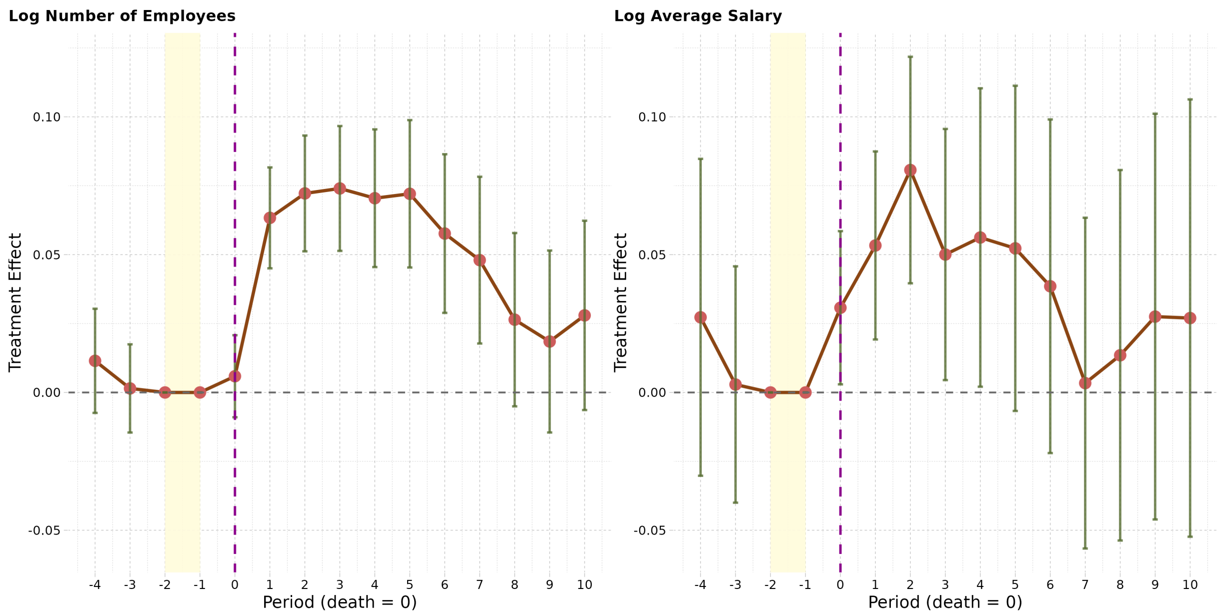
Following Equation (2), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Monthly Worked Hours (Boss Deceased, One Boss): reference = 163.402; Monthly Worked Hours (Boss Deceased, More Than One Boss): reference = 163.402 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.6: Incumbent-level heterogeneities when boss deceased: hours worked



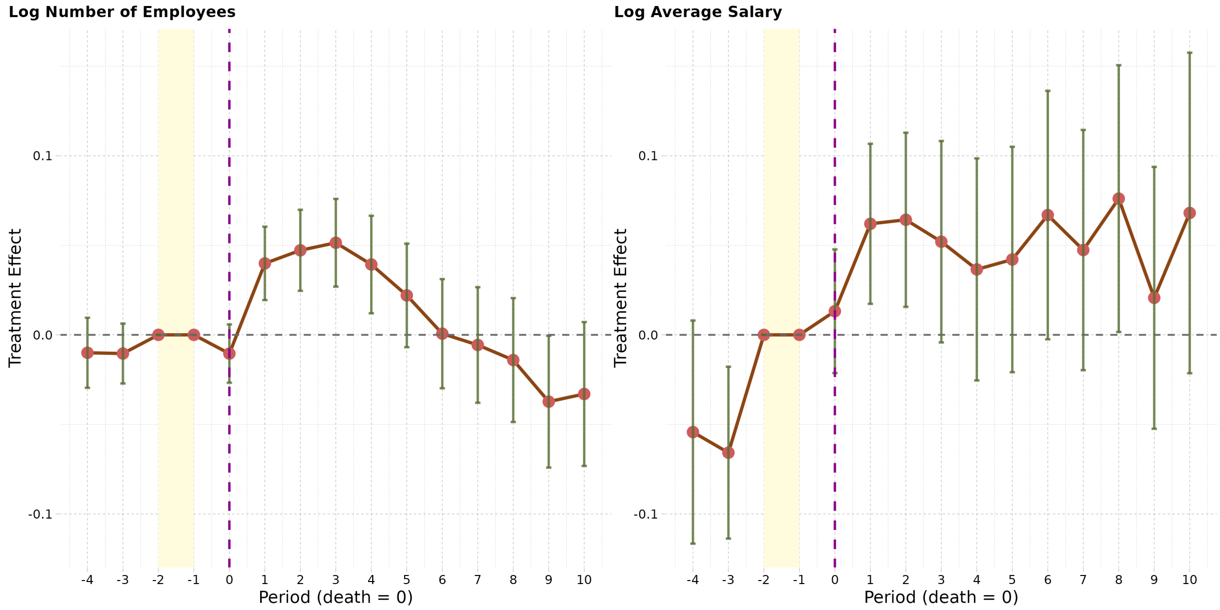
Following Equation (1), the graph shows the event-coefficients β_{treated,t}. A confidence interval of 90% is shown. Log Number of Employees (Balanced Sample): reference = 2.527; Log Average Salary (Balanced Sample): reference = 10.177 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.7: Robust Main Outcomes: Firm Level - Log Employees and Average Salary (Balanced)



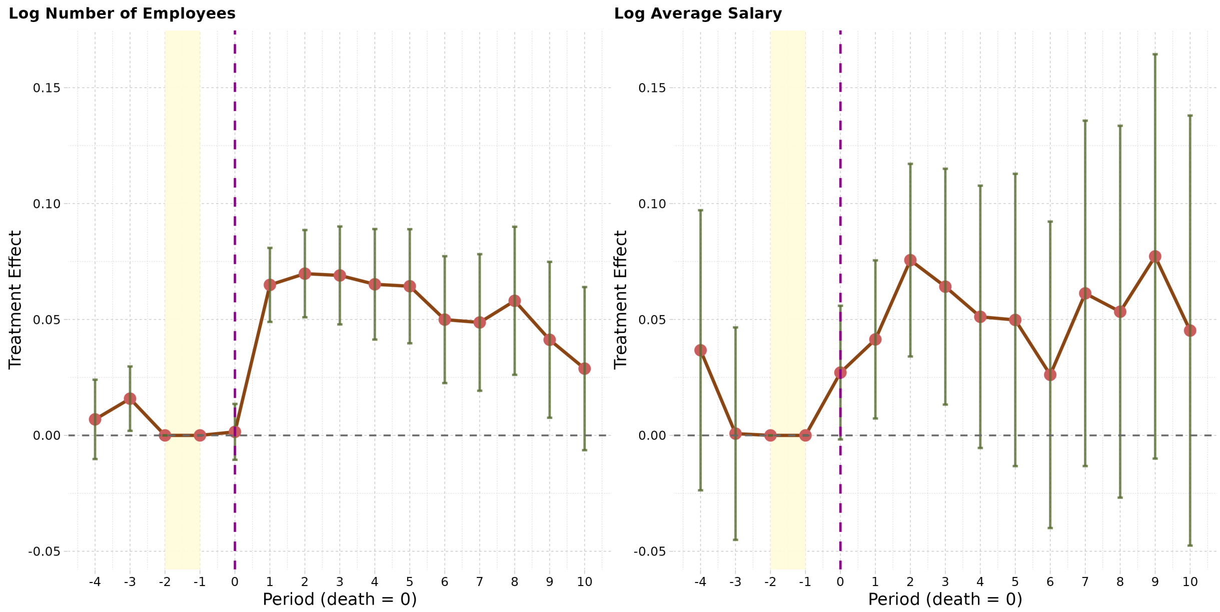
Following Equation (1), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Log Number of Employees: reference = 2.390; Log Average Salary: reference = 10.132 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.8: Robust Main Outcomes: Firm Level - Log Employees and Average Salary (Firms with 30 employees or less)



Following Equation (1), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Log Number of Employees: reference = 2.566; Log Average Salary: reference = 10.241 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.9: Robust Main Outcomes: Firm Level - Log Employees and Average Salary (Treatment defined with sickness days)



Following Equation (1), the graph shows the event-coefficients β{treated,t}. A confidence interval of 90% is shown. Log Number of Employees: reference = 2.375; Log Average Salary: reference = 10.127 Shaded area: omitted periods. Dashed line: event timing. Source: Social security administrative records from 1997-2022.

Figure A.10: Robust Main Outcomes: Firm Level - Log Employees and Average Salary (Higher Salary Ratio)

A.2 Additional Tables

Table A.1: Probit Model on Treatment

Variable	**AME (1)**
Total Employees	0.0010
	(0.3568)
Monthly Employees	-0.0001
	(0.9228)
Female Share of Employees (%)	0.0011***
	(0.0000)
Percentile Dummies	
Percentile $\leq$ 20%	-0.2103
	(0.3909)
Percentile $\leq$ 40%	0.5001***
	(0.0000)
Percentile $\leq$ 60%	-0.0547
	(0.7267)
Percentile $\leq$ 70%	-0.0147
	(0.7910)
Percentile $\leq$ 80%	-0.0826
	(0.1566)
Percentile $\leq$ 85%	-0.0056
	(0.8844)
Percentile $\leq$ 90%	-0.0080
	(0.8377)
Percentile $\leq$ 92.5%	-0.0565*
	(0.0486)
Percentile $\leq$ 95%	-0.0156
	(0.4710)
Sector Dummies	
Sector 1	0.0250
	(0.5657)
Sector 2	0.0203
	(0.6949)
Sector 3	-0.0364
	(0.5591)
Sector 4	-0.0024
	(0.9548)
Sector 5	0.0338
	(0.4997)
Sector 6	-0.0415
	(0.4061)
Sector 7	-0.0087
	(0.8770)
Sector 8	0.0527
	(0.3001)
Observations	4400
Adj. Pseudo R^2	-0.00153

Notes: AMEs from probit estimation. P-values in parentheses. The regression includes an intercept. Omitted categories: Sector 9 and Percentile $>$ 97.5% (Decile 11). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Main Salary Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	0.025 [0.432]	0.020 [0.578]	0.002 [0.957]	0.020 [0.687]	-0.045 [0.249]
-3*treated	0.029 [0.257]	0.014 [0.608]	0.068 [0.211]	0.017 [0.723]	0.114 [0.299]
0*treated	0.045 [0.011]	0.036 [0.058]	0.046 [0.196]	0.011 [0.800]	0.086 [0.112]
1*treated	0.073 [0.000]	0.063 [0.003]	0.076 [0.124]	-0.052 [0.137]	0.214 [0.022]
2*treated	0.082 [0.001]	0.061 [0.020]	0.171 [0.021]	-0.071 [0.093]	0.449 [0.004]
3*treated	0.060 [0.023]	0.054 [0.055]	0.039 [0.620]	-0.195 [0.156]	0.259 [0.017]
4*treated	0.072 [0.020]	0.049 [0.127]	0.168 [0.071]	-0.073 [0.201]	0.459 [0.023]
5*treated	0.093 [0.008]	0.076 [0.042]	0.149 [0.115]	-0.106 [0.107]	0.454 [0.021]
6*treated	0.111 [0.006]	0.098 [0.024]	0.143 [0.138]	-0.114 [0.084]	0.459 [0.023]
7*treated	0.099 [0.019]	0.088 [0.058]	0.125 [0.168]	-0.087 [0.180]	0.407 [0.028]
8*treated	0.078 [0.094]	0.068 [0.190]	0.103 [0.239]	-0.125 [0.100]	0.392 [0.022]
9*treated	0.061 [0.182]	0.047 [0.354]	0.120 [0.211]	-0.114 [0.129]	0.429 [0.026]
10*treated	0.031 [0.522]	0.020 [0.712]	0.067 [0.490]	-0.217 [0.006]	0.409 [0.034]
-4	-0.121 [0.000]	-0.128 [0.000]	-0.048 [0.006]	-0.086 [0.000]	0.015 [0.612]
-3	-0.069 [0.000]	-0.064 [0.000]	-0.073 [0.055]	-0.072 [0.004]	-0.070 [0.423]
0	0.023 [0.045]	0.026 [0.042]	0.030 [0.008]	0.040 [0.012]	0.013 [0.433]
1	0.025 [0.063]	0.031 [0.038]	0.017 [0.569]	0.075 [0.000]	-0.069 [0.280]
2	0.015 [0.422]	0.028 [0.155]	-0.041 [0.492]	0.107 [0.000]	-0.252 [0.072]
3	0.036 [0.053]	0.038 [0.064]	0.051 [0.159]	0.127 [0.000]	-0.061 [0.430]
4	0.024 [0.297]	0.035 [0.138]	-0.020 [0.802]	0.147 [0.000]	-0.258 [0.168]
5	0.004 [0.874]	0.010 [0.728]	-0.004 [0.965]	0.181 [0.000]	-0.256 [0.155]
6	-0.024 [0.444]	-0.027 [0.431]	0.025 [0.763]	0.222 [0.000]	-0.246 [0.184]
7	0.000 [0.988]	-0.004 [0.909]	0.062 [0.409]	0.249 [0.000]	-0.195 [0.237]
8	0.007 [0.853]	0.000 [0.993]	0.078 [0.244]	0.254 [0.000]	-0.170 [0.244]
9	0.031 [0.378]	0.026 [0.499]	0.091 [0.248]	0.295 [0.000]	-0.189 [0.276]
10	0.051 [0.133]	0.045 [0.235]	0.124 [0.124]	0.338 [0.000]	-0.168 [0.335]
Observations	55673	48613	7060	3611	3449
Baseline Mean	10.177	10.195	10.026	10.128	9.988

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table A.3: Main Employee Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	0.015 [0.234]	0.019 [0.150]	-0.003 [0.919]	0.018 [0.674]	-0.039 [0.277]
-3*treated	0.016 [0.173]	0.016 [0.169]	0.018 [0.379]	0.011 [0.722]	0.017 [0.483]
0*treated	0.004 [0.690]	0.009 [0.372]	-0.026 [0.153]	-0.003 [0.907]	-0.050 [0.028]
1*treated	0.050 [0.000]	0.053 [0.000]	0.035 [0.195]	0.104 [0.014]	-0.030 [0.348]
2*treated	0.063 [0.000]	0.064 [0.000]	0.063 [0.067]	0.150 [0.004]	-0.015 [0.747]
3*treated	0.068 [0.000]	0.067 [0.000]	0.079 [0.035]	0.129 [0.019]	0.037 [0.490]
4*treated	0.070 [0.000]	0.071 [0.000]	0.076 [0.057]	0.120 [0.049]	0.047 [0.369]
5*treated	0.072 [0.000]	0.073 [0.000]	0.070 [0.094]	0.088 [0.200]	0.051 [0.323]
6*treated	0.065 [0.000]	0.067 [0.000]	0.065 [0.159]	0.072 [0.326]	0.061 [0.303]
7*treated	0.058 [0.003]	0.058 [0.003]	0.068 [0.161]	0.085 [0.262]	0.045 [0.461]
8*treated	0.060 [0.003]	0.060 [0.005]	0.073 [0.149]	0.076 [0.324]	0.071 [0.296]
9*treated	0.040 [0.053]	0.037 [0.087]	0.074 [0.151]	0.035 [0.669]	0.096 [0.149]
10*treated	0.028 [0.191]	0.023 [0.306]	0.075 [0.166]	0.039 [0.649]	0.087 [0.207]
-4	-0.089 [0.000]	-0.090 [0.000]	-0.087 [0.000]	-0.118 [0.001]	-0.039 [0.161]
-3	-0.038 [0.000]	-0.037 [0.000]	-0.052 [0.001]	-0.066 [0.003]	-0.029 [0.154]
0	0.023 [0.000]	0.017 [0.006]	0.057 [0.000]	0.052 [0.011]	0.065 [0.001]
1	0.020 [0.008]	0.015 [0.039]	0.047 [0.028]	0.022 [0.493]	0.084 [0.000]
2	0.007 [0.423]	0.005 [0.561]	0.019 [0.513]	-0.009 [0.837]	0.060 [0.145]
3	-0.002 [0.856]	-0.001 [0.900]	-0.007 [0.815]	-0.020 [0.635]	0.011 [0.822]
4	-0.012 [0.248]	-0.014 [0.207]	-0.007 [0.841]	-0.007 [0.885]	-0.006 [0.900]
5	-0.020 [0.077]	-0.022 [0.060]	-0.011 [0.743]	-0.020 [0.689]	0.001 [0.976]
6	-0.034 [0.007]	-0.037 [0.003]	-0.013 [0.743]	-0.010 [0.852]	-0.015 [0.780]
7	-0.038 [0.004]	-0.039 [0.003]	-0.030 [0.454]	-0.044 [0.450]	-0.010 [0.853]
8	-0.048 [0.001]	-0.050 [0.001]	-0.036 [0.397]	-0.034 [0.571]	-0.038 [0.520]
9	-0.043 [0.003]	-0.043 [0.003]	-0.042 [0.323]	-0.038 [0.536]	-0.047 [0.413]
10	-0.094 [0.000]	-0.093 [0.000]	-0.102 [0.020]	-0.107 [0.093]	-0.094 [0.102]
Observations	55783	48642	7141	3665	3476
Baseline Mean	2.527	2.583	2.054	2.013	2.069

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

B Supplementary Material

Table B.1: Descriptive Statistics: Individual Level - Firms of 30 Employees or Less

	Incumbent Control	Incumbent Treated	t-test Incumbent	Deceased Control	Deceased Treated	t-test Deceased
Mean Age	39.23	39.46	0.077	44.57	44.99	0.250
Mean Monthly Earnings	31090.43	31703.36	0.008**	37983.42	37939.21	0.965
Mean Tenure (years)	5.95	6.07	0.088	6.72	7.14	0.078
Mean Monthly Hours	163.21	162.6	0.146	177.2	174.73	0.001***
Percent Female	29.76	33.29	0.000***	17.98	17.98	1.000
N	19469	18940		1913	1913	

Table B.2: Firm-level Descriptives - Firms of 30 Employees or Less

Controls	Potential Treated	Controls	P-value	
Total Employees	12.61	12.23	12.55	0.201
Percent Female	38.53	31.79	27.70	0.000***
Sector (Mode)	4.00	4.00	4.00	
Number of Workers	5.74	81.34	88.86	0.001**
Number of Bosses	0.48	12.75	12.84	0.797
Number of Daily Workers	0.82	20.41	22.48	0.151
N	5908375.00	1913.00	1913.00	

Table B.3: Descriptive Statistics: Individual Level - Sick Days

	Incumbent Control	Incumbent Treated	t-test Incumbent	Deceased Control	Deceased Treated	t-test Deceased
Mean Age	39.84	39.59	0.076	44.87	44.75	0.770
Mean Monthly Earnings	36003.94	37538.53	0.000***	42556.94	42919.19	0.770
Mean Tenure (years)	5.91	5.9	0.948	6.71	6.74	0.914
Mean Monthly Hours	163.22	162.6	0.164	176.8	172.79	0.000***
Percent Female	32.01	33.47	0.004**	17.88	17.88	1.000
N	17174	17733		1426	1426	

Table B.4: Firm-level Descriptives - Sick Days

Controls	Potential Treated	Controls	P-value	
Total Employees	12.61	15.27	14.62	0.090
Percent Female	38.53	32.26	30.00	0.020*
Sector (Mode)	4.00	4.00	4.00	
Number of Workers	5.74	101.49	105.91	0.199
Number of Bosses	0.48	11.51	12.44	0.041*
Number of Daily Workers	0.82	28.01	26.04	0.337
N	5908375.00	1426.00	1426.00	

Table B.5: Descriptive Statistics: Individual Level - Salary Ratio above 0.9

	Incumbent Control	Incumbent Treated	t-test Incumbent	Deceased Control	Deceased Treated	t-test Deceased
Mean Age	39.06	39.42	0.010**	44.11	44.75	0.094
Mean Monthly Earnings	30166.32	31174.3	0.000***	37589.9	36958.51	0.553
Mean Tenure (years)	5.81	5.94	0.080	6.94	7.02	0.753
Mean Monthly Hours	163.51	162.61	0.038*	176.53	174.7	0.015*
Percent Female	30.67	33.42	0.000***	17.4	17.4	1.000
N	17785	17291		1764	1764	

Table B.6: Firm-level Descriptives - Salary Ratio above 0.9

Controls	Potential Treated	Controls	P-value	
Total Employees	12.61	12.15	12.48	0.200
Percent Female	38.53	31.83	28.23	0.000***
Sector (Mode)	4.00	4.00	4.00	
Number of Workers	5.74	79.99	87.82	0.001***
Number of Bosses	0.48	12.66	13.22	0.171
Number of Daily Workers	0.82	19.42	21.67	0.110
N	5908375.00	1764.00	1764.00	

Table B.7: Total Bill and Mean Salary Results

Period	Log Total Bill	Log Mean Salary (New)
-4*treated	0.025 [0.587]	—
-3*treated	0.034 [0.351]	0.014 [0.822]
0*treated	0.012 [0.686]	0.018 [0.742]
1*treated	0.108 [0.002]	0.089 [0.093]
2*treated	0.152 [0.000]	0.069 [0.214]
3*treated	0.123 [0.003]	-0.013 [0.833]
4*treated	0.166 [0.000]	0.142 [0.020]
5*treated	0.182 [0.000]	0.010 [0.873]
6*treated	0.184 [0.001]	0.139 [0.048]
7*treated	0.198 [0.001]	-0.071 [0.304]
8*treated	0.163 [0.013]	0.120 [0.108]
9*treated	0.135 [0.040]	0.071 [0.253]
10*treated	0.077 [0.253]	—
-4	-0.183 [0.000]	—
-3	-0.092 [0.000]	-0.099 [0.019]
0	0.109 [0.000]	-0.025 [0.471]
1	0.086 [0.001]	0.016 [0.672]
2	0.046 [0.170]	0.023 [0.544]
3	0.060 [0.057]	0.053 [0.183]
4	0.020 [0.586]	-0.038 [0.429]
5	-0.005 [0.906]	0.043 [0.265]
6	-0.041 [0.359]	-0.017 [0.747]
7	-0.058 [0.238]	0.093 [0.038]
8	-0.045 [0.384]	0.001 [0.980]
9	-0.027 [0.592]	0.180 [0.000]
10	0.005 [0.921]	—
Observations	55783	24716
Baseline Mean	12.573	0.000

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.8: Retention Rate Incumbent Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	0.008 [0.312]	0.006 [0.482]	0.026 [0.307]	0.014 [0.728]	0.020 [0.556]
-3*treated	0.003 [0.644]	-0.001 [0.884]	0.037 [0.086]	0.053 [0.102]	0.008 [0.778]
0*treated	-0.002 [0.638]	-0.004 [0.459]	0.010 [0.568]	0.019 [0.424]	-0.009 [0.706]
1*treated	-0.003 [0.724]	0.003 [0.674]	-0.050 [0.068]	-0.078 [0.086]	-0.065 [0.049]
2*treated	-0.002 [0.786]	0.004 [0.649]	-0.054 [0.079]	-0.075 [0.112]	-0.081 [0.050]
3*treated	-0.001 [0.926]	0.003 [0.789]	-0.029 [0.379]	-0.046 [0.351]	-0.053 [0.257]
4*treated	-0.008 [0.430]	-0.003 [0.753]	-0.045 [0.177]	-0.044 [0.364]	-0.086 [0.067]
5*treated	-0.003 [0.754]	0.000 [0.996]	-0.029 [0.378]	-0.032 [0.502]	-0.067 [0.142]
6*treated	-0.002 [0.875]	0.004 [0.704]	-0.048 [0.151]	-0.058 [0.229]	-0.075 [0.104]
7*treated	0.002 [0.868]	0.006 [0.556]	-0.036 [0.284]	-0.062 [0.191]	-0.054 [0.246]
8*treated	0.004 [0.674]	0.009 [0.378]	-0.038 [0.260]	-0.096 [0.035]	-0.030 [0.528]
9*treated	0.003 [0.784]	0.008 [0.438]	-0.042 [0.200]	-0.106 [0.019]	-0.027 [0.564]
10*treated	0.001 [0.893]	0.007 [0.518]	-0.043 [0.187]	-0.102 [0.020]	-0.035 [0.459]
-4	-0.288 [0.000]	-0.286 [0.000]	-0.301 [0.000]	-0.321 [0.000]	-0.274 [0.000]
-3	-0.194 [0.000]	-0.191 [0.000]	-0.220 [0.000]	-0.248 [0.000]	-0.183 [0.000]
0	-0.038 [0.000]	-0.039 [0.000]	-0.029 [0.024]	-0.049 [0.006]	-0.003 [0.856]
1	-0.135 [0.000]	-0.138 [0.000]	-0.111 [0.000]	-0.162 [0.000]	-0.045 [0.055]
2	-0.215 [0.000]	-0.217 [0.000]	-0.193 [0.000]	-0.253 [0.000]	-0.114 [0.000]
3	-0.287 [0.000]	-0.287 [0.000]	-0.291 [0.000]	-0.343 [0.000]	-0.223 [0.000]
4	-0.345 [0.000]	-0.346 [0.000]	-0.337 [0.000]	-0.397 [0.000]	-0.258 [0.000]
5	-0.396 [0.000]	-0.396 [0.000]	-0.393 [0.000]	-0.453 [0.000]	-0.315 [0.000]
6	-0.441 [0.000]	-0.443 [0.000]	-0.421 [0.000]	-0.472 [0.000]	-0.355 [0.000]
7	-0.486 [0.000]	-0.489 [0.000]	-0.467 [0.000]	-0.519 [0.000]	-0.398 [0.000]
8	-0.524 [0.000]	-0.527 [0.000]	-0.501 [0.000]	-0.546 [0.000]	-0.443 [0.000]
9	-0.555 [0.000]	-0.558 [0.000]	-0.526 [0.000]	-0.565 [0.000]	-0.475 [0.000]
10	-0.582 [0.000]	-0.586 [0.000]	-0.548 [0.000]	-0.592 [0.000]	-0.491 [0.000]
Observations	749385	695835	53550	22920	30630
Baseline Mean	0.921	0.922	0.914	0.921	0.921

Notes: Following Equation (2), the table shows the regresion coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: t3 and t4 (reference periods). Event timing: period t5 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.9: Log Monthly Wage Incumbent Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	0.015 [0.047]	0.014 [0.061]	0.019 [0.493]	0.035 [0.375]	-0.014 [0.708]
-3*treated	0.005 [0.355]	0.006 [0.335]	0.002 [0.935]	0.001 [0.965]	-0.009 [0.748]
0*treated	-0.003 [0.575]	-0.007 [0.244]	0.022 [0.317]	0.005 [0.891]	0.037 [0.194]
1*treated	0.004 [0.552]	0.002 [0.787]	0.023 [0.443]	-0.019 [0.743]	0.056 [0.116]
2*treated	0.002 [0.807]	0.002 [0.821]	0.005 [0.881]	-0.017 [0.747]	0.023 [0.577]
3*treated	0.014 [0.154]	0.013 [0.187]	0.021 [0.566]	-0.012 [0.842]	0.049 [0.288]
4*treated	0.002 [0.838]	0.007 [0.528]	-0.033 [0.390]	-0.057 [0.368]	-0.010 [0.837]
5*treated	-0.002 [0.888]	0.003 [0.835]	-0.035 [0.414]	-0.112 [0.168]	0.027 [0.595]
6*treated	-0.001 [0.958]	0.001 [0.918]	-0.015 [0.741]	-0.052 [0.471]	0.031 [0.620]
7*treated	-0.004 [0.809]	-0.003 [0.818]	-0.000 [0.992]	0.004 [0.959]	0.016 [0.815]
8*treated	0.000 [0.986]	0.001 [0.972]	0.000 [0.998]	0.011 [0.901]	0.014 [0.844]
9*treated	-0.003 [0.852]	-0.004 [0.813]	0.005 [0.935]	0.015 [0.882]	0.008 [0.908]
10*treated	-0.005 [0.797]	-0.004 [0.846]	-0.011 [0.861]	-0.028 [0.813]	-0.004 [0.954]
-4	-0.061 [0.000]	-0.062 [0.000]	-0.047 [0.018]	-0.086 [0.004]	0.001 [0.969]
-3	-0.033 [0.000]	-0.035 [0.000]	-0.013 [0.278]	-0.035 [0.037]	0.012 [0.480]
0	0.031 [0.000]	0.028 [0.000]	0.052 [0.000]	0.059 [0.002]	0.043 [0.018]
1	0.047 [0.000]	0.045 [0.000]	0.064 [0.000]	0.082 [0.000]	0.045 [0.073]
2	0.068 [0.000]	0.063 [0.000]	0.109 [0.000]	0.120 [0.000]	0.099 [0.001]
3	0.081 [0.000]	0.078 [0.000]	0.110 [0.000]	0.129 [0.000]	0.089 [0.016]
4	0.107 [0.000]	0.099 [0.000]	0.165 [0.000]	0.184 [0.000]	0.146 [0.000]
5	0.122 [0.000]	0.116 [0.000]	0.169 [0.000]	0.216 [0.000]	0.122 [0.002]
6	0.141 [0.000]	0.135 [0.000]	0.183 [0.000]	0.237 [0.000]	0.129 [0.010]
7	0.162 [0.000]	0.155 [0.000]	0.210 [0.000]	0.242 [0.000]	0.180 [0.001]
8	0.177 [0.000]	0.172 [0.000]	0.213 [0.000]	0.240 [0.000]	0.187 [0.001]
9	0.204 [0.000]	0.201 [0.000]	0.226 [0.000]	0.234 [0.001]	0.218 [0.000]
10	0.222 [0.000]	0.218 [0.000]	0.254 [0.000]	0.251 [0.001]	0.258 [0.000]
Observations	421669	390337	31332	12147	19185
Baseline Mean	10.219	10.262	9.888	10.219	10.219

Notes: Following Equation (2), the table shows the regresion coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: t3 and t4 (reference periods). Event timing: period t5 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.10: Monthly Hours Worked Incumbent Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	1.262 [0.009]	1.278 [0.011]	1.106 [0.534]	3.373 [0.169]	-0.480 [0.850]
-3*treated	1.056 [0.011]	0.946 [0.027]	1.937 [0.194]	1.078 [0.650]	2.718 [0.184]
0*treated	-1.232 [0.004]	-0.766 [0.076]	-4.935 [0.005]	-11.976 [0.001]	-0.587 [0.681]
1*treated	0.364 [0.444]	0.240 [0.616]	1.465 [0.448]	-1.900 [0.652]	3.939 [0.014]
2*treated	0.266 [0.605]	0.089 [0.866]	1.792 [0.359]	2.004 [0.609]	1.801 [0.362]
3*treated	0.832 [0.139]	0.605 [0.300]	2.755 [0.166]	2.324 [0.549]	2.488 [0.223]
4*treated	0.713 [0.244]	0.789 [0.211]	0.171 [0.939]	-0.699 [0.873]	0.190 [0.933]
5*treated	0.716 [0.281]	0.216 [0.753]	4.942 [0.034]	5.812 [0.177]	4.218 [0.115]
6*treated	0.475 [0.508]	-0.075 [0.920]	5.009 [0.047]	5.645 [0.211]	3.624 [0.204]
7*treated	0.783 [0.314]	0.227 [0.779]	5.321 [0.046]	6.502 [0.161]	3.768 [0.249]
8*treated	1.919 [0.026]	1.195 [0.176]	7.695 [0.013]	10.286 [0.060]	4.960 [0.183]
9*treated	0.970 [0.252]	0.075 [0.931]	8.061 [0.007]	7.956 [0.166]	6.755 [0.062]
10*treated	0.802 [0.359]	-0.132 [0.884]	8.196 [0.006]	11.001 [0.027]	5.246 [0.167]
-4	-1.050 [0.002]	-1.032 [0.003]	-1.182 [0.323]	-1.628 [0.304]	-0.592 [0.745]
-3	-0.726 [0.013]	-0.683 [0.022]	-1.068 [0.337]	-0.621 [0.664]	-1.546 [0.372]
0	-0.416 [0.113]	-0.391 [0.138]	-0.614 [0.567]	-0.790 [0.656]	-0.380 [0.705]
1	-0.794 [0.015]	-0.804 [0.016]	-0.719 [0.563]	0.188 [0.928]	-1.712 [0.162]
2	-0.764 [0.037]	-0.690 [0.062]	-1.355 [0.355]	-1.469 [0.529]	-1.221 [0.468]
3	-1.178 [0.003]	-1.019 [0.012]	-2.459 [0.079]	-3.610 [0.111]	-1.169 [0.450]
4	-1.518 [0.001]	-1.631 [0.000]	-0.597 [0.700]	-1.751 [0.502]	0.632 [0.689]
5	-1.445 [0.002]	-1.149 [0.016]	-3.843 [0.019]	-4.657 [0.064]	-2.969 [0.146]
6	-2.065 [0.000]	-1.686 [0.002]	-5.044 [0.009]	-7.419 [0.015]	-2.569 [0.252]
7	-2.312 [0.000]	-1.858 [0.002]	-5.907 [0.006]	-8.229 [0.010]	-3.572 [0.202]
8	-3.345 [0.000]	-2.712 [0.000]	-8.271 [0.001]	-11.582 [0.003]	-4.896 [0.134]
9	-2.449 [0.000]	-1.714 [0.009]	-8.087 [0.000]	-10.679 [0.001]	-5.393 [0.080]
10	-2.477 [0.000]	-1.791 [0.007]	-7.680 [0.001]	-11.313 [0.001]	-4.044 [0.209]
Observations	451368	419154	32214	12490	19724
Baseline Mean	163.402	163.924	159.126	163.402	163.402

Notes: Following Equation (2), the table shows the regresion coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: t3 and t4 (reference periods). Event timing: period t5 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.11: Monthly Days Worked Incumbent Results

Period	Main	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	0.068 [0.315]	0.108 [0.103]	-0.265 [0.388]	-0.235 [0.609]	-0.145 [0.706]
-3*treated	0.095 [0.102]	0.090 [0.133]	0.128 [0.547]	-0.245 [0.476]	0.452 [0.092]
0*treated	-0.220 [0.001]	-0.122 [0.058]	-1.004 [0.000]	-2.369 [0.000]	-0.270 [0.219]
1*treated	0.056 [0.394]	0.045 [0.505]	0.153 [0.551]	-0.514 [0.344]	0.518 [0.041]
2*treated	0.038 [0.576]	-0.016 [0.815]	0.484 [0.071]	0.189 [0.706]	0.706 [0.022]
3*treated	0.074 [0.321]	0.013 [0.861]	0.575 [0.041]	0.159 [0.768]	0.686 [0.011]
4*treated	0.036 [0.658]	0.006 [0.940]	0.285 [0.367]	-0.087 [0.888]	0.411 [0.162]
5*treated	0.125 [0.176]	0.042 [0.652]	0.808 [0.026]	0.692 [0.328]	0.813 [0.025]
6*treated	0.061 [0.520]	-0.016 [0.871]	0.697 [0.060]	0.415 [0.554]	0.672 [0.056]
7*treated	0.113 [0.261]	0.025 [0.811]	0.828 [0.027]	0.658 [0.349]	0.766 [0.051]
8*treated	0.238 [0.039]	0.142 [0.222]	1.000 [0.023]	0.875 [0.265]	0.908 [0.056]
9*treated	0.151 [0.164]	0.028 [0.799]	1.115 [0.007]	0.669 [0.444]	1.148 [0.010]
10*treated	0.072 [0.518]	-0.071 [0.536]	1.212 [0.003]	1.316 [0.066]	0.977 [0.050]
-4	-0.026 [0.593]	-0.054 [0.250]	0.209 [0.359]	0.406 [0.248]	-0.013 [0.963]
-3	-0.048 [0.218]	-0.053 [0.189]	-0.002 [0.988]	0.177 [0.410]	-0.197 [0.327]
0	-0.134 [0.000]	-0.133 [0.001]	-0.137 [0.317]	-0.355 [0.108]	0.129 [0.358]
1	-0.245 [0.000]	-0.231 [0.000]	-0.354 [0.019]	-0.409 [0.071]	-0.289 [0.135]
2	-0.252 [0.000]	-0.211 [0.000]	-0.573 [0.004]	-0.541 [0.068]	-0.606 [0.017]
3	-0.301 [0.000]	-0.247 [0.000]	-0.738 [0.000]	-1.006 [0.004]	-0.439 [0.026]
4	-0.337 [0.000]	-0.311 [0.000]	-0.532 [0.021]	-0.765 [0.057]	-0.289 [0.165]
5	-0.421 [0.000]	-0.356 [0.000]	-0.939 [0.001]	-1.145 [0.017]	-0.725 [0.010]
6	-0.445 [0.000]	-0.394 [0.000]	-0.838 [0.005]	-1.260 [0.015]	-0.400 [0.145]
7	-0.501 [0.000]	-0.426 [0.000]	-1.086 [0.000]	-1.484 [0.004]	-0.689 [0.043]
8	-0.663 [0.000]	-0.578 [0.000]	-1.314 [0.001]	-1.720 [0.007]	-0.902 [0.028]
9	-0.564 [0.000]	-0.459 [0.000]	-1.362 [0.000]	-1.740 [0.000]	-0.968 [0.009]
10	-0.565 [0.000]	-0.465 [0.000]	-1.324 [0.000]	-1.820 [0.001]	-0.824 [0.055]
Observations	435158	403981	31177	12042	19135
Baseline Mean	27.368	27.365	27.391	27.368	27.368

Notes: Following Equation (2), the table shows the regresion coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: t3 and t4 (reference periods). Event timing: period t5 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.12: Log Average Salary: Above/Below Median Results

Period	Deceased High Salary	Deceased Low Salary
-4*treated	-0.015 [0.725]	0.047 [0.355]
-3*treated	0.005 [0.885]	0.026 [0.500]
0*treated	0.046 [0.086]	-0.002 [0.906]
1*treated	0.087 [0.004]	0.011 [0.555]
2*treated	0.104 [0.008]	0.005 [0.805]
3*treated	0.076 [0.062]	-0.008 [0.744]
4*treated	0.079 [0.074]	0.020 [0.619]
5*treated	0.114 [0.025]	0.018 [0.683]
6*treated	0.108 [0.057]	0.072 [0.193]
7*treated	0.063 [0.279]	0.114 [0.067]
8*treated	0.024 [0.720]	0.116 [0.080]
9*treated	-0.013 [0.843]	0.133 [0.061]
10*treated	-0.046 [0.503]	0.100 [0.139]
-4	-0.082 [0.000]	-0.164 [0.000]
-3	-0.039 [0.019]	-0.098 [0.001]
0	0.031 [0.059]	0.037 [0.006]
1	0.035 [0.071]	0.036 [0.020]
2	0.011 [0.712]	0.051 [0.002]
3	0.039 [0.159]	0.058 [0.000]
4	0.039 [0.213]	0.027 [0.425]
5	0.006 [0.873]	0.030 [0.406]
6	-0.005 [0.898]	-0.028 [0.553]
7	0.048 [0.265]	-0.051 [0.357]
8	0.054 [0.240]	-0.044 [0.456]
9	0.099 [0.014]	-0.055 [0.388]
10	0.104 [0.014]	-0.007 [0.907]
Observations	33250	22423
Baseline Mean	10.193	10.157

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.13: Number of Employees: Above/Below Median Results

Period	Deceased High Salary	Deceased Low Salary
-4*treated	0.023 [0.148]	-0.019 [0.268]
-3*treated	0.017 [0.219]	-0.008 [0.567]
0*treated	0.006 [0.640]	-0.024 [0.040]
1*treated	0.037 [0.013]	0.042 [0.008]
2*treated	0.055 [0.002]	0.042 [0.028]
3*treated	0.061 [0.001]	0.046 [0.022]
4*treated	0.057 [0.005]	0.058 [0.009]
5*treated	0.064 [0.002]	0.051 [0.029]
6*treated	0.065 [0.004]	0.035 [0.169]
7*treated	0.052 [0.029]	0.034 [0.228]
8*treated	0.048 [0.065]	0.045 [0.128]
9*treated	0.017 [0.529]	0.043 [0.161]
10*treated	0.010 [0.717]	0.022 [0.480]
-4	-0.094 [0.000]	-0.070 [0.000]
-3	-0.039 [0.000]	-0.026 [0.012]
0	0.014 [0.047]	0.050 [0.000]
1	0.012 [0.135]	0.046 [0.000]
2	-0.007 [0.540]	0.045 [0.002]
3	-0.019 [0.118]	0.041 [0.008]
4	-0.025 [0.056]	0.023 [0.178]
5	-0.035 [0.015]	0.018 [0.324]
6	-0.049 [0.002]	0.006 [0.759]
7	-0.052 [0.001]	0.000 [0.992]
8	-0.062 [0.000]	-0.009 [0.694]
9	-0.050 [0.004]	-0.016 [0.501]
10	-0.104 [0.000]	-0.064 [0.008]
Observations	33314	22469
Baseline Mean	2.565	2.478

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.14: Company Survival Event Study

Period	All Firms	Employee Deceased	Boss Deceased	Boss Deceased, One Boss	Boss Deceased, Multiple Bosses
-4*treated	-0.001 [0.737]	-0.001 [0.693]	0.001 [0.931]	0.002 [0.820]	-0.003 [0.775]
-3*treated	0.002 [0.447]	0.002 [0.414]	0.000 [0.967]	-0.003 [0.712]	0.001 [0.882]
0*treated	-0.002 [0.053]	-0.003 [0.058]	-0.002 [0.501]	0.001 [0.775]	-0.005 [0.311]
1*treated	-0.028 [0.000]	-0.006 [0.308]	-0.171 [0.000]	-0.314 [0.000]	-0.033 [0.141]
2*treated	-0.032 [0.000]	-0.005 [0.574]	-0.204 [0.000]	-0.333 [0.000]	-0.083 [0.010]
3*treated	-0.027 [0.007]	-0.006 [0.575]	-0.164 [0.000]	-0.294 [0.000]	-0.040 [0.344]
4*treated	-0.031 [0.006]	-0.010 [0.397]	-0.167 [0.000]	-0.296 [0.000]	-0.047 [0.313]
5*treated	-0.028 [0.020]	-0.011 [0.406]	-0.140 [0.000]	-0.257 [0.000]	-0.035 [0.465]
6*treated	-0.023 [0.064]	-0.006 [0.637]	-0.134 [0.000]	-0.243 [0.000]	-0.037 [0.465]
7*treated	-0.015 [0.267]	0.004 [0.767]	-0.137 [0.000]	-0.261 [0.000]	-0.026 [0.625]
8*treated	-0.017 [0.215]	0.005 [0.747]	-0.157 [0.000]	-0.306 [0.000]	-0.017 [0.750]
9*treated	-0.013 [0.343]	0.010 [0.509]	-0.164 [0.000]	-0.298 [0.000]	-0.042 [0.450]
10*treated	-0.016 [0.277]	0.008 [0.587]	-0.171 [0.000]	-0.296 [0.000]	-0.062 [0.271]
-4	0.001 [0.497]	0.002 [0.374]	-0.002 [0.648]	-0.001 [0.858]	-0.004 [0.588]
-3	-0.001 [0.366]	-0.002 [0.338]	0.000 [0.900]	0.001 [0.790]	-0.001 [0.866]
0	0.002 [0.038]	0.001 [0.063]	0.002 [0.341]	0.002 [0.452]	0.003 [0.481]
1	-0.032 [0.000]	-0.033 [0.000]	-0.021 [0.008]	-0.021 [0.036]	-0.022 [0.110]
2	-0.066 [0.000]	-0.069 [0.000]	-0.045 [0.000]	-0.050 [0.002]	-0.038 [0.034]
3	-0.112 [0.000]	-0.110 [0.000]	-0.122 [0.000]	-0.124 [0.000]	-0.120 [0.000]
4	-0.152 [0.000]	-0.150 [0.000]	-0.163 [0.000]	-0.170 [0.000]	-0.153 [0.000]
5	-0.183 [0.000]	-0.180 [0.000]	-0.200 [0.000]	-0.215 [0.000]	-0.177 [0.000]
6	-0.214 [0.000]	-0.212 [0.000]	-0.227 [0.000]	-0.244 [0.000]	-0.202 [0.000]
7	-0.256 [0.000]	-0.257 [0.000]	-0.250 [0.000]	-0.267 [0.000]	-0.227 [0.000]
8	-0.284 [0.000]	-0.285 [0.000]	-0.277 [0.000]	-0.284 [0.000]	-0.268 [0.000]
9	-0.318 [0.000]	-0.321 [0.000]	-0.298 [0.000]	-0.312 [0.000]	-0.276 [0.000]
10	-0.345 [0.000]	-0.350 [0.000]	-0.311 [0.000]	-0.335 [0.000]	-0.276 [0.000]
Observations	64977	56213	8764	4742	4022
Baseline Mean	0.000	0.000	0.000	0.000	0.000

Notes: Coefficients are shown with p-values in brackets. Baseline Mean is the pre-treatment mean for omitted periods. Event time: t5 = death. Standard errors clustered at firm level. Source: Social security administrative records, 1997-2022.

Table B.15: Robustness Check: Balanced Sample Outcomes

Period	Log Average Salary (Balanced Sample)	Log Number of Employees (Balanced Sample)
-4*treated	0.058 [0.111]	0.004 [0.826]
-3*treated	0.075 [0.001]	0.008 [0.598]
0*treated	0.066 [0.007]	0.011 [0.468]
1*treated	0.073 [0.016]	0.056 [0.001]
2*treated	0.093 [0.007]	0.068 [0.000]
3*treated	0.073 [0.052]	0.062 [0.001]
4*treated	0.075 [0.087]	0.050 [0.016]
5*treated	0.072 [0.136]	0.050 [0.020]
6*treated	0.104 [0.052]	0.043 [0.059]
7*treated	0.098 [0.064]	0.038 [0.109]
8*treated	0.069 [0.199]	0.035 [0.152]
9*treated	0.052 [0.371]	0.021 [0.407]
10*treated	0.037 [0.548]	0.018 [0.482]
-4	-0.136 [0.000]	-0.096 [0.000]
-3	-0.078 [0.000]	-0.037 [0.000]
0	0.015 [0.276]	0.013 [0.098]
1	0.024 [0.215]	0.019 [0.055]
2	0.023 [0.379]	0.019 [0.118]
3	0.036 [0.173]	0.016 [0.219]
4	0.028 [0.382]	0.016 [0.243]
5	0.035 [0.321]	0.013 [0.368]
6	0.004 [0.928]	0.002 [0.898]
7	0.043 [0.277]	-0.009 [0.603]
8	0.068 [0.080]	-0.014 [0.398]
9	0.079 [0.057]	-0.018 [0.316]
10	0.080 [0.062]	-0.077 [0.000]
Observations	28551	28590
Baseline Mean	10.177	2.527

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean of outcome variable for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.16: Robustness Check: Main Table - Firms of 30 Employees or Less

Period	Log Number of Employees	Log Average Salary
-4	-0.083 [0.000]	-0.130 [0.000]
-4*treated	0.011 [0.318]	0.027 [0.435]
-3	-0.024 [0.000]	-0.070 [0.000]
-3*treated	0.001 [0.880]	0.003 [0.912]
0	0.012 [0.032]	0.009 [0.457]
0*treated	0.006 [0.515]	0.031 [0.069]
1	0.000 [0.980]	0.005 [0.744]
1*treated	0.063 [0.000]	0.053 [0.010]
2	-0.005 [0.594]	-0.008 [0.682]
2*treated	0.072 [0.000]	0.081 [0.001]
3	-0.009 [0.318]	0.017 [0.407]
3*treated	0.074 [0.000]	0.050 [0.071]
4	-0.019 [0.064]	0.005 [0.836]
4*treated	0.070 [0.000]	0.056 [0.088]
5	-0.028 [0.014]	0.007 [0.792]
5*treated	0.072 [0.000]	0.052 [0.145]
6	-0.038 [0.002]	0.016 [0.535]
6*treated	0.058 [0.001]	0.039 [0.295]
7	-0.041 [0.002]	0.058 [0.016]
7*treated	0.048 [0.009]	0.003 [0.926]
8	-0.024 [0.065]	0.049 [0.078]
8*treated	0.026 [0.167]	0.013 [0.741]
9	-0.034 [0.014]	0.036 [0.250]
9*treated	0.018 [0.357]	0.028 [0.538]
10	-0.101 [0.000]	0.037 [0.276]
10*treated	0.028 [0.180]	0.027 [0.576]
Observations	48038	47921
Baseline Mean	2.390	10.132

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.17: Robustness Check: Main Table - Sick Days

Period	Log Number of Employees	Log Average Salary
-4	-0.082 [0.000]	-0.111 [0.000]
-4*treated	-0.010 [0.400]	-0.054 [0.152]
-3	-0.029 [0.000]	-0.049 [0.000]
-3*treated	-0.010 [0.305]	-0.066 [0.024]
0	0.028 [0.000]	0.049 [0.001]
0*treated	-0.010 [0.291]	0.013 [0.529]
1	0.025 [0.002]	0.027 [0.226]
1*treated	0.040 [0.001]	0.062 [0.023]
2	0.027 [0.005]	0.043 [0.066]
2*treated	0.047 [0.001]	0.064 [0.030]
3	0.025 [0.016]	0.061 [0.021]
3*treated	0.051 [0.001]	0.052 [0.128]
4	0.029 [0.012]	0.075 [0.007]
4*treated	0.039 [0.018]	0.037 [0.332]
5	0.033 [0.009]	0.103 [0.000]
5*treated	0.022 [0.210]	0.042 [0.272]
6	0.040 [0.002]	0.090 [0.007]
6*treated	0.001 [0.971]	0.067 [0.113]
7	0.035 [0.010]	0.138 [0.000]
7*treated	-0.006 [0.774]	0.047 [0.245]
8	0.031 [0.031]	0.134 [0.000]
8*treated	-0.014 [0.504]	0.076 [0.093]
9	0.029 [0.057]	0.191 [0.000]
9*treated	-0.037 [0.096]	0.021 [0.642]
10	-0.035 [0.042]	0.143 [0.001]
10*treated	-0.033 [0.176]	0.068 [0.211]
Observations	35251	35177
Baseline Mean	2.566	10.241

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.

Table B.18: Robustness Check: Main Table - Salary Ratio above 0.9

Period	Log Number of Employees	Log Average Salary
-4	-0.082 [0.000]	-0.134 [0.000]
-4*treated	0.007 [0.507]	0.037 [0.317]
-3	-0.043 [0.000]	-0.077 [0.000]
-3*treated	0.016 [0.061]	0.001 [0.978]
0	0.023 [0.000]	0.023 [0.068]
0*treated	0.002 [0.835]	0.027 [0.122]
1	0.011 [0.115]	0.020 [0.222]
1*treated	0.065 [0.000]	0.041 [0.046]
2	0.006 [0.421]	-0.001 [0.970]
2*treated	0.070 [0.000]	0.076 [0.003]
3	0.001 [0.884]	0.005 [0.824]
3*treated	0.069 [0.000]	0.064 [0.038]
4	-0.004 [0.673]	0.013 [0.593]
4*treated	0.065 [0.000]	0.051 [0.137]
5	-0.010 [0.361]	0.012 [0.650]
5*treated	0.064 [0.000]	0.050 [0.194]
6	-0.022 [0.070]	0.031 [0.283]
6*treated	0.050 [0.003]	0.026 [0.516]
7	-0.030 [0.018]	-0.004 [0.906]
7*treated	0.049 [0.007]	0.061 [0.176]
8	-0.045 [0.002]	0.006 [0.865]
8*treated	0.058 [0.003]	0.053 [0.274]
9	-0.048 [0.001]	-0.021 [0.597]
9*treated	0.041 [0.044]	0.077 [0.145]
10	-0.094 [0.000]	-0.002 [0.967]
10*treated	0.029 [0.178]	0.045 [0.423]
Observations	44396	44300
Baseline Mean	2.375	10.127

Notes: Following Equation (1), the table shows the regression coefficients with p-values in brackets. Baseline Mean shows pre-treatment mean for omitted periods: -2 and -1 (reference periods). Event timing: period 0 corresponds to death occurrence. Standard errors clustered at firm level. Source: Social security administrative records from 1997-2022.