Labor Misallocation and Public-Sector Performance*

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Abstract

Leveraging personnel and intervention data from the Italian Fire and Rescue Service, we study how allocative frictions affect public sector performance. First, we document persistent delays in managerial turnover: retiring managers take months to be replaced. Second, exploiting delayed turnover and managerial rotations, we show that shortages of middle managers significantly slow interventions, while the absence of top managers has no short or long-run effects. Finally, we show that dispersion in marginal performance to pay is an observable sufficient statistic to evaluate labor misallocation in public organizations and estimate that intervention times are 9.3 percent longer than under the efficient allocation.

Keywords: Public sector performance; Labor misallocation; Managerial turnover; Public sector managers. *JEL Codes*: J24; J45; L32; D61; H11.

1 Introduction

The public sector is the largest employer in industrialized countries, accounting for an average of 18.6 percent of total workers [OECD, 2023]. Since most public

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organizations operate as monopolies in service provision and lack competitive incentives, this significant portion of the labor force may not be efficiently allocated [Dixit, 2002]. Inefficiencies in the public sector can severely hinder economic performance by imposing an excessive tax burden and delivering suboptimal levels of public goods [Hall and Jones, 1999; Acemoglu et al., 2001].

Besides limited competition, the weight of institutional rules create frictions that can further distort the allocation of labor. Turnover is delayed by the mismatch between continuous retirements and discrete hirings through civil service exams [Giorgiantonio et al., 2016]. An adequate response to local demand shocks (e.g. natural events) is limited by the moving costs of worker relocation [Schmutz and Sidibé, 2019]. Career progression often depends on seniority rather than merit or organizational needs [Bertrand and Schoar, 2003]. These allocative frictions can distort performance in all public sector organizations and are especially consequential at the managerial level. Managers are scarce and their absence can have spillover effects on the work of many.

Despite the economic relevance of public employment, there is limited knowledge about the extent, nature and consequences of its allocative inefficiencies. This paper provides empirical evidence of allocative frictions in the public sector and quantifies to what extent labor misallocation reduces public-sector performance. For this, we analyze the case study of the Italian Fire and Rescue Service. This is an ideal setting because fire departments constantly evaluate their own performance measuring their intervention time, a crucial determinant of property damages, injuries and casualties [Wrack, 2008; Corpo Nazionale dei Vigili del Fuoco, 2023a]. Moreover, the Fire Service is characterized by a clear hierarchical structure, which allows to analyze misallocation across job positions and the impact of different levels of management on public-sector performance.

Our empirical analysis draws on a unique dataset covering all 6.9 million interventions carried out by the Italian Fire and Rescue Service between 2014 and 2022. For each intervention, we observe the precise timing of the dispatch call, departure from the fire station, arrival on scene, departure from the scene, and return to the station, each recorded to the minute through a radio button on the firetruck. In addition, squad leaders file reports identifying the station involved, the nature and cause of the intervention, the area burned, and whether any civilians or firefighters were injured or killed. We link these operational records with monthly matched employer-employee data on public sector workers from the Italian social security institute (INPS). This dataset provides demographic characteristics, monthly earnings, contract type, rank, fire department, and exit cause (e.g. age-related retirement) for every firefighter over the same period.

We document the presence of substantial delays in the turnover of firefighters in all positions along the hierarchical structure: it takes more than one year to completely replace retirees in a fire department. Firefighters are forced to retire upon reaching a certain age, creating an exogenous variation that we leverage to estimate whether interventions slow down in the months following age-based retirements. Using a difference-in-differences design, the paper estimates how temporary personnel shortages affect public-sector performance, analyzing the effects at each rank of the fire department's hierarchy.

First, the results indicate that delayed turnover among middle managers significantly increases intervention times in the short term. A 10 percentage-point rise in the retirement rate of middle managers leads to a 2.8 percent increase in intervention time, driven by longer on-scene times (4.8 percent) while response or return times are not affected. In contrast, retirements of top managers have an impact on intervention duration that is not statistically different from zero. These results suggest that the leadership of middle managers is critical in determining public sector performance, whereas the lack of top management is less consequential in the short-term. Second, exploiting the rotation of top managers across departments in an AKM model [Abowd et al., 1999], we show that top managers explain a negligible share of performance variance across departments in the long term as well.

Several tests help isolate the mechanisms underlying the slowdown associated with shortages of middle managers. First, the absence of any effect on response times rules out reoptimization across stations as a main channel. Second, although retirements reduce the average age and tenure of middle managers, interactions between retirement rates and leader experience show no differential effect, suggesting that losses of accumulated human capital are not central. Third, controlling for intervention-type fixed effects, together with additional tests on the urgency of interventions, indicate that the composition of tasks remains unchanged, ruling out endogenous task selection. By contrast, the effects are present only in periods of high capacity utilization, when leader shortages bind. In multi-squad interventions, retirements lengthen total intervention time and reduce the extent of parallel work across squads on scene. Taken together, the evidence points to capacity constraints and coordination frictions as the key mechanisms driving the short-run performance effects of middle-manager retirements.

A caveat of this analysis is that delayed turnover represents only one of the possible sources of inefficiency in public employment, namely the one that can be analyzed within our reduced-form framework. Filling vacancies while keeping the average workforce constant over time would require potentially costly transfers across departments and a more gradual hiring path.

Finally, we develop a model of optimal labor allocation in a public-sector organization. The government aims to minimize total intervention time subject to the observed budget constraint and a performance production function. Performance is defined as the reciprocal of intervention time and it is modeled by a Cobb Douglas production function using the department-month workforce in each rank as inputs. We estimate the labor elasticities of performance by regressing log intervention times on the log workforce in each rank, instrumented with lagged retirement rates as in the reduced form analysis. Efficiency requires that the *marginal performance to pay* be equalized across all departments, positions, and time periods. This is equal to the product of the labor elasticity of performance and the ratio of total intervention time to the labor cost of each position in a department-month. Because elasticities are constant within positions and data on intervention times and labor costs are observed, dispersion in the log marginal performance to pay provides an easy-to-measure sufficient statistic for misallocation in public organizations, analogous to dispersion in log marginal revenue products across firms in the private sector [Hsieh and Klenow, 2009]. Simulations indicate that observed staffing generates intervention times that are on average 9.3 percent longer than under the efficient allocation. The largest inefficiency arises from the distribution of labor across hierarchical ranks, with an excess of resources devoted to top management relative to middle management and basic firefighters.

The misallocation of factors of production has been studied extensively in the private sector [Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017; Sraer and Thesmar, 2023]. In comparison, the public sector, where the absence of competition and the weight of institutional constraints suggest an even greater scope for misallocation, has received little attention. A reason is that high-frequency performance data combined with matched employer-employee records are rarely available in public organizations. To our knowledge, the only exception is Walter [2020], who uses cross-sectional data on schools of different countries and a model of education production to measure the misallocation of teachers. Our paper provides novel causal evidence on allocative frictions in the public sector and develops a sufficient-statistics method to quantify labor misallocation that can be applied to any public organization with data on personnel and performance.

This paper also contributes to the growing literature on the role of managerial skills in shaping public sector performance. The empirical evidence for top managers is mixed. Muñoz and Otero [2024] find that higher pay for public hospital CEOs reduced hospital mortality by attracting managers with stronger managerial skills, while Janke et al. [2019] find no evidence that rotation of CEOs influences the financial performance or quality of service in public hospitals. By contrast, middle managers have been shown to improve the performance of smaller units in education, healthcare, social security, and policing [Bloom et al., 2015; Tsai et al., 2015; Fenizia, 2022; Facchetti et al., 2025]. The heterogeneity in estimated effects across levels of management may reflect differences in identification strategies and institutional settings across studies. Our analysis enables a direct comparison of the impact of workers at different positions within the hierarchy of the same public organization, from entry level employees to senior managers.

The remainder of the paper is organized as follows. Section 2 provides institutional background on the Fire and Rescue Service, including its hiring and retirement rules. Section 3 describes the data and presents summary statistics. Section 4 outlines the empirical strategy and documents delays in turnover. Section 5 estimates the impact of turnover on performance and explores the underlying mechanisms. Section 6 shows that the dispersion in marginal performance to pay is a sufficient statistics to quantify the efficiency losses from misallocation and decomposes its sources in a labor allocation model. Section 7 concludes.

2 Institutional background

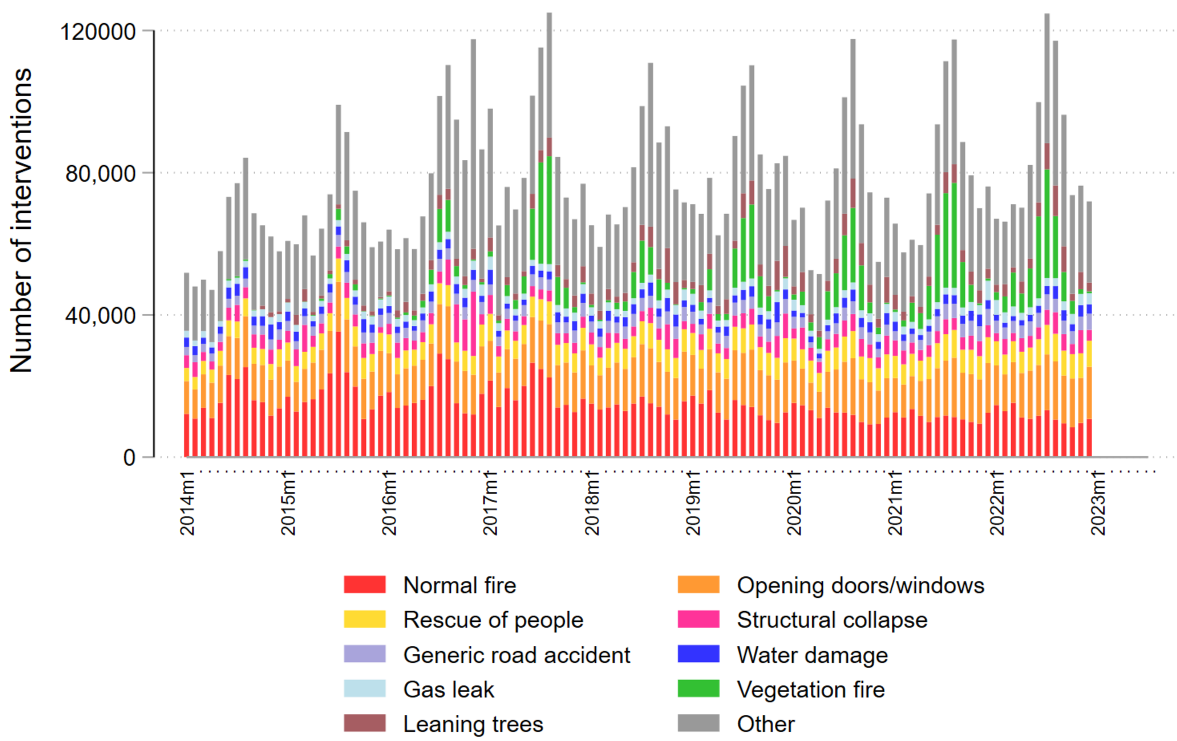
The Fire and Rescue Service. As of 2022, the Italian Fire and Rescue Service is composed by 851 fire stations coordinated by one fire department in each of the 100 provinces (Figure A3).[1] It covers the entire country except for the autonomous provinces of Aosta, Bolzano and Trento which have independent fire services [Corpo Nazionale dei Vigili del Fuoco, 2023c]. The Service has the duty to prevent and extinguish fires as well as to perform rescue and safety operations in a wide range of scenarios from domestic accidents to public calamities.

There are 113 different categories and 98 different causes of intervention in the data provided by the Fire Service. We define a 'type of intervention' as a category–cause pair. Figure 1 reports the nine most frequent categories of interventions (all others are grouped in 'Other') and their monthly numbers from 2014 to

[1] There are 159 additional fire stations run by volunteers, but we exclude them from the analysis.

2022. The figure shows large swings in demand due to natural hazard events, such as normal and vegetation fires in summers or the earthquakes that caused structural collapses at the end of 2016. Frequent causes include general inattention, electrical failures, faulty machinery, wear and tear, illness, and earthquakes.

Figure 1: Monthly number of firefighters' interventions by category

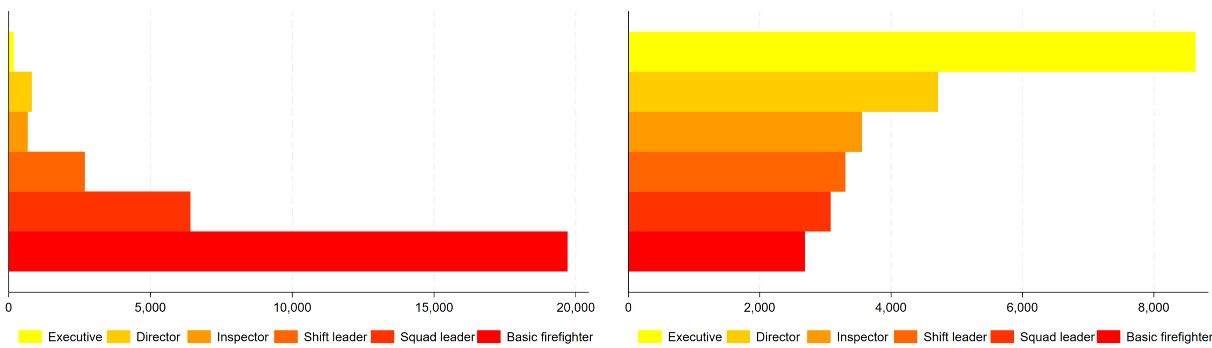


Note: This histogram show the monthly number of firefighters' interventions by category of interventions from 2014 to 2022. Data provided by the Italian Fire and Rescue Service. The figure reports the nine most frequent types of interventions, all the other types are grouped in the category 'Other'.

Firefighters are ranked in a hierarchical structure in the following ascending order: Basic Firefighters, Squad Leaders, Shift Leaders, Inspectors, Directors, Executives. Squad and shift leaders are *middle managers* that supervise basic firefighters in day-to-day operations on the ground. Inspectors, Directors, Executives are *top managers* that lead entire departments, inspect the equipment, train new recruits, manage resources and plan large-scale strategies. Firefighters are promoted to a higher position only if they reach certain seniority and educational levels and succeed in a competitive exam. In Section A.1, we provide a detailed explanation of the responsibilities of each position and the requirements to obtain a promotion.

During an intervention, four Basic Firefighters and a Squad Leader are grouped in teams of five (squads) and equipped with a firetruck. A squad cannot intervene if the squad leader is absent. Generally, in a fire department there are six basic firefighters and two squad leaders per squad so that the squad can function even when three basic firefighters or one squad leader are absent due to days of rest or sick leaves. Each provincial fire department has an operations center led by a shift leader that receives intervention requests by phone, assigns the intervention to one or more fire stations in the province and decides how many squads to send.

Figure 2: Average number of firefighters and income by hierarchical position



(a) Number of workers

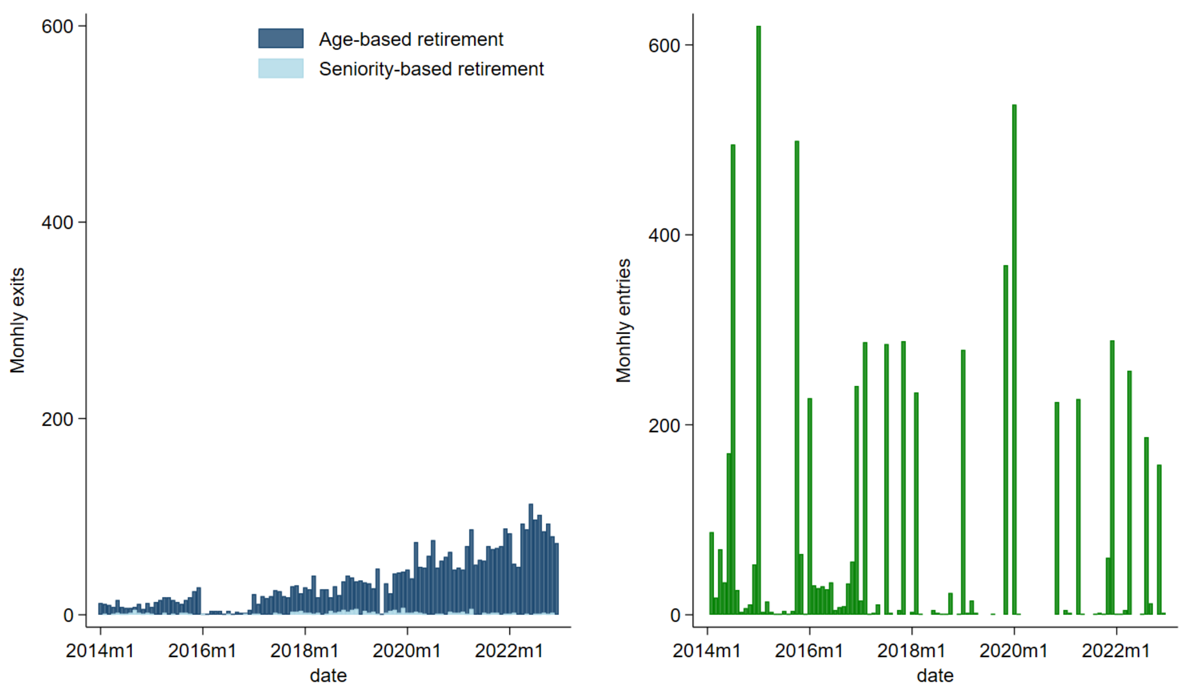
(b) Monthly gross income

Note: These figures show the average number of firefighters and their average monthly gross income (in 2015 Euros) by hierarchical position in 2014-2022. Data provided by INPS.

The labor force size decreases and the gross income increases with ranking, as we can see in Panel (a) and (b) of Figure 2. Basic firefighters represent 65 percent of the labor force, middle managers represent 30 percent of the labor force, and top managers count for the remaining 5 percent. On average, firefighters earn 2.7 thousand Euros, Squad Leaders 3.1, Shift Leaders 3.3, Inspectors 3.6, Directors 4.7, and Executives 8.6. The number of firefighters slightly increased from 29.6 to 31.6 thousand units over 2014-2022 (Figure A4). The real income of each position remained relatively stable over the years (Figure A5).

Retirements and hires. There are two criteria that effectively constitute a lower and an upper bound for retirement (Table A2). First, there is a minimum seniority at which firefighters are *eligible* to retire. Second, there is a maximum age at which firefighters are effectively *forced* to retire, independently of their seniority (Decree-law 165/1997).[2] Since the maximum retirement age is relatively low (61 years and 3 months of age in 2014) and the pension amount is lower for firefighters that retire earlier, around 96 percent retire when they reach the maximum retirement age (Table A3 and Figure 3). Therefore, the timing of most retirements depends on an exogenous characteristic (age), rather than on an individual decision.

Figure 3: Monthly exits and entries in the Fire and Rescue Service



Note: The left panel shows the number of monthly exits from the Fire and Rescue service, divided by type. The right panel shows the number of monthly entries in the Fire and Rescue Service. A monthly entry is defined as the first time a person is observed working in the Fire and Rescue Service according to the data obtained from INPS (except for January 2014, the first month in the panel).

The age distribution of firefighters is heterogeneous across fire departments

[2]According to INPS data, only 0.03 percent of retirements occur after the maximum retirement age.

(Figure A6a). Accordingly, the average age-related retirement rate over 2014-2022 is also very heterogeneous across provinces, varying from 1 to 24.8 percent (Figure A6b). While monthly retirements are continuous over the months, the number of new hires is lumpy and not synchronized with retirements (Figure 3).[3] As outlined in Section A.1, firefighters are recruited and promoted through national competitive exams held at irregular intervals. These exams can span over a year and are followed by several additional months of centralized training [Corpo Nazionale dei Vigili del Fuoco, 2024]. New hires are heterogeneous across provinces varying from 0 to 15.3 percent, but not geographically correlated with retirement rates (Figure A7).

3 Data

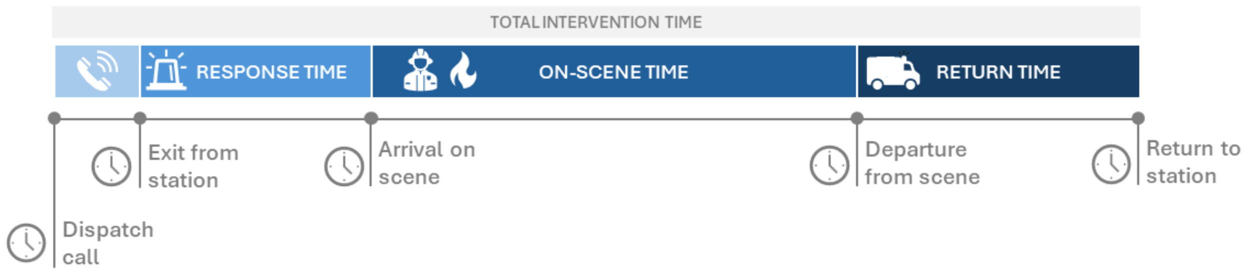
The Fire and Rescue Service provided data on all interventions occurred in Italy from 2008 to 2022. We restrict the analysis to the 6.9 million interventions occurred from 2014 to 2022 because personnel data is only available for this time span. A single observation is a squad-intervention pair, which is identified by the year, the province, the intervention number and the ordinal number of the squad involved in the intervention.[4] Hence, we are able to track the number of squads involved in each intervention and the amount of time each squad is engaged in that intervention. Squads from different fire stations can be called for the same intervention.

Each observation records the exact date, hour, and minute of five key events (Figure 4): (i) the dispatch call from the department operations center to the fire station, (ii) squad exit from the station, (iii) arrival at the intervention scene, (iv) departure from the scene, and (v) return to the station. The dispatch time is logged by the operations center, whereas the subsequent four timestamps are recorded by

[3]The number of retirees falls for some months in 2016 and 2019 when the retirement-age limit was increased.

[4]We do not observe the identity of the firefighters within a squad and we cannot track the same squad across several interventions.

Figure 4: Timeline of an intervention



squad leaders by pressing a button on the firetruck radio. After each intervention, squad leaders also complete a report documenting the station and department, the intervention's category and cause, the number of hectares burned, and any civilian or firefighter injuries or casualties.

For data on personnel, we use matched employer-employee monthly data from 2014 to 2022 on public-sector workers collected by INPS. This contains demographic characteristics, monthly income, exit cause (e.g. age-related-retirement), type of contract (permanent, volunteer), rank and fire department for each firefighter.[5] We link personnel and interventions data at fire-department level.

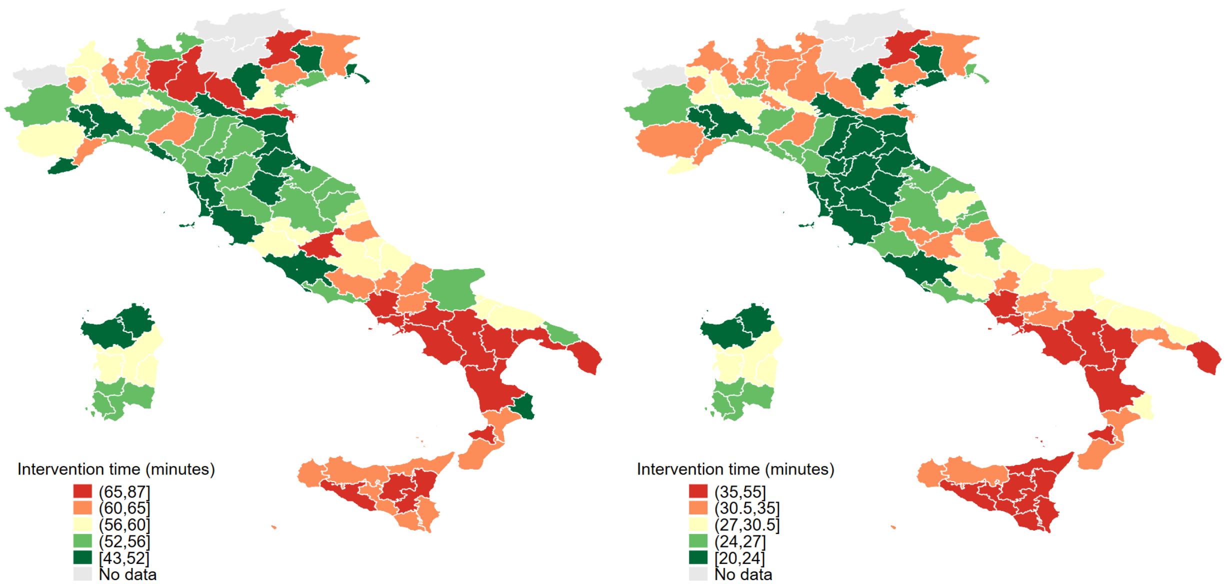
Summary statistics. To assess the effectiveness of firefighters' performance we mainly focus on total intervention time: the number of hours from the dispatch call to the time the squad returns to the station. This is the sum of the dispatch time, the response time, the on-scene time, and the return time (Figure 4).

Intervention times are commonly used by Fire Services of most countries to evaluate the performance of their fire departments [Wrack, 2008; Corpo Nazionale dei Vigili del Fuoco, 2023b]. Higher intervention times are associated with higher casualties, injuries, property loss and environmental damages [Wrack, 2008]. Figure A8 confirms in our data that injuries, casualties and hectares burned are positively correlated with intervention time, in line with fire growth models and previous findings [Ramachandran, 1986].

[5]There are also *professionals* that have technical roles such as accountants, administrators and computer engineers. We exclude them from the analysis.

Figure 5 shows that interventions take longer in the South, both in terms of total duration (Panel a) and on-scene time (Panel b), in line with previous evidence of spatial disparities in performance across Italian public-sector organizations [Cugno et al., 2022; Mocetti and Roma, 2021; Baltrunaite et al., 2021].[6]

Figure 5: Median intervention time and on-scene time by province



(a) Intervention time

(b) On-scene time

Note: Panels (a) shows the median intervention time (in minutes) by province for all interventions. Panels (b) shows the median on-scene time (in minutes) by province for all interventions.

Table A5 shows the average, standard deviation, minimum, maximum and non-missing observations for each of the main variables used in the analysis. Interventions last around one hour and a half, on average. The distribution of intervention times is right-skewed with few interventions lasting more than two hours (Figure A9). There is essentially no variation in dispatch time, which is almost always one minute. On average, response times are shorter (16 minutes) than return times (21 minutes), while the majority of the intervention is spent on scene (53 minutes).

Dispatch times are always observed because they are automatically recorded by the operations center, whereas missing values in the other timing measures

[6] The spatial heterogeneity in intervention times does not appear to depend on intervention urgency (Figure A10), intervention type (Figure A12), or the density of fire stations (Figure A3).

occur because they rely on the squad leader manually pressing the corresponding button on the firetruck radio. Return times are missing in about 20 percent of the observations, typically when a squad proceeds directly from one intervention to another without returning to the station. For these cases, total intervention time is measured as the minutes from the emergency call to departure from the scene, and we include an indicator for such observations as a control in the regressions.

The type of the intervention affects how time-sensitive the intervention is. We classify as urgent those interventions where human life is at risk.[7] On average, urgent interventions are more complex and last about 25 minutes longer than non-urgent ones. Civilian injuries and casualties are not common, occurring in 2.2 and 0.5 percent of the interventions, respectively. Firefighters' injuries and casualties are even more rare. On average, 0.1 hectares burn in an intervention with most interventions having zero hectares burned.

Fire departments do not usually work at full capacity. 35 percent of the actively working firefighters are actively employed in interventions on average, but this hides considerable heterogeneity across hours of the day, seasons and space due to large volatility in demand (Figure 8).[8] More than two thirds of the interventions involve a single squad but few interventions necessitate many, leading to an average of 2 squads per intervention.

Regarding the amount of personnel (Panel B of Table A5), the number of basic firefighters is around three times the number of squad leaders, which correspond to the proportion of six basic firefighters to two squad leaders assigned to each squad. The number of retirements are heterogeneous across positions (Table A4). Panel B of Table A5 shows that middle managers have the largest monthly age-dependent retirement rate on average (0.32 percent), followed by middle managers

[7]Urgent interventions include fires, explosions, gas leaks, transport accidents, landslides, earthquakes, floods, and search-and-rescue operations. Non-urgent interventions comprise activities such as recovery of goods, removal of debris, handling of leaning trees, pest control, animal rescues, door or window openings, elevator rescues, and safety checks.

[8]Capacity utilization can exceed 100 percent, indicating the occasional aid from squads of other provincial fire departments.

(0.24), and basic firefighters (0.01).[9]

4 Empirical strategy

Delayed turnover. We start by documenting the presence of delayed turnover across all ranks of the Fire Service. We focus on age-dependent retirements, which occur when firefighters reach an age at which they are forced to retire. This reduces endogeneity concerns due to firefighters postponing or anticipating their retirement depending on the performance of the department or the lack of substitutes.

Let L_{pdt} denote the number of firefighters and R_{pdt} the number of age-dependent retirements in position p, fire department d, and month t. Normalize these variables by the average number of firefighters of position p working for fire department d across all months of available data ($\overline{L_{pd}}$) and denote them with lower capital letters $l_{pdt} = L_{pdt}/\overline{L_{pd}}$ and $r_{pdt} = R_{pdt}/\overline{L_{pd}}$. This normalization accounts for department size and allows departments to have zero firefighters of position p in period t. Define the growth rate of p personnel as $g_{pdt} = l_{pdt} - l_{pdt-1}$.

To analyze how quickly departments can recover the number of firefighters in position p when some of their firefighters in position p retire, we estimate the following:

$$g_{pdt} = \sum_{h=\underline{h}}^{\overline{h}} \beta_h r_{pdt-h} + \eta_d + \gamma_t + \nu_{dt} \tag{1}$$

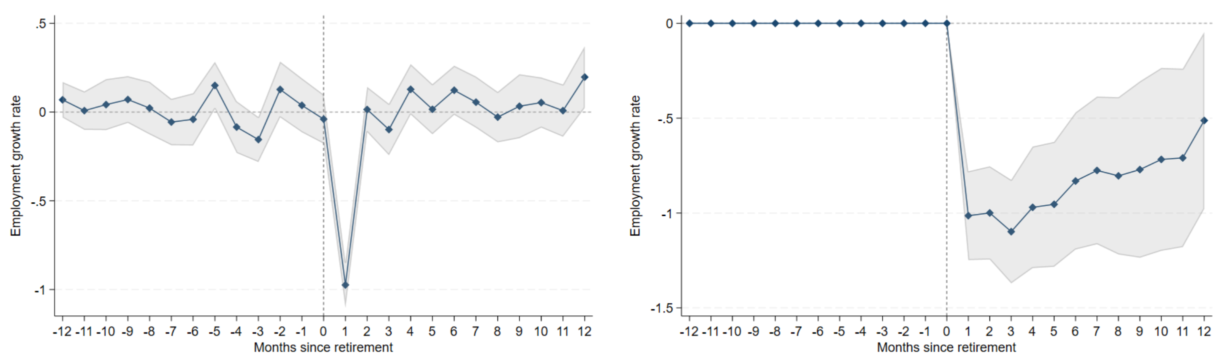
This specification includes month and department fixed effects and includes twelve lags to show the dynamic impacts of retirements on the labor force and twelve leads to detect pre-trends ($\overline{h} = \underline{h} = 12$). We cluster standard errors at department level.

If turnover is perfectly timed, no coefficient β_h for any $h \in [\underline{h}, \overline{h}]$ would be significantly different from 0. The number of new retirees would be immediately

[9] We can attribute the elevated retirement rate among shift leaders to being the highest position attainable solely through seniority and an internal exam, without requiring a degree or passing a public competitive exam (Table A1).

compensated by the number of new hires in the same position. If there is some anticipation effect, we would expect a significantly positive coefficient $\beta_h > 0$ for some $h \leq 0$. This would arise if departments train new recruits in anticipation of scheduled retirements. If, instead, turnover is delayed, the immediate effect would be a negative β_1 close to -1, with the cumulative effect $\sum_{h=1}^{\tilde{h}} \beta_h$ gradually returning to zero after some period $\tilde{h} > 0$. A larger $\tilde{h}$ would indicate a longer lag in turnover adjustment (see Appendix Section A.2 for a proof).

Figure 6: Effect of age-related retirements on employment growth



(a) Temporary (12 months)

(b) Cumulative (12 months)

Note: We restrict the sample to firefighters that have a permanent contract. Data provided by INPS.

Figure 6 shows the estimates of β_h for $h \in [-12, 12]$ in Equation (1) and confirms the presence of lagged turnover in fire departments. The estimate for β_1 is negative and not statistically different from -1. The estimates for β_h with $h < 0$ oscillates around 0 with no positive trend. The sum of the coefficients $\sum_{h=0}^{\tilde{h}} \beta_h$ is significantly negative up to $\tilde{h} = 12$ months after the retirement shock. Only half of age-related retirements are replaced within a year. This already suggests the presence of misallocation over time: if the allocation of workers were optimal before the retirement, the retiree should be immediately replaced by another firefighter.

Figures A14 and A15 show the estimates of β_h for $h \in [-12, 12]$ in Equation (1), separately for each position. Turnover appears to be lagged in all positions by several months, even though the lag appears to be shorter for basic firefighters than for the other higher positions. Retirements of most positions are not fully replaced within one year.

One way fire departments could compensate for the loss of a firefighter is to increase the employment of volunteers. This should not occur as volunteers operate in separate fire stations and do not replace retired firefighters unless they are permanently hired through national competitive exams. Let $v_{dt} = \frac{V_{dt}}{L}$ denote the full-time-equivalent volunteering rate, where V_{dt} is the number of days of a volunteer's work in the department-month divided by the average monthly working days of a firefighter.[10] Figure A13 shows the estimates of β_h using v_{dt} as the dependent variable. The employment of volunteers does not increase after the retirement of a firefighter.

Identification of the impact of delayed turnover. After having shown that there is lagged turnover in every position after a firefighter retires, we can estimate the impact of the temporary drop in the labor force on the outcome variables, using the following 'reduced-form' regression:

$$ln(h_{idt}) = \sum_{p \in \mathcal{P}} \alpha_p r_{pdt-1} + \zeta_d + \phi_t + \lambda X_{idt} + u_{isdt} \quad (2)$$

For intervention squad i from department d in month t, we regress the logarithm of intervention time, $\ln(h_{idt})$, on the lagged retirement rates of position p firefighters in department d. We include department and month fixed effects to capture time invariant heterogeneity and common shocks. For interventions (but not for retirements) we can identify not only the department but also the fire station, which allows us to add fire station fixed effects among the controls X_{idt}. We further include type by month fixed effects to account for time varying characteristics of interventions (for example, wildfires are harder to extinguish in summer).[11] We

[10] We assume the working day of a volunteer coincides with the 12-hour shift of a firefighter. Firefighters work 2 shifts every 4 days, for a total of 15 shifts per month [Comando Vigili del Fuoco Milano, 2023]. To obtain V_{dt}, we divide the observed working days of all volunteers in the department-month by 15.

[11] Type by month and fire station fixed effects make month and department fixed effects redundant, but we retain them for consistency with the AKM analysis of Section 5.3.

also control for an indicator that flags squad interventions with missing return times, where intervention time is measured up to the arrival on scene. In all specifications, standard errors are clustered at the department level. The error term is denoted u_{idt}.

The parameters of interest are α_p for each firefighter position p. α_p can be interpreted as the percentage change in the expected intervention time for a one percentage-point increase in the retirement rate of position-p firefighters.The identification strategy relies on two assumptions: first, that in the absence of retirements, average intervention times across fire departments would have followed parallel trends; and second, that treatment effects are homogeneous across months and departments [de Chaisemartin and D'Haultfœuille, 2020]. We relax the second assumption by applying the estimator of de Chaisemartin et al. [2024], which is robust to heterogeneous treatment effects and accommodates settings where treatment is continuous and non absorbing, as in our case. This estimator also allows us to analyze the dynamic effects of delayed turnover over multiple months using the following event-study for each rank p:

$$ln(h_{idt}) = \sum_{\underline{h}}^{\overline{h}} \alpha_h r_{pdt-h} + \zeta_d + \phi_t + \lambda X_{idt} + u_{isdt} \tag{3}$$

In Section 6.1, we instrument the logarithm of position specific labor with the corresponding retirement rate to obtain two stage least squares estimates of the labor elasticities of performance used in the labor allocation model.

5 Results

5.1 The Impact of Delayed Turnover on Public Service Performance

Column 1 of Table 1 shows that delayed turnover among middle managers leads to slower intervention times. The geometric mean of intervention time is 61 minutes ($e^{0.023} \cdot 60$). A 10 percentage-point rise in the retirement rate of middle managers prolongs interventions by 2.8 percent in the following month. This effect is entirely driven by a 4.8 percent increase of on-scene time from a geometric mean of 29 minutes. Retirement rates of middle managers do not affect response or return times (columns 2-4 of Table 1). Conversely, the absence of top managers does not have a significant impact on any measure of intervention time.

Table 1: Effect of age-based retirement rate on intervention time, by hierarchical position.

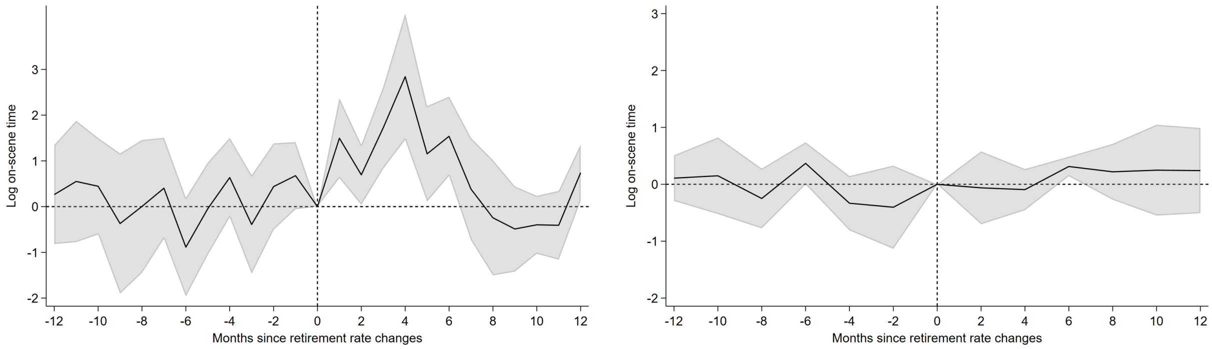
	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
Middle manager retirement rate	0.283**	0.035	0.477***	0.046
	(0.140)	(0.156)	(0.167)	(0.143)
Top-manager retirement rate	-0.013	-0.027	-0.043	0.076
	(0.045)	(0.054)	(0.058)	(0.051)
Observations	6683472	5269420	6210737	5098218
Mean	0.023	-1.637	-0.712	-1.430

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate and the logarithm of the number of middle managers and top managers on the outcome variable indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

In Figure 7 we show the dynamic impacts of the retirement rate of middle and top managers on the logarithm of intervention time, using the estimator proposed by de Chaisemartin et al. [2024] that is robust to heterogeneous treatment effects. The estimator compares the evolution of intervention times of departments whose retirement rate changes in a certain period (switchers) to departments whose retirement rate remain the same as switchers' retirement rate in the initial period (stayers). The estimated treatment effects are the weighted average of switchers' slopes of ln intervention time with respect to the retirement rate, where switchers receive a weight proportional to the absolute value of their retirement rate change.

Figures 7a and A16a show that departments experiencing an increase in middle managers' monthly retirement rate report longer on-scene and total intervention times in the following six months, whereas there is no clear trend in the twelve months before. On the other hand, we do not observe a rise in total intervention and on-scene time after top managers retire (Figures 7b and A16b).

Figure 7: Dynamic effects of retirements of middle managers on on-scene time



(a) Middle managers (b) Top managers

Note: This figure shows the placebo and dynamic effects of retirements of middle managers (a) and top managers (b) on the logarithm of on-scene time in the year prior to and after an increase in the retirement rate. The effects are estimated using the estimator by de Chaisemartin et al. [2024], which is robust to heterogeneous treatment effects. The red lines indicate 95 percent confidence intervals.

Table 2 breaks down the effects by rank. The increase in on-scene times is driven by the retirements of shift and squad leaders. A 10-percentage-point rise in their retirement rates lengthens on-scene times by 4.7 and 1.4 percent, respectively. The estimated effects for basic firefighters are also positive and sizable, but they are imprecisely estimated and not statistically different from zero. Retirements among top management positions have negligible and statistically insignificant effects.

We can rationalize these findings by considering that middle managers are directly engaged in day-to-day field operations, while top managers focus primarily on long-term strategic planning. As a result, the absence of middle-level managers can immediately impair the effectiveness of public service, whereas short-term vacancies in top management positions appear to have no short-term effect.

Table 2: Effect of age-based retirement rate by position on intervention time.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
Basic firefighters retirement rate	0.227	1.060	0.655	-1.159
	(0.984)	(1.113)	(1.360)	(0.857)
Squad leaders retirement rate	0.401*	0.359	0.469*	0.084
	(0.228)	(0.263)	(0.257)	(0.215)
Shift leaders retirement rate	0.081*	0.003	0.136***	0.044
	(0.041)	(0.046)	(0.050)	(0.040)
Inspectors retirement rate	-0.009	-0.011	-0.015	0.021
	(0.021)	(0.023)	(0.026)	(0.020)
Directors retirement rate	0.021	0.028	-0.014	0.079
	(0.055)	(0.055)	(0.082)	(0.058)
Executives retirement rate	0.001	-0.001	-0.009	0.012
	(0.016)	(0.020)	(0.018)	(0.017)
Observations	6683472	5269420	6210737	5098218
Mean	0.023	-1.628	-0.714	-1.426

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of firefighters indicated in each row on the outcome variables indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

5.2 Mechanisms

The results in Section 5.1 show that retirements among middle managers significantly lengthen intervention times, an effect entirely driven by longer on-scene durations. To shed light on the underlying mechanisms, we examine six potential channels: reallocation across stations, task selection, human capital, capacity constraints, work fatigue, and coordination frictions. We exploit the richness of our data to assess the empirical relevance of each mechanism.

Reallocation across stations and task selection. We can rule out the possibility that departments respond to shortages of squad leaders by reallocating interventions to squads from more distant stations. Such reallocation would increase travel distance, thereby lengthening response and return times. However, the estimates in columns 2 and 4 of Table 1 show no evidence of changes in these time components.

Another potential mechanism is task selection: when leaders are scarce, departments might postpone or drop less urgent or less complex interventions. This would make the observed set of interventions disproportionately demanding, mechanically increasing average on-scene times. Yet our specifications include detailed type-of-intervention fixed effects, which absorb variation in task composition. Moreover, we find no evidence that retirements affect the likelihood that an intervention is classified as urgent (Table A9). If departments were facing personnel shortages, we would expect them to delay non-urgent tasks and prioritize urgent ones. Instead, Table A10 shows that delays are actually *larger* for urgent interventions than for non-urgent ones. This pattern has important policy implications, as it suggests that shortages of middle managers can slow down operations precisely when speed is most critical.

Human capital. If leaders accumulate human capital through repeated interventions, replacing experienced leaders with inexperienced ones may reduce squad performance. We use leaders' age and tenure as proxies for human capital. A 10-percentage-point increase in the retirement rate of middle managers lowers their average age by about three months (0.28 years) and their average tenure by about one month (0.08 years), although the latter effect is not statistically significant (Table A11). To test the human-capital mechanism, we interact middle-manager retirement rates with the average tenure or age of the remaining squad leaders in the month following retirement (Tables A13 and A14). The interaction coefficients are not statistically different from zero, suggesting that losses in accumulated leader human capital are unlikely to explain the observed slowdown.

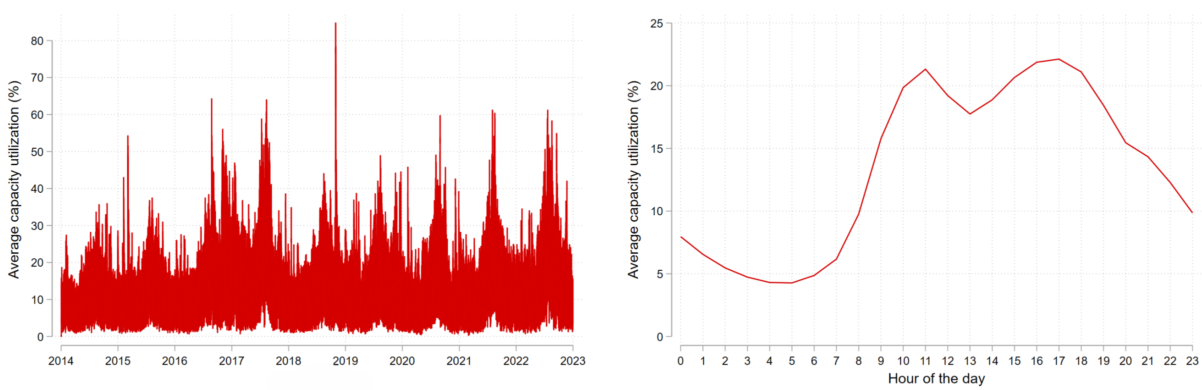
Capacity constraints. Since each squad must be accompanied by a squad leader, retirements may mechanically reduce the number of deployable squads. When capacity utilization is low, remaining leaders can typically cover shortages; when capacity utilization is high, leader scarcity becomes binding. According to their contract, basic firefighters and middle managers are required to work for 133.5 twelve-hour shifts per year, with a thirty-minute lunch break per shift [UIL, 2022]. Therefore, they spend on duty 17.5 percent of the year: $\overline{h} = \frac{133.5 \cdot (12-0.5)}{365.25 \cdot 24} = 0.175$.

We define the capacity utilization of fire department d during hour κ as:

$$C_{d\kappa} \equiv \frac{\sum_i 5 \cdot h_{id\kappa}}{N_{dt} \cdot \overline{h}}, \tag{4}$$

where $h_{id\kappa}$ is the time spent on intervention i by five firefighters from department d during hour κ, and N_{dt} is the number of basic firefighters and middle managers employed in department d in month t. Figure 8 shows that capacity utilization varies substantially over time, with peaks above 60 percent during summer days and rush hours.

Figure 8: Capacity utilization



(a) By date-hour

(b) By hour of the day

Note: Panel (a) shows the national average of capacity utilization in each hour of the analyzed period (2014-22). Panel (b) shows the national average of capacity utilization in each hour of the day. Capacity utilization is defined as the number of working basic firefighters and middle managers engaged in interventions during a given hour.

Table 3 shows that the performance effects of retirements are concentrated entirely in periods of high capacity utilization. A 10 percentage-point increase in the retirement rate of middle managers raises intervention times by 4.2 percent and on-scene times by 7.5 percent when departments operate above the median level of capacity utilization, with the effect driven primarily by squad leaders and shift leaders (Table A15). When capacity utilization is below the median, retirements have no detectable impact on intervention times. This pattern is consistent with rationing: middle-manager shortages bind only when demand for leaders is high relative to supply, forcing departments to allocate leaders across simultaneous incidents. Table A16 also shows that both the probability of deploying multiple squads and the logarithm of the number of squads sent decline when middle managers retire, although neither effect is statistically significant.

Table 3: Effect of age-based retirement rate by position on intervention time, by middle manages and top managers. Heterogeneity by capacity utilization.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
	Below median capacity utilization			
Middle manager retirement rate	0.026	-0.011	0.111	-0.046
	(0.088)	(0.114)	(0.117)	(0.110)
Top-manager retirement rate	-0.022	-0.059	-0.079	0.039
	(0.040)	(0.046)	(0.052)	(0.053)
Observations	3611002	3065048	3364156	2894083
Mean	-0.086	-1.702	-0.852	-1.527
	Above median capacity utilization			
Middle manager retirement rate	0.421***	0.014	0.747***	0.076
	(0.133)	(0.136)	(0.160)	(0.131)
Top-manager retirement rate	-0.004	-0.004	-0.025	0.100*
	(0.050)	(0.053)	(0.069)	(0.054)
Observations	3598288	2582847	3313071	2573200
Mean	0.119	-1.542	-0.592	-1.324

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate and the logarithm of the number of firefighters indicated in each row on the outcome variables indicated in each column, by below and above median capacity utilization. We exclude for the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and month fixed effects. Standard errors are clustered at fire-station level. *Mean* is the average of the dependent variable in the regression sample.

Work fatigue. When retirements reduce the workforce, remaining leaders and squads face longer or more intense shifts, which can lower productivity on scene. This mechanism would be consistent with evidence that fatigue can affect performance in high-stakes operational settings [Chalfin and Gonçalves, 2023]. Basic firefighters and middle managers have work shifts that span 12 hours, always starting and ending at either 08:00 or 20:00.[12] We create an indicator for whether an intervention starts before and continues past the scheduled shift end, and a continuous variable indicating the number of minutes beyond the scheduled shift end. We regress these two variables on middle-manager retirement rates to check whether retirements induce an increase in overtime. We do not find any significant effect on working overtime either on the intensive or the extensive margin (column 2 and 3 of Table A17). However, we do find a marginally significant increase in capacity utilization, meaning that even if they do not work overtime, squads are more intensively employed during their working hours (column 1).

Coordination frictions. Leader shortages can also create coordination frictions within interventions. About 28 percent of interventions involve more than one squad (Figure A11). When multiple squads are deployed, limited leadership may delay the arrival of additional squads, reduce their ability to operate simultaneously, or hinder real-time task allocation. To capture this mechanism, we construct a *co-ordination index*, defined as the ratio of the average on-scene time across all S squads involved in an intervention to the total span of the incident:

$$coordination = \frac{\sum_{s=1}^{S} (T_s^{departure} - T_s^{arrival})/S}{\max\{T_s^{departure}\} - \min\{T_s^{arrival}\}}.$$

The index equals 1 if all squads are present for the entire duration of the incident and work fully in parallel. It equals $1/S$ if squads work sequentially with no overlap. Column (3) of Table 4 shows that a 10 percentage-point increase in the retirement rate of middle managers lowers the coordination index by 0.4 percent. The same increase in retirements also raises total intervention time and total on scene time across all squads, from the call of the first squad to the return of the last, by 2.9 and 5.5 percent, respectively (columns 1 and 2).

[12]The recurring work schedule for basic firefighters and middle managers is structured as follows: one day shift is followed by a 24-hour rest period, succeeded by one night shift, which is then followed by a 48-hour rest period. Top managers work standard office hours from 08:00 to 18:00, Monday to Friday.

Table 4: Effect of age-based retirement rate on coordination between squads, by hierarchical position.

	(1) Log intervention time across all squads	(2) Log on-scene time across all squads	(3) Coordination index
Middle manager retirement rate	0.293**	0.547***	-0.040**
	(0.132)	(0.167)	(0.017)
Top-manager retirement rate	-0.013	-0.046	-0.006
	(0.050)	(0.060)	(0.009)
Observations	6711833	6417160	6416549
Mean	0.147	-0.546	0.930

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate and the logarithm of the number of middle managers and top managers on the outcome variable indicated in each column. In all regressions except for columns (1) and (2) we restrict the sample to interventions that involved more than one squad. All time variables are in log hours. All dependent variables are windsorized at the 1st and 99th percentile. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include, number of squads, fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Taken together, these findings indicate that middle-manager retirements impair performance primarily through capacity constraints and coordination frictions, rather than through losses in accumulated experience or changes in task or station allocation.

5.3 Long-term effects of top managers

Since top managers are less involved in daily field operations and more focused on long-term strategies, their impact is expected to unfold over longer periods. We evaluate their long-term contribution to departmental performance by leveraging their mobility across departments within an AKM framework [Abowd et al., 1999].

Top-manager characteristics. We ensure a one-to-one mapping between departments and top managers by defining the top manager of department d in month t as the highest-ranking officer in that department.[13] Table A18 reports summary statis-

[13] When multiple individuals share the same rank, we choose the one with the highest career level, tenure, age, and salary, in that order.

tics on top-manager characteristics. Column 1 includes all top managers, while Column 2 restricts the sample to those who served in at least two different fire departments over the sample period (movers). The two groups are demographically similar: only 4-6 percent are female, and the average age is 57, which can be explained by their high seniority. Movers have 2.4 less years of experience than the whole sample of top managers, who on average have 29 years of tenure. A large share of top managers are born in Southern Italy (42-46 percent) or the Islands (20-21 percent), consistent with higher public-sector wage premia and lower private-sector opportunities in these regions.

AKM estimation. Table 5 describes the structure of our sample for the AKM estimation for the long-term impact of top managers [Abowd et al., 1999]. The full sample contains 100 fire departments and 338 top managers. 138 of them (40 percent) move at least once from a department to another during the sample period. The high fraction of movers is due to the fact that top-level executive positions last for three years and executive have to work for at least 3 different departments to obtain a level-promotion [Gazzetta Ufficiale, 2017].[14] Due to the staggered nature of these tenures, only a limited number of vacancies become available each year, which constrains the extent to which executives can sort across departments. The top-manager and department effects are separately identified only within a set of departments connected by manager mobility [Abowd et al., 1999]. All departments have at least one mover and they all belong to one connected set, except one department that represents an additional isolated set.[15]

In contrast, Table A20 shows that mobility among middle managers is very limited: only 12 out of 771 (2 percent) are ever transferred to a different department. This results in 88 small connected sets, making it infeasible to meaningfully estimate the long-term contribution of middle managers to variation in department performance.

[14] Top executive positions are renewable, up to a maximum of ten years in total [Gazzetta Ufficiale, 2017].

[15] The isolated set is Nuoro.

There are 579 switches among top-managers, but these include several short-term switches. We define long-term switches as changes in top management at time t in which the outgoing manager held the position for at least one year (from $t-12$ to $t-1$) and the incoming manager remains in the role for at least one year (from t to $t+12$). Note that this definition excludes switches involving a leadership gap between the two managers, which are instead exploited for identification in Section 5.1. If we restrict the sample to departments that experienced at least one long-term switch, the number of fire departments is reduced to 74 and the number of top managers to 276, among whom 132 are movers (48 percent). In this balanced sample, there are 113 long-term switches and 3 connected sets, two of which are isolated.[16]

Table 5: Top-manager characteristics

	(1) All departments	(2) Departments with ≥ 1 long-term switches
A. Demographics		
# Top managers	338	276
# Top managers in > 1 department	138	132
# Departments	100	74
# Departments with ≥ 1 movers	99	73
# Connected sets	2	3
# Top-manager switches	579	113

Notes: This table shows the structure of the full sample of departments (column 1) and for the sample of departments with at least one long-term switch (column 2). A long-term switch is a change in top management where the outgoing manager held the position for at least one year and the incoming manager remains in the role for at least one year. Number of switches in top managers is the number of all switches in column 1 and the number of long-term switches in column 2.

To quantify the share of variance of ln total intervention time that is explained by top managers, we estimate the following regression in the largest connected sets of departments with at least one long-term change of a top manager [Bertrand and Schoar, 2003]:

$$ln(h_{idt}) = \theta_d + \mu_{p(d,t)} + X_{idt} + w_{idt} \tag{5}$$

[16] The two isolated sets are Nuoro and Latina.

θ_d denote department fixed effects, $\mu_{p(d,t)}$ denote top-manager fixed effects and X_{idt} are month-by-type of intervention fixed effects.

Table 6: Analysis of variance of log total intervention duration. *Balanced sample*

	(1)	(2)	(3)	(4)	(5)	(6)
R-squared	0.005	0.218	0.233	0.237	0.238	0.238
Adjusted R-squared	0.005	0.201	0.216	0.220	0.221	0.221
Month FE	YES	YES	YES	YES	YES	YES
Type-by-month FE	NO	YES	YES	YES	YES	YES
Department FE	NO	NO	NO	YES	YES	NO
Manager FE	NO	NO	YES	NO	YES	NO
Department-by-manager FE	NO	NO	NO	NO	NO	YES
N	5596604	5596604	5596604	5596604	5596604	5596604

Notes: This table analyzes how much of the variance in log intervention duration is explained by the top manager, fire department, month and month-by-type of intervention components. *N* represents the number of interventions with non-missing duration. The p-value tests the null hypothesis that top-manager fixed effects are jointly zero. We restrict the sample the sample of departments with at least one long-term switch.

This analysis is based on the assumption that leaders' moves are as-good-as random, conditional on fire department and month-by-type fixed effects. This assumption would be violated if leaders are sent to fire departments on the basis of their comparative advantage or in response to fire-department idiosyncratic trends in performance and transitory shocks. Month fixed effects account for only 0.5 percent of the variation in log intervention duration (column 1). Given the substantial heterogeneity in intervention complexity, most of the explained variation comes from month-by-type fixed effects, which raise the adjusted R^2 by 0.151 (columns 1-2) followed by department fixed effects (+0.020, columns 2-3). Columns 4 and 5 of Table 6 shows that adding top-manager fixed effects to a model with department fixed effects and month-by-type of intervention fixed effects results in an increase of adjusted R^2 of only 0.001. The quality of top managers fixed effects seems to explain very little variation in firefighters' performance, even in the long term.

In Appendix Section A.3 we perform an array of tests on the potential endogeneity of top-manager mobility. The evidence shows no evidence of sorting or comparative advantage: departments replacing high- and low-quality managers experience symmetric performance changes (Figure A1), residuals are close to zero across all combinations of manager and department effects quintiles (Figure A2), and including manager–department fixed effects barely increases explanatory power (column 6 of Table 6). Moreover, there are no systematic pre-trends or correlations between baseline performance and incoming manager quality, supporting the validity of the exogenous mobility assumption (Figure A1).

Variance decomposition. To better quantify the relative importance of top-managers, permanent department characteristics, and type-by-month characteristics, we perform a variance decomposition. Applying a variance decomposition to equation (5), the variance of ln total intervention time can be decomposed:

$$\begin{aligned}\mathrm{Var}(\ln(h_{idt})) = {} & \mathrm{Var}(\theta_d) + \mathrm{Var}(\mu_{p(d,t)}) + \mathrm{Var}(X_{idt}) + \mathrm{Var}(w_{idt}) \\ & + 2 \cdot \mathrm{Cov}(\theta_d, \mu_{p(d,t)}) + 2 \cdot \mathrm{Cov}(\mu_{p(d,t)}, X_{idt}) + 2 \cdot \mathrm{Cov}(\theta_d, X_{idt})\end{aligned} \tag{6}$$

Table 7: Variance-covariance decomposition

	(1) (Component)	(2) (Share)
Var(Ln(h))	0.6397	100.00 %
Var(Top manager)	0.0023	0.36 %
Var(Department)	0.0153	2.39 %
Var(Month-type)	0.1309	20.46 %
Var(Residual)	0.4896	76.54 %
Cov(Top manager, Department)	-0.0019	-0.58 %
Cov(Top manager, Month-type)	0.0004	0.11 %
Cov(Department, Month-type)	0.0009	0.29 %
N	5427480	

Notes: This table reports the variance-covariance decomposition of log total intervention time in the largest connected set. The model includes manager, department, and month-by-type fixed effects. Covariances are multiplied by 2 in the shares.

Andrews et al. [2008] show that the sample variances of managers and department effects are upward biased, and their covariance is downward biased (when covariates are orthogonal to fixed effects). This bias worsens with limited mobility in the data [Abowd et al., 1999]. Table 7 reports bias-corrected estimates of the variance of manager and department effects, as well as their covariance, using the bias-correction method proposed by Andrews et al. [2008]. Again, most of the performance variation is explained by type-by-month fixed effects (16 percent), whereas manager fixed effects explain only 0.34 percent of the variance in log total intervention time.[17]

6 The model

6.1 The model setup

In this section we build a model to quantify the reduction in total intervention time if firefighters were allocated optimally across fire departments. We aim to find the constrained efficient allocation of workers, holding constant the total factor productivity of each intervention, wages and government expenditures.

Let $\mathcal{T}$ denote the set of months from 2014 to 2022, $\mathcal{D}$ the set of departments, and $\mathcal{P}$ the set of positions: basic firefighter, middle manager, and top manager. The social planner chooses the number of firefighters L_{pdt} for each job position, department and month to minimize the total intervention time:

$$
\begin{aligned}
\min_{\{L_{pdt}\}_{p\in\mathcal{P},d\in\mathcal{D},t\in\mathcal{T}}} & \sum_t \sum_d \sum_i h_{idt} \\
s.t. \quad & \frac{1}{h_{idt}} = A_{idt} \prod_p L_{pdt}^{\psi_p} \quad \forall\, i, d, t \\
& \sum_t \sum_d \sum_p w_{pt} L_{pdt} \leq \sum_t \sum_d \sum_p G_{pdt} \\
& \psi_p > 0 \;\forall\, p
\end{aligned}
\tag{7}
$$

Total intervention time is a natural performance metric used internally by the Fire and Rescue Service, but abstracts from other potential objectives, such as

[17] The covariance between top-manager and department effects is slightly negative. This negative assortative matching result is in line with similar evidence found in other Italian public-sector organizations [Fenizia, 2022].

minimizing the incidence of extreme delays, prioritizing urgent interventions, or incorporating equity considerations across territories.[18] The output of a squad i is the number of interventions completed by the squad in an hour, that is the reciprocal of the intervention time. This is modelled as a Cobb-Douglas production function in which the factors of production are the number of firefighters in each position in the department in that time period. The Cobb–Douglas specification implies constant elasticities of performance with respect to labor inputs. Although this assumption is standard, it is not innocuous, and the quantitative magnitude of the efficiency losses we report should be interpreted as conditional on the assumed production structure.

Each squad has a idiosyncratic total factor productivity A_{idt}, which captures the productivity of department d and of the squad involved in the intervention i, but also the type of intervention i, spatial characteristics (e.g. the quality of infrastructures) and temporal shocks (e.g. weather conditions).[19] Since y_{dt} and L_{pdt} are observed and ψ_p is estimated outside of the model, we can recover the idiosyncratic TFP of each intervention as $A_{idt} = \frac{1}{h^o_{idt} \prod_p (L^o_{pdt})^{\psi_p}}$ where h^o_{idt} and L^o_{pdt} are the observed intervention duration for intervention i and the observed position-p number of firefighters in department d and month t, respectively. Figure A17 shows that on average the Centre and North of Italy have a larger TFP than the South, in line with the shorter average intervention duration observed in Figure 5.

ψ_p is the elasticity of output y_{dt} with respect to the number of firefighters in position p. As long as there is a positive marginal product for each type of labor ($\psi_p > 0$ for all p) the problem has a unique global minimum.[20] We estimate each elasticity of output with respect to labor position ψ_p by exploiting the retirements

[18] While these alternative objectives would generally lead to different optimal allocations, they share the common implication that performance improves when labor is reallocated toward departments, positions and periods with higher marginal productivity.

[19] In the reduced-form analysis (Equation 9), TFP is modelled as the sum of fire-station, month-by-type of intervention fixed effects, the controls and the regression residual.

[20] After plugging the equality constraint, the objective function becomes $A^{-1}_{idt} \prod_p L^{-\psi_p}_{pdt}$. If $\psi_p > 0$ for all p, the objective function is strictly convex as all the leading principal minors of its Hessian are strictly positive. Given the linear budget constraint, the optimization problem is a convex optimization problem with a unique global minimum.

of firefighters in each position which caused a temporary drop in personnel in that position. Formally, for each position p we use the following two-stage instrumental variable regression:

$$ln(L_{pdt}) = \pi_p r_{pdt-1} + \mu_d + \delta_t + \xi X_{idt} + \omega_{pdt} \tag{8}$$

$$ln(h_{idt}) = -\psi_p ln(\hat{L}_{pdt}) + \sigma_d + \rho_t + \chi X_{idt} + \nu_{idt} \tag{9}$$

We regress the logarithm of intervention time on the logarithm of the labor force of each position, instrumented by their retirement rates in the previous period. The parameter of interest is $-\psi_p$, the labor elasticity of intervention time which we use in the model to measure misallocation. We will plug these estimated elasticities in the model to obtain the optimal labor allocations.[21]

We report the impact of the lagged retirement rate on the logarithm of the workforce by position in Table A6. The lagged retirement rate has a significantly negative effect on the logarithm of middle and top managers. Lagged retirements are a sufficiently strong instrument for middle and top managers according to standard criteria [Stock and Yogo, 2002], with an F-statistic of 35.5 and 23.0 respectively. When we disaggregate across positions, the instrument remains relatively strong for most positions, except for basic firefighters and squad leaders.[22]

The estimates shown in table A22 are $\psi_f = 0.379$, $\psi_m = 0.203$ and $\psi_d = 0.025$ for basic firefighters, middle managers and directors, respectively (Table 2). We assume the elasticity of inspectors and executives are 0, because the estimates are positive. Hence, the only top-managers to which the model will allocate resources are directors.

Our framework is close in spirit to the one used by Walter [2020] to measure

[21] The additional identifying assumptions required for the instrumented difference-in-differences are: 1) the labor force in different fire departments would have evolved in parallel in absence of retirements; 2) the effect of retirements on the labor force is always negative (monotonicity); 3) retirements affect intervention time only through the labor force reduction and do not affect past intervention times or past labor force [Hudson et al., 2017].

[22] Table A7 shows that the number of FTE volunteers employed does not significantly increase when there is a rise in the retirement rate of any position of firefighters.

misallocation of teachers in a cross-section of schools. We expand this model by allowing for multiple time periods and multiple positions of workers, with different elasticities of production and real wages w_{pt}. In this way we can quantify the extent of three different types of misallocation: misallocation of firefighters across fire departments, across job positions and over time. The real wage w_{pt} is the observed monthly average wage deflated to 2015 Euros earned by position-p firefighters in the year of month t. Observing wages and workforce, we can measure government expenditures for all firefighters of the same position in each fire department and month as $G_{pdt} = w_{pt} L^{o}_{pdt}$.

6.2 Dispersion in Marginal Performance to Pay as a sufficient statistic

Define $A_{dt}^{-1} \equiv \sum_i A_{idt}^{-1}$ and let λ denote the Lagrange multiplier of the government budget constraint. The first-order conditions are:

$$MPL_{pdt} \equiv \psi_p A_{dt}^{-1} L_{pdt}^{-1} \prod_{\tilde{p}} L_{\tilde{p}dt}^{-\psi_{\tilde{p}}} = \lambda w_{pt} \quad \forall\, p, d, t \tag{10}$$

The first-order conditions (10) imply that, in the efficient allocation, the marginal performance of labor (MPL_{pdt}) for each position, department and month is proportional to the corresponding wage.

Hence, efficiency requires that the *marginal performance to pay* ratio must be equalized across departments, positions, and time:

$$\frac{MPL_{pdt}}{w_{pt}} = \lambda \qquad \forall\, p, d, t \tag{11}$$

This condition is the public-sector analogue of the equalization of marginal revenue products across firms in the private sector as shown by Hsieh and Klenow [2009]. Intuitively, if two departments exhibit different marginal performance of a given labor position, reallocating workers from the lower- to the higher-marginal-performance department would reduce total intervention time without increasing expenditures.

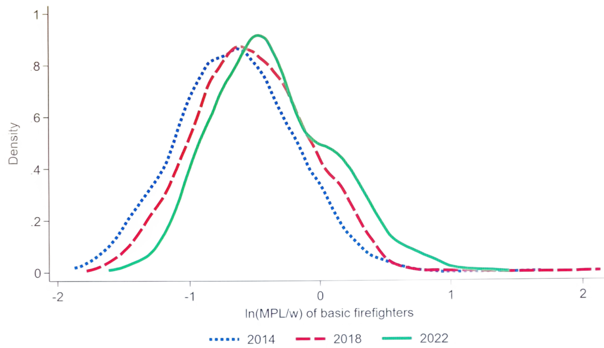
Let $h_{dt} \equiv \sum_i h_{idt}$ denote the total time squads from department d spent on interventions in month t. Using the production function, MPL_{pdt} can be shown to be equal to the product of labor elasticity of performance and the ratio between total intervention time and labor:

$$\frac{MPL_{pdt}}{w_{pt}} = \psi_p \frac{h_{dt}}{w_{pt} L_{pdt}}, \tag{12}$$

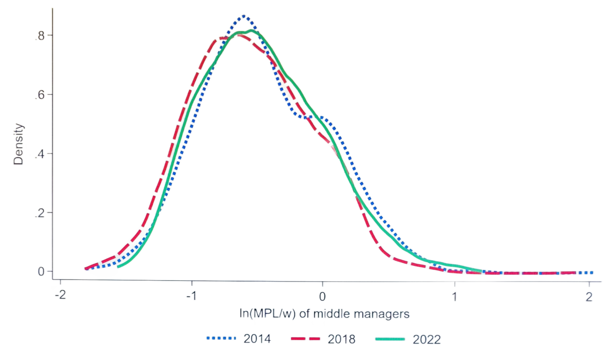
For a given labor position p, the dispersion of $\log(MPL_{pdt}/w_{pt})$ across departments and time is a sufficient statistic for misallocation that can be easily measured using observed variables. It is simply equal to the variance of the logarithm of the ratio of total intervention time over the labor cost:

$$var\left(log\left(\frac{MPL_{pdt}}{w_{pt}}\right)\middle| p = \tilde{p}\right) = var\left(log\left(\frac{h_{dt}}{w_{\tilde{p}t} L_{\tilde{p}dt}}\right)\right) \tag{13}$$

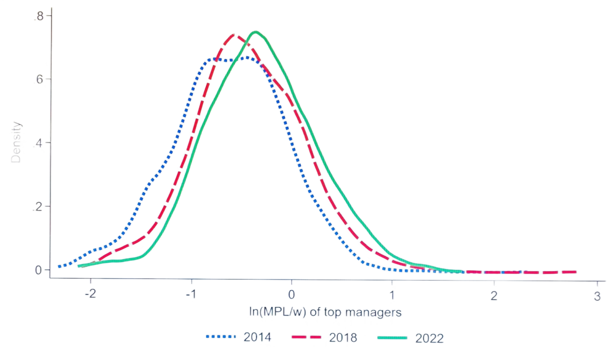
Figure 9: The distribution of log marginal performance to pay over the years



(a) Basic firefighters



(b) Middle managers

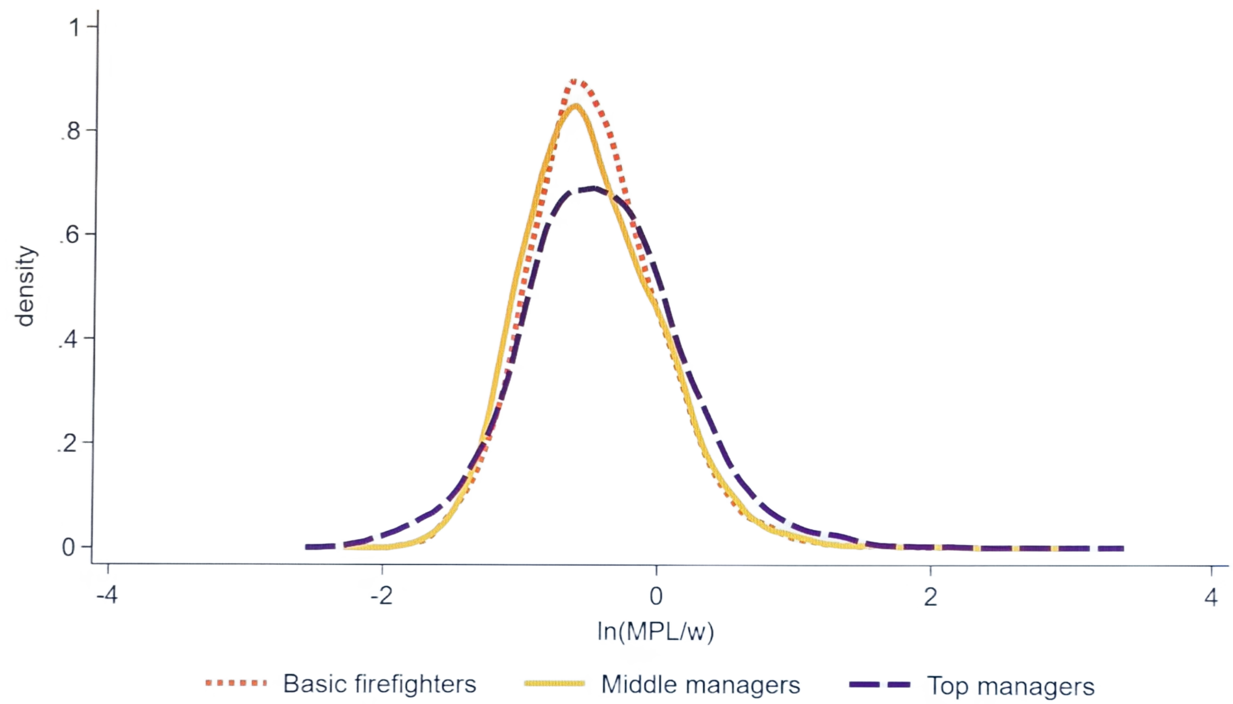


(c) Top managers

Note: These figures show the distribution of log marginal performance to pay for each position across all departments and months in 2014, 2018 and 2022. As defined in equation (13), this measure equals the logarithm of the ratio between the total time spent on interventions in a department–month and the corresponding labor cost for that position in that department–month.

If marginal performance per unit of wage were equalized across departments, the variance in (13) would be zero, indicating an efficient allocation of labor and a minimization of total intervention time. Conversely, greater dispersion in this statistic reflects a higher degree of misallocation across departments and months within a position. The variance of marginal performance to pay has remained relatively stable over time for all three positions (Figure 9), but the distribution gradually shifted to the right, suggesting that departments have become more productive on average. Among positions, top managers exhibit the greatest degree of misallocation, followed by middle managers and basic firefighters (Figure 10).

Figure 10: The distribution of log marginal performance to pay in each position



Note: This figure shows the distribution of log marginal performance to pay for each position across all departments and months from 2014 to 2022. As defined in equation (13), this measure equals the logarithm of the ratio between the total time spent on interventions in a department–month and the corresponding labor cost for that position in that department–month.

6.3 Model solution

We can find the $T \cdot P \cdot D$ optimal labor allocations $\{L_{pdt}\}$ by solving a system of linear equations composed by the budget constraint and by the $T \cdot P \cdot D - 1$ linearly independent ratios of first-order conditions:

$$\frac{\psi_p L_{pdt}^{-1} A_{dt}^{-1} \prod_{\tilde{p}} L_{\tilde{p}dt}^{-\psi_{\tilde{p}}}}{\psi_1 A_{11}^{-1} L_{111}^{-1} \prod_{\tilde{p}} L_{\tilde{p}11}^{-\psi_{\tilde{p}}}} = \frac{w_{pt}}{w_{11}} \quad \forall (p, d, t) \neq (1, 1, 1) \tag{14}$$

which equalize the ratio of marginal products to the ratio of factor prices. The solution of this system is:

$$L^*_{pdt} = \frac{\sum_t \sum_d \sum_p G_{pdt}}{\sum_s \sum_e \sum_q \left[\frac{A_{dt}}{A_{es}} \prod_{\tilde{p}} \left(\frac{w_{\tilde{p}s}}{w_{\tilde{p}t}} \right)^{\psi_{\tilde{p}}} \right]^{1/(1+\sum_{\tilde{p}} \psi_{\tilde{p}})} \frac{\psi_q}{\psi_p} w_{pt}} \quad \forall\, p, d, t \tag{15}$$

The more productive is a department relative to the others, the less workers should be allocated to that department. The more elastic is intervention time with respect to the supply of position-p firefighters (relative to the other positions) the more firefighters of this position should be employed. The higher the wage of firefighters relative to other positions, times and departments, the lower should be their employment.

L^*_{pdt} is the efficient allocation of firefighters over space, time and positions, which achieves the minimum intervention time $H^* = \sum_t \sum_d \sum_i h_{idt}(L^*_{1dt}, ..., L^*_{pdt})$. The percentage increase in observed total intervention time with respect to the unconstrained efficient level is $\mu^o = \frac{H^o - H^*}{H^*}$.

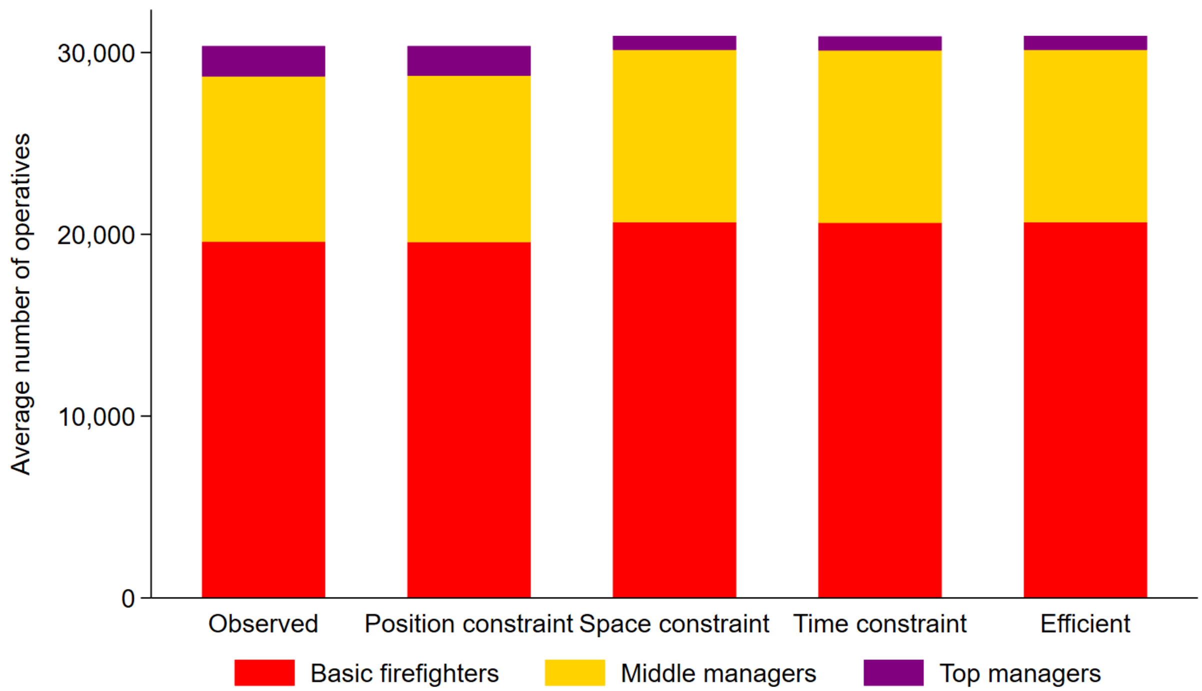
Appendix Section A.4 details how we quantify misallocation along three dimensions: across space, over time, and across ranks. To do so, we impose additional constraints requiring that the government maintain the observed shares of total national expenditures by department, month, and job position, respectively.

6.4 Simulations

The efficient allocation of labor reduces average intervention time from 87 to 79 minutes (Table A23 and Figure A18), which makes the observed average intervention time 9.3 percent longer than optimal. The largest source of inefficiency is misallocation over job positions (+2.7 percent higher intervention time with respect to the efficient allocation), followed by space (+1.9 percent) and time misallocation (+1.5 percent). If performance can be improved given a fixed level of resources, it also follows that, for a given performance target, public expenditure could be reduced through a more efficient allocation of labor.

The three constraints together do not explain the entire amount of inefficiency, as they correspond to $T + D + S$ restrictions while the first-order conditions are $T \cdot D \cdot S$. The social planner can obtain a better labor allocation, even holding constant the total amount of resources allocated to each job position, fire department, or month. For instance, suppose department A lacks basic firefighters and has an abundance of squad leaders in a certain month, while department B has an abundance of basic firefighters and lacks squad leaders in the same month, as presented in Figure A20. The planner could optimally reallocate basic firefighters from B to A and squad leaders from A to B in correct proportions according to their wages, without affecting the total amount of resources devoted to each position, to each department and to each month. Therefore, even without changing the government budget over time, space, or job positions, the public administration can substantially improve its performance, simply by transferring workers across departments.

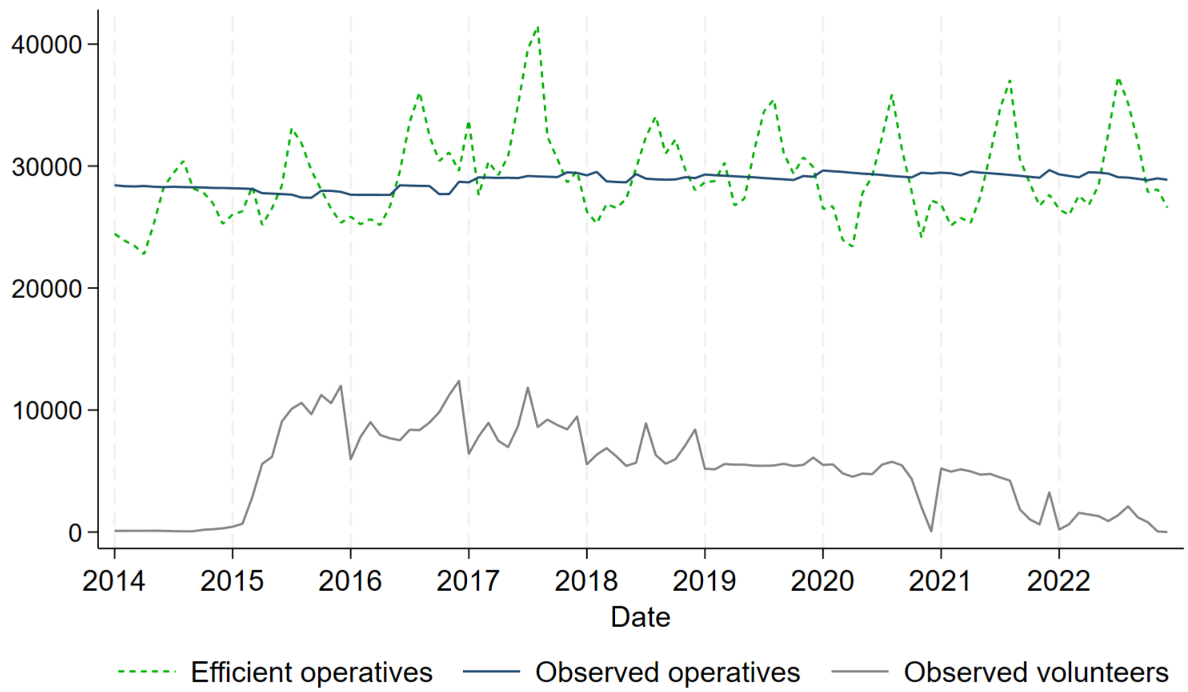
Figure 11: Average labor force by position, observed and counterfactuals



Note: This figure shows the average number of firefighters by position that are: observed in the data; simulated under a constrained efficient labor allocation with position, space and time constraints; simulated under an efficient labor allocation. Data provided by INPS.

In the optimal allocation, the number of basic firefighters and middle managers should rise by 5.4 and 4.4 percent, corresponding to 1,059 and 396 additional employees, respectively, while the number of top managers should fall by 53.5 percent, or 891 positions (Figure 11). Because basic firefighters and middle managers are less costly than top managers, the total labor force under the constrained efficient allocation increases by 1.9 percent, equivalent to 565 additional employees overall.

Figure 12: Observed vs efficient workforce over time



Note: This figure shows the number of basic firefighters and middle managers in the observed data (the blue solid line) relative to the efficient labor allocation (the green dashed line). The number of observed volunteers employeed is shows by the gray solid line. Data provided by INPS.

Firefighters should be reallocated from the more productive Center-North to the less productive South, in order to speed up the longer intervention times of Southern departments (Figures 5 and A19). This model implication hinges on the strong assumption that the government cannot improve total factor productivity of Southern fire departments in order to improve their performance. Finally, Figure 12 shows that the efficient allocation (dashed green line) is more volatile over time than the observed allocation (solid blue line). The observed workforce remains stable at around thirty thousand firefighters between 2014 and 2022, whereas the optimal allocation would have required higher staffing during summer months and following natural disasters, such as the earthquakes in Central Italy between August 2016 and January 2017. Although volunteers, who are hired and paid on a daily basis, could help smooth these fluctuations, their employment (solid gray line) does not appear to fully track the seasonal pattern of demand.

7 Conclusions

This paper explores the presence of labor misallocation in the public sector, analyzing the case of the Italian Fire and Rescue Service. We document systematic delays in turnover across the hierarchy, with adverse effects on performance. Temporary shortages of middle managers significantly slow interventions, whereas the absence of top managers has no measurable effect either in the short or the long-run. A caveat of the reduced-form analysis is that it captures only one margin of inefficiency in public employment, namely that arising from delayed turnover.

For this reason, we use the turnover shocks to estimate position-specific labor elasticities and embed them in a model of labor allocation in a public institution. The simulations indicate that the observed allocation generates intervention times that are on average 9.3 percent longer than under the efficient allocation, with the largest inefficiency arising from the distribution of labor across ranks. Efficient allocation requires equalizing the marginal performance to pay across departments, positions and time periods. The dispersion in marginal performance to pay represents an observable sufficient statistic that can be used to quantify and correct labor misallocation in any public-sector organization, as long as performance and personnel data are available.

The findings carry direct policy implications. Greater flexibility in workforce allocation would make the public sector more resilient to fluctuations in supply and demand. Anticipating retirements in hiring plans, decentralizing recruitment to local units, and adjusting staff allocation to demand fluctuations would help prevent leadership gaps and mitigate short-term shortages. Such reforms would strengthen the capacity of public organizations to sustain service quality under demographic and demand pressures.

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Appendix A Appendix

A.1 Firefighters' tasks and career

According to their position, firefighters are responsible for different tasks. Basic Firefighters perform rescue, prevention, and surveillance activities on the ground. They are also in charge of driving vehicles, engaging in radio and telecommunications activities, as well as basic equipment maintenance.

Each squad is composed by four Basic Firefighters (including the driver) and a Squad Leader, who coordinates the squad members and drafts a report at the end of each intervention. Shift Leaders coordinate multiple squads of the same station during a work shift, taking operational responsibility on the ground and optimizing resources during interventions.

Inspectors perform technical-inspection activities, draft office acts, and manage contractual procedures for work, services, and supplies. They assist with general management activities of their assigned structure, contribute to intervention plans for urgent rescue, civil defense, and civil protection activities, and draft detailed projects for their implementation.

Directors are managers in charge of fire stations and offices not reserved for Executives. They propose intervention plans for rescue and civil defense activities and autonomously carry out interventions within their competence area. In the event of civil protection emergencies, they may be entrusted with the responsibility of managing complex and articulated operational groups and engage in study and research activities.

Executives are in charge of central directorates, regional offices, provincial fire departments and training centres. They manage the internal organization, the human and instrumental resources of the office and follow the training of the staff. They direct the activities of urgent technical rescue and civil protection, and can exercise spending powers within the limits of the funds assigned to them [Corpo Nazionale dei Vigili del Fuoco, 2023c].

Competitive exams to become Basic Firefighter, Inspector or Director are open to the general population, whereas exams for the other four positions are accessible to internal candidates only. These exams are conducted at irregular intervals and can extend over several months. For example, between 2008 and 2024, there were four exams held to recruit basic firefighters. Each exam included a preliminary screening test, a physical aptitude assessment, an oral examination, and medical evaluations. The entire process—from the exam announcement to the completion of medical checks—lasted over a year. [Corpo Nazionale dei Vigili del Fuoco, 2024]. Before starting to work as a Basic Firefighter, Inspector or Director, the new appointee has to attend a six-month practical and theoretical course in a fire training centre (nine-month for Directors) and a three-month traineeship in a local fire department [Gazzetta Ufficiale, 2017]. The six positions are further divided according to more granular levels, reached after meeting specified seniority requirements [Gazzetta Ufficiale, 2017]. All positions and levels as well the exams, the seniority and education requirements to access each one of them are listed in Table A1.

A.2 Estimation of turnover delay

Let E_{pdt} the number of entries (hires, promotions, transfers) in position p, fire department d, and month t and normalize it by the average number of firefighters of position p working for fire department d across all months of available data $e_{pdt} = E_{pdt}/\overline{L_{pd}}$.

As in Cellini et al. [2010], assume that the effects of a retirement on the labor force depend only on the time elapsed since retirement and not on the time period in which retirement occurred or on the history of retirements. That is, $\frac{de_{pdt}}{dr_{pdt-k}}$ and $\frac{dr_{pdt}}{dr_{pdt-k}}$ can depend on k but not on t or on $\{r_{pd1}, ..., r_{pdt-1}\}$. Note that the labor flow equation is $l_{pdt} = l_{pdt-1} + e_{pdt-1} - r_{pdt-1}$. Iterating, we obtain $l_{pdt} = l_{pdt-\tilde{h}} + \sum_{h=1}^{\tilde{h}} e_{pdt-h} - \sum_{h=1}^{\tilde{h}} r_{pdt-h}$. If turnover is perfectly timed, we have $\frac{\partial e_{pdt-1}}{\partial r_{pdt-1}} = 1$ and $\beta_1 = \frac{d(l_{pdt}-l_{pdt-1})}{dr_{pdt-1}} = 0$. If turnover is lagged, we have

$\frac{\partial e_{pdt-1}}{\partial r_{pdt-1}} = 0$ and $\beta_1 = \frac{d(l_{pdt}-l_{pdt-1})}{dr_{pdt-1}} = -1$. If the labor force is restored after $\tilde{h}$ periods: $l_{pdt} - l_{pdt-\tilde{h}} = 0$ and $\sum_{h=1}^{\tilde{h}} e_{pdt-h} = \sum_{h=1}^{\tilde{h}} r_{pdt-h}$. Differentiating both sides, $\sum_{h=1}^{\tilde{h}} \frac{\partial e_{pdt-h}}{\partial r_{pdt-\tilde{h}}} - \sum_{h=1}^{\tilde{h}-1} \frac{\partial r_{pdt-h}}{\partial r_{pdt-\tilde{h}}} = 1$. Then, under the stated assumption we have $\sum_{h=1}^{\tilde{h}} \beta_h = \sum_{h=1}^{\tilde{h}} \frac{d(l_{pdt}-l_{pdt-1})}{dr_{pdt-h}} = \sum_{h=1}^{\tilde{h}} \frac{\partial e_{pdt-1}}{\partial r_{pdt-h}} - \sum_{h=2}^{\tilde{h}} \frac{\partial r_{pdt-1}}{\partial r_{pdt-h}} - 1 = \sum_{h=1}^{\tilde{h}} \frac{\partial e_{pdt-h}}{\partial r_{pdt-\tilde{h}}} - \sum_{h=1}^{\tilde{h}-1} \frac{\partial r_{pdt-h}}{\partial r_{pdt-\tilde{h}}} - 1 = 0$.[23]

A.3 AKM Validity checks.

Endogenous mobility driven by department-specific trends in log intervention time could mask the true long-term impact of top managers. To assess this possibility, we follow Card et al. [2013] and model the error term in (5) as the sum of three random effects:

$$w_{idt} = m_{p(d,t)} + u_{dt} + s_{idt} \tag{16}$$

Here, $m_{p(d,t)}$ is an idiosyncratic productivity premium or penalty specific to the match between top manager p and department d. u_{dt} is a unit-root component capturing persistent trends in department performance, and s_{idt} represents transitory shocks.[24]

Three types of sorting would violate the identifying assumption of exogenous mobility: (1) if top managers select into departments based on comparative advantage of their match $m_{p(d,t)}$; (2) if higher-quality managers are systematically assigned to departments experiencing a drift in performance u_{dt}; or (3) if top managers are reallocated in response to transitory negative shocks s_{idt}.

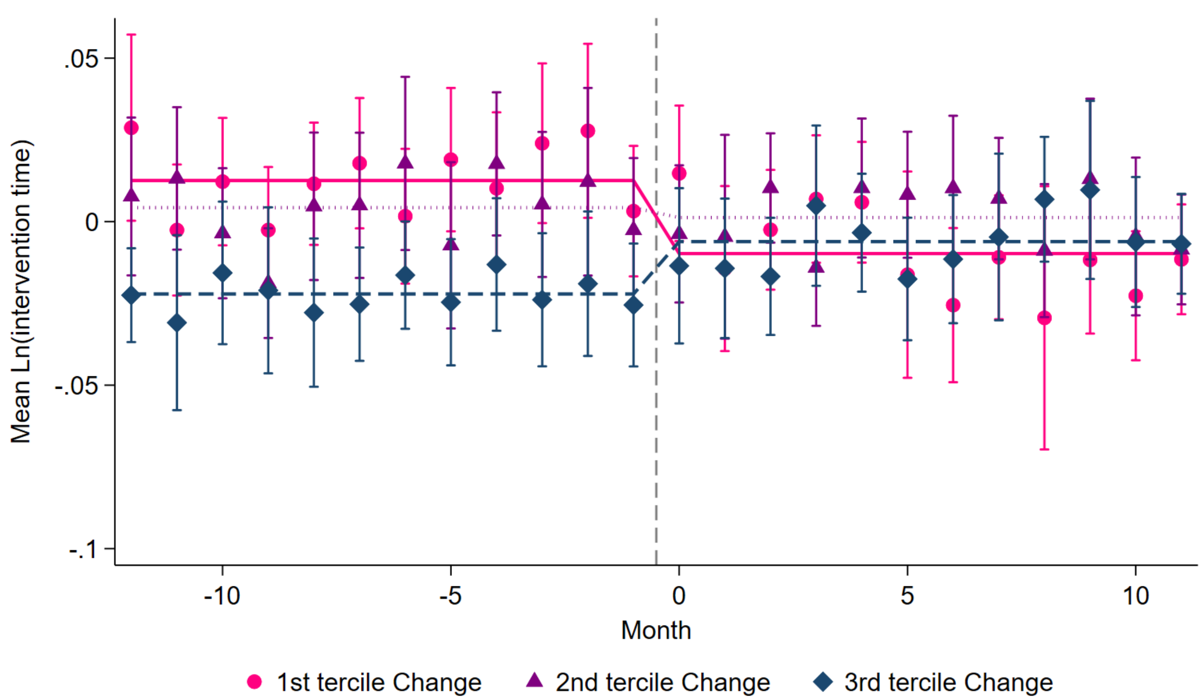
If match effects are negligible, a manager should have the same impact on performance regardless of department, and replacing a high-quality with a low-quality manager should have an effect equal in magnitude and opposite in sign to

[23] Note that normalizing by the *average* labor force in each department, which is constant over time, allows to interpret the sum of the coefficients β_h as the cumulative effect of retirements on the labor force. A sum of the coefficients equal to 0 implies a return to the original labor force. This would not generally be true if we normalize by the labor force in the previous period, which varies over time.

[24] The assumptions are: $m_{p(d,t)}$ has mean zero for all top managers and departments; both u_{dt} and s_{idt} have mean zero for each department, with u_{dt} following a unit-root process.

replacing a low-quality with a high-quality one. Figure A1 plots average residuals from equation (5) in quarters surrounding a change in top management, by terciles of the change in top-manager fixed effects ($\mu_{\text{incoming}} - \mu_{\text{outgoing}}$). The confidence intervals of the three terciles overlap in all periods, confirming that top-manager quality has a limited effect on department performance. The first and third terciles exhibit changes in performance of similar magnitude and opposite sign. Moreover, changes in top managers of comparable performance (second tercile) generate no improvement for the department, consistent with the absence of sorting on comparative advantage.[25]

Figure A1: Average log intervention time for departments with a long-term change in top manager, by tercile of changes in top-manager FE.

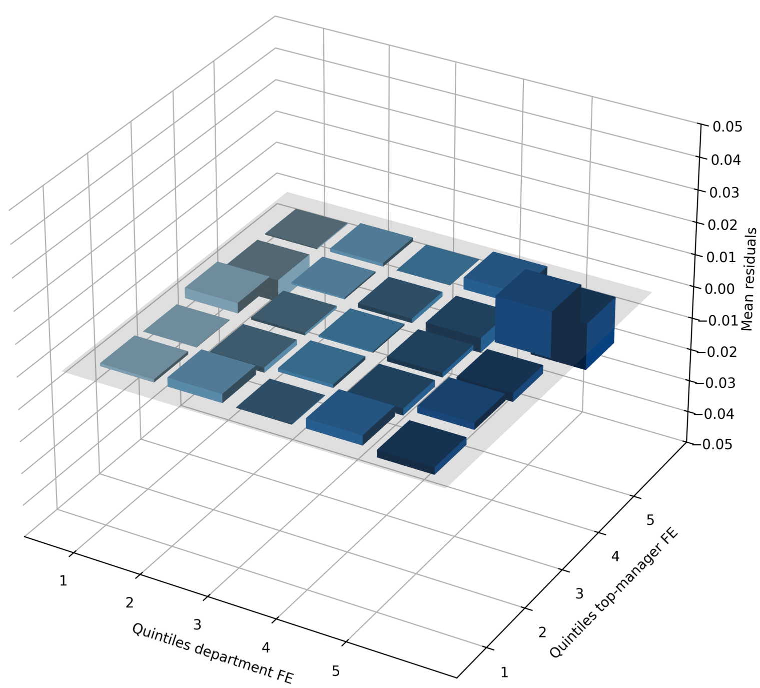


Note: This figure plots the average residuals of log intervention time (regressed on department and month-type effects) and the associated 95-percent confidence intervals before and after a long-term change in top-manager. The residuals are estimated on the largest connected set. The figure plots three types of long-term changes, by terciles of the change of top-managers fixed effects: (1) an increase in managerial quality (diamonds), (2) a decrease (circles), and (3) no change (triangles). The horizontal axis reports the distance in months relative to the long-term change in top manager.

[25] The fact that pre-event performance in the second tercile is closer to that of the first tercile does not threaten identification: the assumption of as-good-as-random mobility, conditional on department and time-by-type fixed effects, allows for transfers based on the permanent components of performance and managerial ability.

If match effects played a substantial role, including top manager-by-department fixed effects would increase explanatory power relative to the additively separable specification in (5). In practice, the adjusted R^2 rises only marginally, from 0.187 to 0.188 (columns 5-6 of Table 6), providing empirical support for the additive separability assumption. This conclusion is reinforced by the distribution of residuals across department–manager pairs. If we group estimated department and manager effects into quintiles (Figure A2), mean residuals are all close to zero, with the largest being only 0.014 in absolute value.

Figure A2: Mean residuals, by quintiles of top-manager and department effects.



Note: This figure shows mean residuals of log intervention duration obtained regressing equation (5), averaged across cells defined by the combination of quintiles of estimated top-manager effects and quintiles of estimated department effects.

If high-quality managers were systematically transferred to departments with deteriorating performance, the estimated importance of top managers' quality would be biased downward. However, Figure A1 shows no upward or downward pre-trends before a managerial change, and the flat pre-event trajectories also rule out reallocations triggered by transitory shocks (e.g., short-term negative performance). Table A21 formally tests for such pre-trends by reporting correlations between baseline department performance and either the fixed effects of incoming top managers (column 1) or the change in top-manager fixed effects (column 2). In both cases, correlations are not significant, confirming no systematic link between ability of top managers and prior department performance or performance growth.

A.4 Quantification of sources of misallocation

For an optimal allocation of workers, their marginal products must be equal to their price ratio across space, time and job position.[26] To measure the extent of misallocation across space, we add the following constraints to the model: $\sum_t \sum_p w_{pt} L_{pdt} = \sum_t \sum_p G_{pdt}$ for all d. In this scenario, the government cannot change the share of total national expenditures spent for each fire department that is observed in the data. Solving problem (7) with this additional constraint, we obtain the constrained-efficient allocation $\{L^{CS}_{pdt}\}$:

$$L^{CS}_{pdt} = \frac{\sum_p \sum_t G_{pdt}}{\sum_q \sum_s \left[\frac{A_{dt}}{A_{ds}} \prod_{\tilde{p}} \left(\frac{w_{\tilde{p}s}}{w_{\tilde{p}t}} \right)^{\psi_{\tilde{p}}} \right]^{1/(1+\sum_{\tilde{p}} \psi_{\tilde{p}})} \frac{\psi_q}{\psi_p} w_{pt}} \quad \forall\, p, d, t \tag{20}$$

The total intervention time is $H^{CS} \geq H^*$ and the percentage increase in total intervention time with respect to the unconstrained efficient level $\mu^{CS} = \frac{H^{CS} - H^*}{H^*}$

[26] Three subsets of the set of equations (14) have to be satisfied to obtain an optimal allocation across space, time and job position, respectively:

$$A_{dt} L_{pdt} \prod_{\tilde{p}} L^{\psi_{\tilde{p}}}_{\tilde{p}dt} = A_{\tilde{d}t} L_{p\tilde{d}t} \prod_{\tilde{p}} L^{\psi_{\tilde{p}}}_{\tilde{p}\tilde{d}t} \quad \forall p, d, \tilde{d}, t \tag{17}$$

$$\frac{L_{pdt} \prod_{\tilde{p}} L^{\psi_{\tilde{p}}}_{pd\tilde{t}} A_{d\tilde{t}}}{L_{pdt} \prod_{\tilde{p}} L^{\psi_{\tilde{p}}}_{\tilde{p}dt} A_{dt}} = \frac{w_{pt}}{w_{p\tilde{t}}} \quad \forall p, d, t, \tilde{t} \tag{18}$$

$$\frac{\psi_p}{\psi_{\tilde{p}}} \frac{L_{\tilde{p}dt}}{L_{pdt}} = \frac{w_{pt}}{w_{\tilde{p}t}} \quad \forall p, \tilde{p}, d, t \tag{19}$$

is our measure of misallocation over space.

To measure the extent of misallocation over time, we add the following constraints to the model: $\sum_d \sum_p w_{pt} L_{pdt} = \sum_d \sum_p G_{pdt}$ for all t. In this scenario, the government cannot change the share of total national expenditures spent in each time period that is observed in the data (e.g. for instance due to electoral or budget concerns). Solving problem (7) with this additional constraint, we obtain the constrained-efficient allocation $\{L_{pdt}^{CT}\}$:

$$L_{pdt}^{CT} = \frac{\sum_p \sum_d G_{pdt}}{\sum_q \sum_e \left[\frac{A_{dt}}{A_{et}}\right]^{1/(1+\sum_{\tilde{p}} \psi_{\tilde{p}})} \frac{\psi_q}{\psi_p} w_{pt}} \quad \forall\, p, d, t \tag{21}$$

The total intervention time is $H^{CT} \geq H^*$ and the percentage increase in total intervention time with respect to the unconstrained efficient level $\mu^{CT} = \frac{H^{CT} - H^*}{H^*}$ is our measure of misallocation over time.

To measure the extent of misallocation across job positions, we add the following constraints to the model: $\sum_t \sum_d w_{pt} L_{pdt} = \sum_t \sum_d G_{pdt}$ for all p. In this scenario, the government cannot change the share of total national expenditures over the years spent on each firefighter position that is observed in the data. The same share of public funds will go to basic firefighters, to Squad Leaders and to Shift Leaders as observed in the data. Solving problem (7) with this additional constraint, we obtain the constrained-efficient allocation $\{L_{pdt}^{CP}\}$:

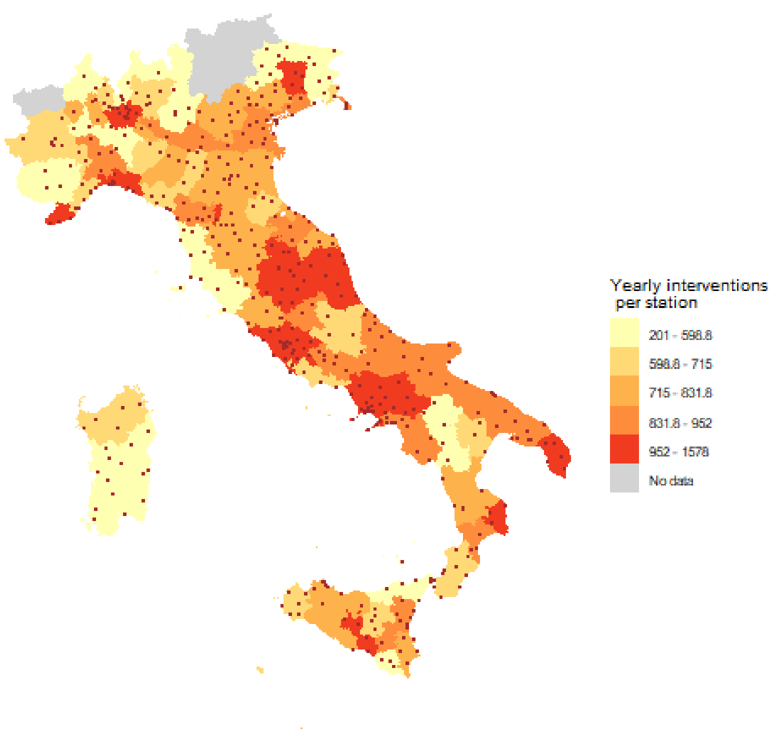
$$L_{pdt}^{CP} = \frac{\sum_d \sum_t G_{pdt}}{\sum_e \sum_s \left[\frac{A_{dt}}{A_{es}} \prod_{\tilde{p}} \left(\frac{w_{\tilde{p}s}}{w_{\tilde{p}t}}\right)^{\psi_{\tilde{p}}}\right]^{1/(1+\sum_{\tilde{p}} \psi_{\tilde{p}})} w_{pt}} \quad \forall\, p, d, t \tag{22}$$

The total intervention time is $H^{CP} \geq H^*$ and the percentage increase in total intervention time with respect to the unconstrained efficient level $\mu^{CP} = \frac{H^{CP} - H^*}{H^*}$ is our measure of misallocation over job positions.

The system of equations (17)-(19) contains $P \cdot D \cdot T$ linearly independent equations that pin down $P \cdot D \cdot T$ unknowns $\{L_{pdt}\}$. The first counterfactual imposes D additional constraints and the set of equations (17) do not generally hold anymore. The second counterfactual imposes T additional constraints and the set of equations (18) do not generally hold anymore. The third counterfactual imposes P additional constraints and the set of equations (19) do not generally hold anymore. Note that the other two sets of equations continue to hold.

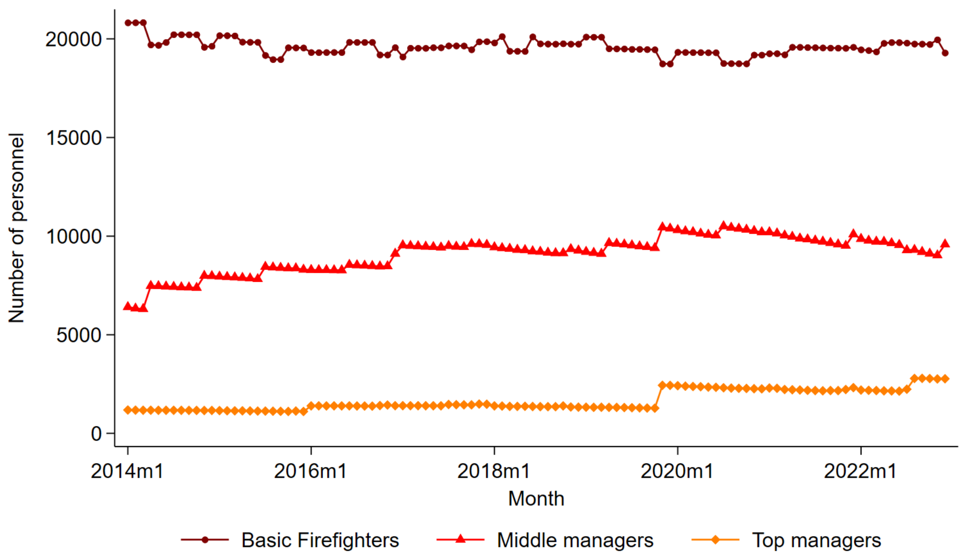
A.5 Additional Figures

Figure A3: Fires station location and density of interventions



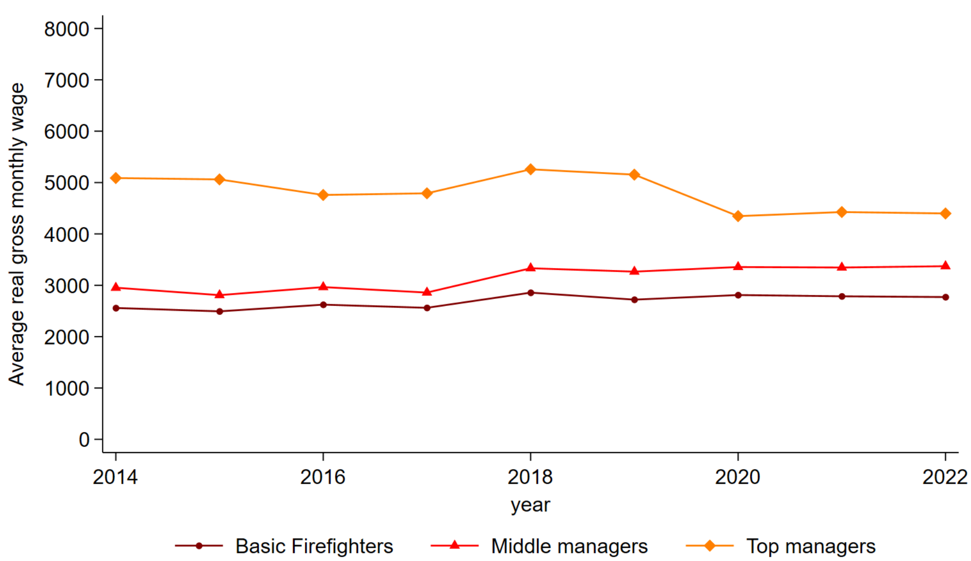
Note: This map shows the average yearly number of interventions per fire station by province (from yellow to red). A brown dot indicates the location of a fire station.

Figure A4: Number of personnel over time by hierarchial position



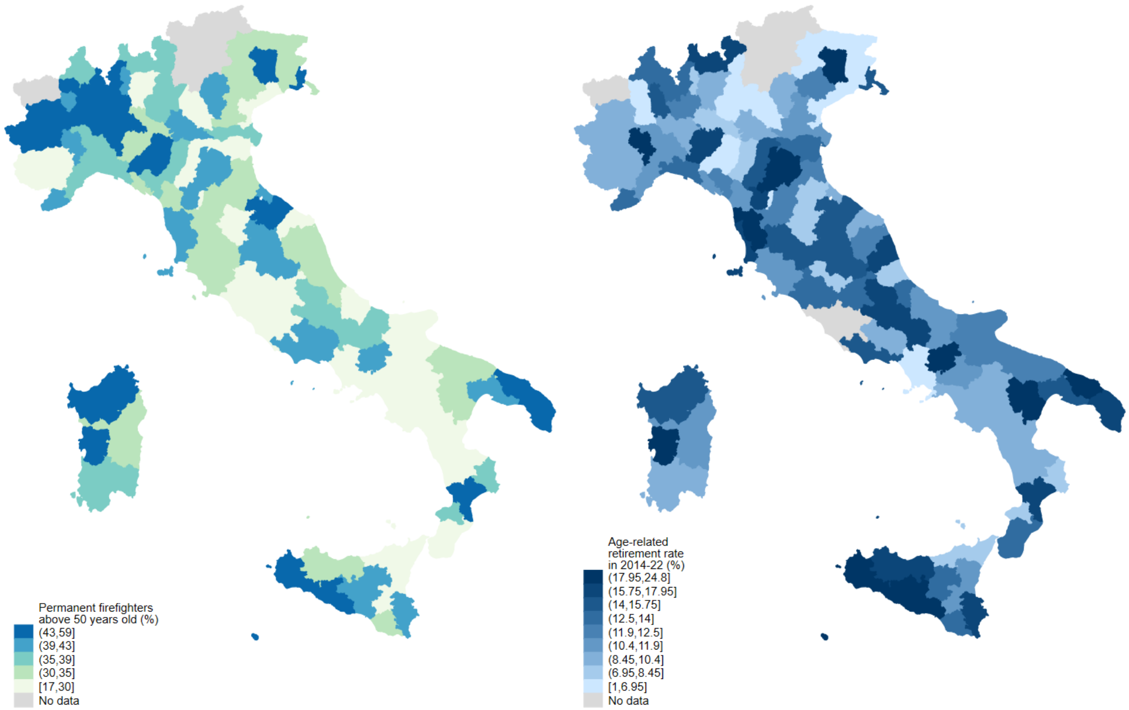
Note: The figure shows the number of personnel in each month from 2014 to 2022 by hierarchical position. Data provided by INPS

Figure A5: Average monthly gross income over time by hierarchical position



Note: The figure shows the yearly average of monthly gross income (in 2015 Euros) by hierarchical position from 2014 to 2022. Data provided by INPS.

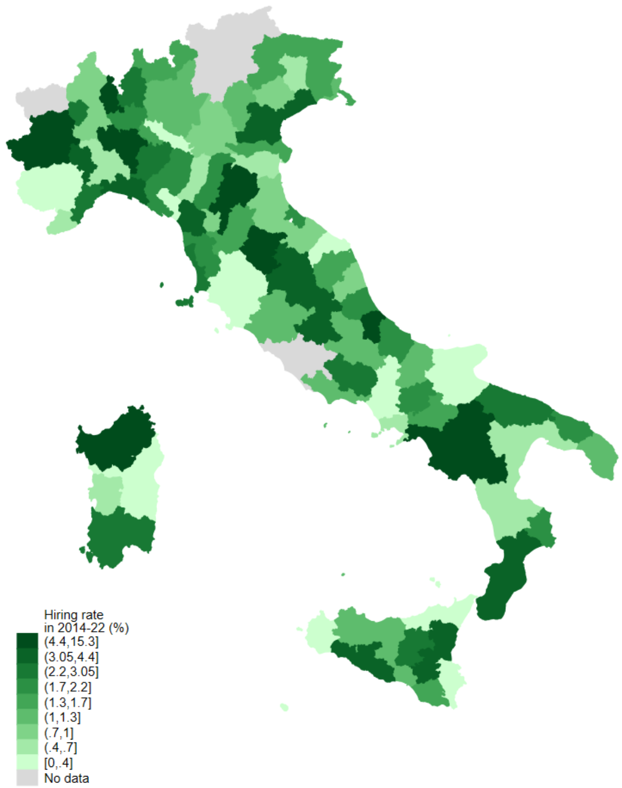
Figure A6: Shares of firefighters above 50 and age-related retirement rates by province



(a) Fraction above 50 years old in January 2014 (b) Retirement rate in 2014-2022

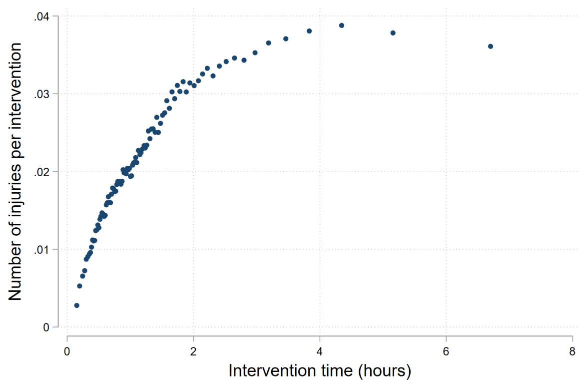
Note: Panel (a) shows the average fraction of firefighters above 50 years of age in each province over 2014-2022. Panel (b) shows the average age-related retirement rate of firefighters in each province over 2014-2022. The average age-related retirement rate is the ratio between the total number of age-related retirees in 2014-2022 divided by the total number of firefighters that worked for at least one month in 2014-2022. Data provided by INPS.

Figure A7: Hiring rates by province in 2014-2022

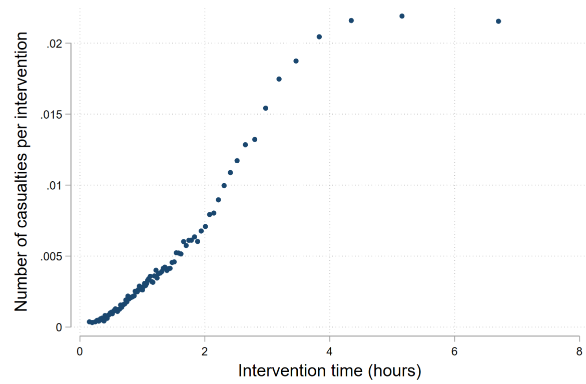


Note: The figure shows the number of firefighters appearing in the data for the first time (interpreted as new hires) divided by the number of firefighters in the same month. Data provided by INPS.

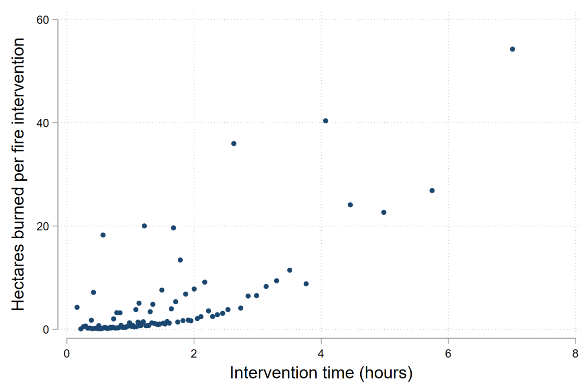
Figure A8: Injuries, casualties and hectares burned against intervention time



(a) Injuries



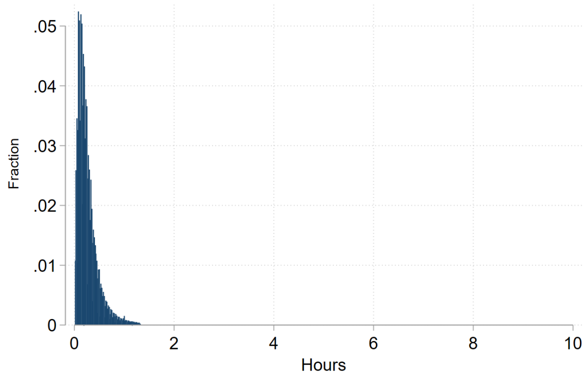
(b) Casualties



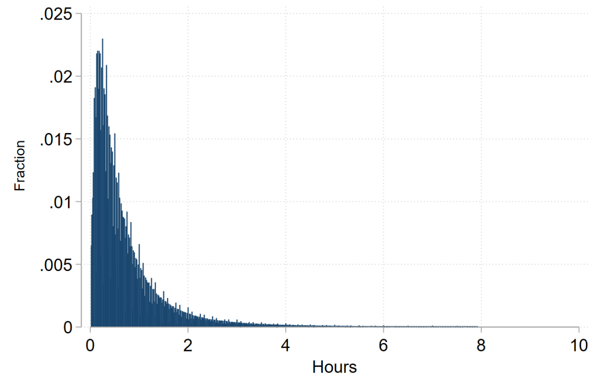
(c) Hectares burned

Note: These figures show the average number of injuries per intervention (Panel a), casualties per intervention (Panel b) and hectares burned per intervention against fires (Panel c) in 100 equal-sized bins. Each bin corresponds to a percentile of the distribution of intervention times in hours.

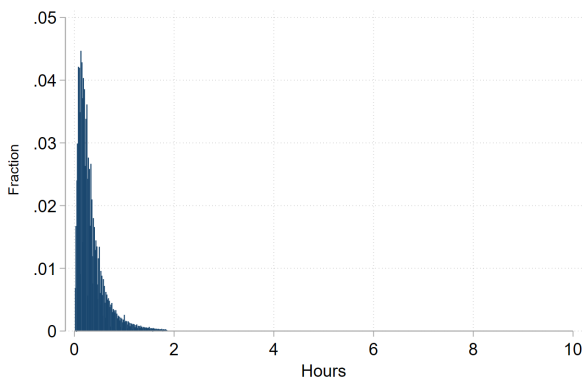
Figure A9: Distribution of intervention and intervention segment times



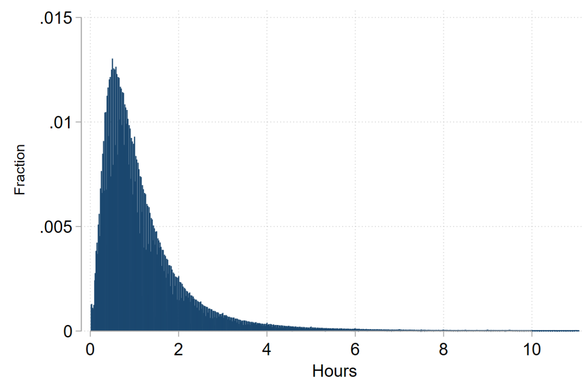
(a) Response time



(b) On-scene time



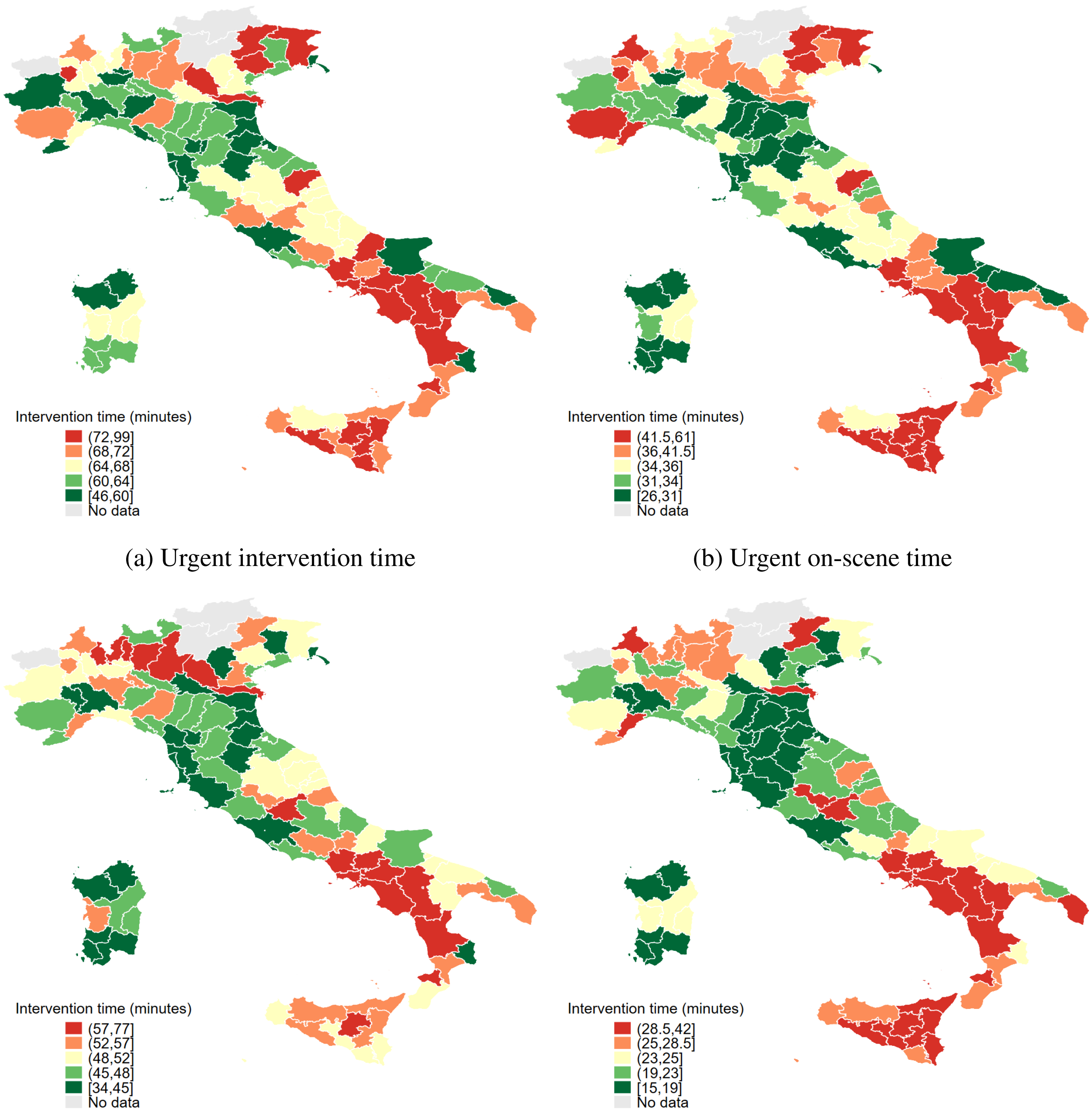
(c) Return time



(d) Intervention time

Note: Panel (a) shows the distribution of the arrival times: the number of hours from when the squad exits the fire station to when it arrives at the intervention site. Panel (b) shows the distribution of on-scene time: the number of hours from when the squad arrives at the intervention site to when it leaves the intervention site. Panel (c) shows the distribution of return times: the number of hours from when the squad leaves the intervention site to when it returns to the fire station. Panel (d) shows the distribution of intervention times: the number of hours from when the squad exits the fire station to when it returns to the fire station.

Figure A10: Median intervention time and on-scene time by province, urgent and non-urgent interventions



(a) Urgent intervention time

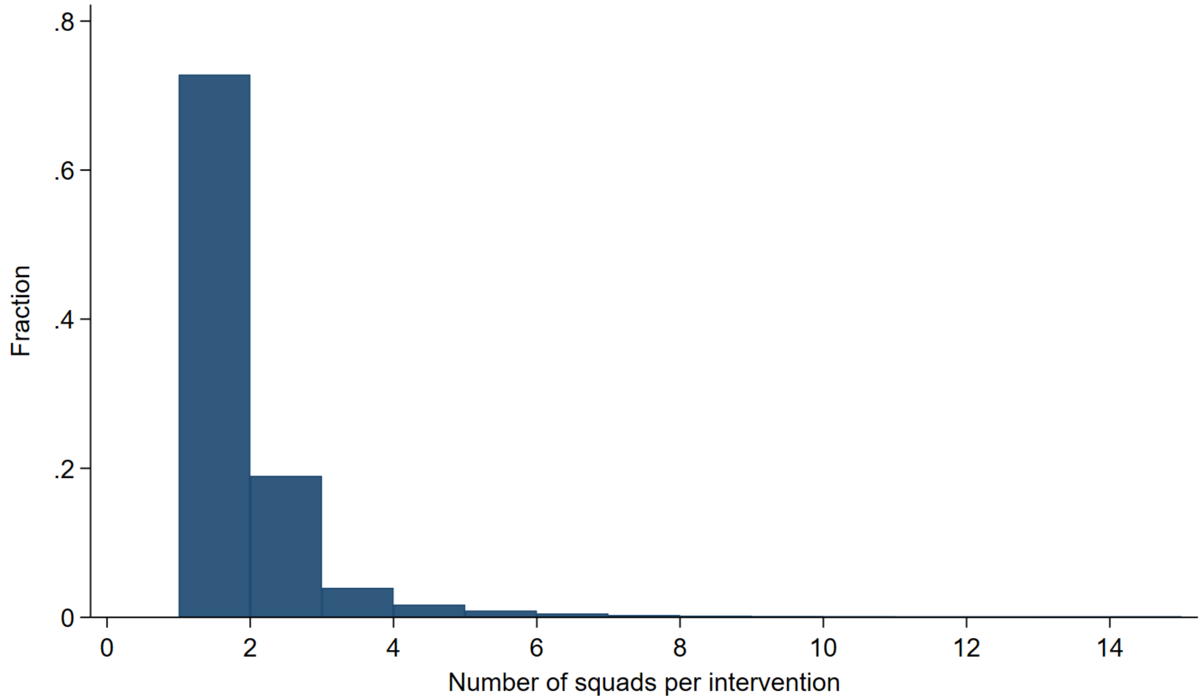
(b) Urgent on-scene time

(c) Non-urgent intervention time

(d) Non-urgent on-scene time

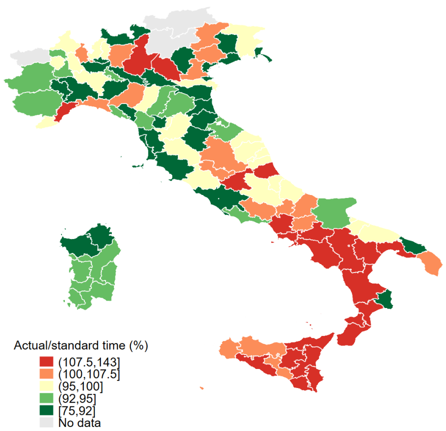
Note: Panels (a) and (c) show the median intervention time (in minutes) by province for urgent interventions and non-urgent interventions in 2014-2022. Panels (b) and (d) show the median on-scene time (in minutes) by province for urgent interventions and non-urgent interventions in 2014-2022. Urgent interventions include fires, explosions, gas leaks, transport accidents, landslides, earthquakes, floods, people searches and rescues. Non-urgent interventions include recovery of goods, removal of debris, leaning trees, pest control, animal rescues, elevator rescues, door/window openings, safety checks.

Figure A11: Distribution of the number of squads per intervention

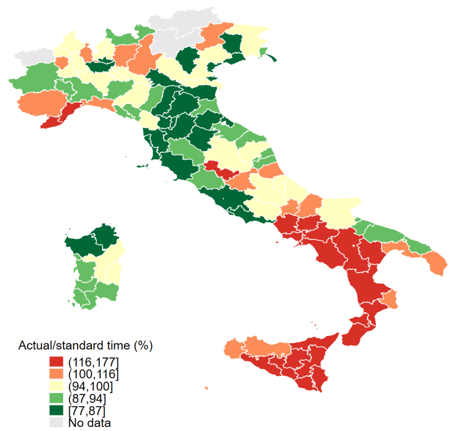


Note: The figure shows the distribution of the number of squads involved in an intervention. Each bar correspond to the fraction of interventions that involve a number of squads indicated in the horizontal axis

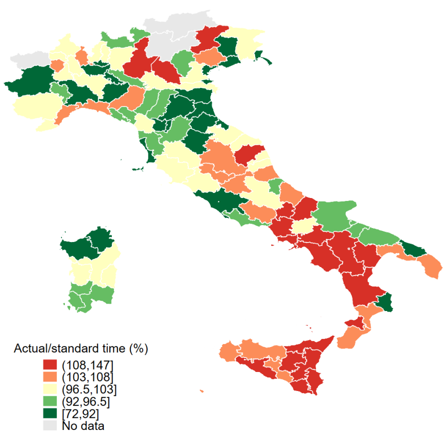
Figure A12: Median intervention and on-scene time over standard time by province



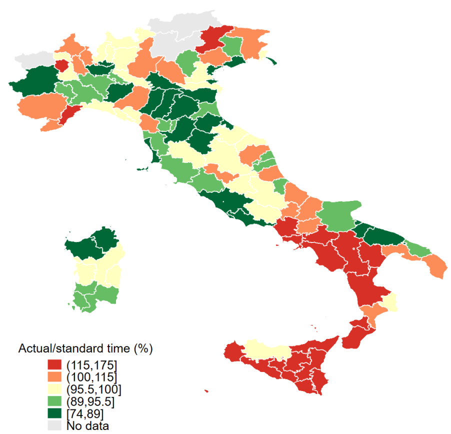
(a) Intervention time, all



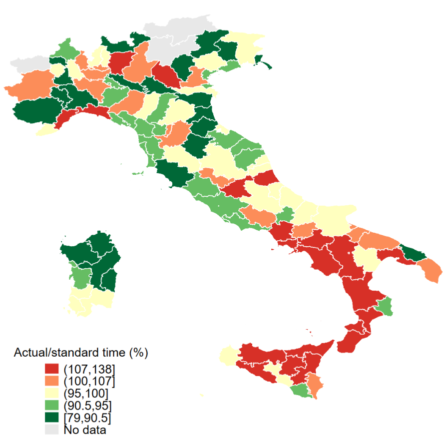
(b) On-scene time, all



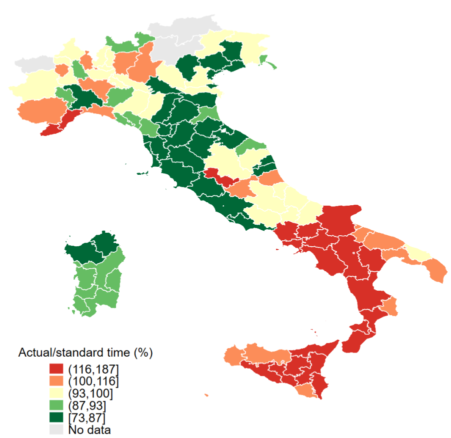
(c) Intervention time, urgent



(d) On-scene time, urgent



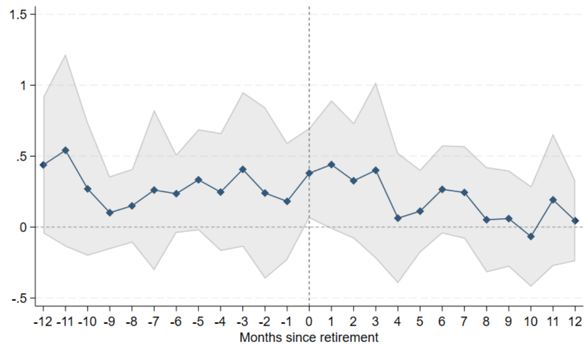
(e) Intervention time, non-urgent



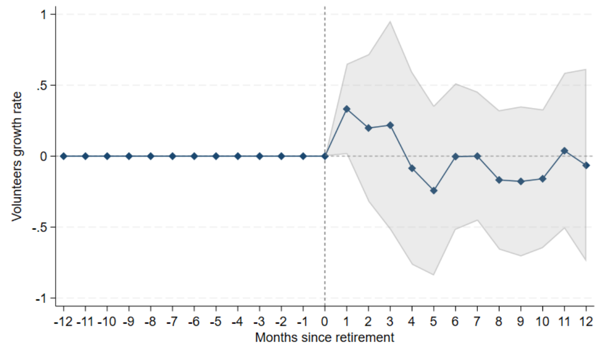
(f) On-scene time, non-urgent

Note: Panels (a), (c) and (e) show the median intervention time (in minutes) divided by the standard intervention time for each type of intervention by province for all interventions, urgent interventions and non-urgent interventions in 2014-2022. Panels (b), (d) and (f) show the median on-scene time (in minutes) divided by the standard on-scene time for each type of intervention by province for all interventions, urgent interventions and non-urgent interventions in 2014-2022. The standard intervention time is the national median intervention time in 2014-2022 for that type of intervention.

Figure A13: Effect of age-related retirements on growth of FTE volunteers



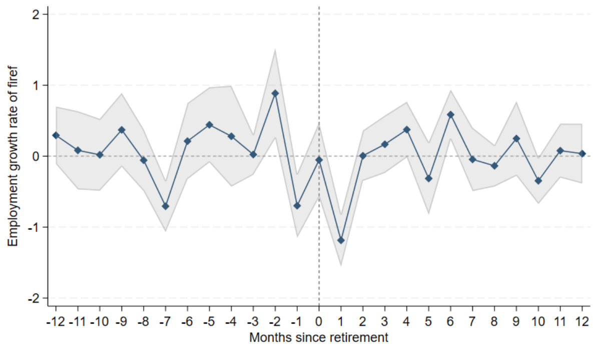
(a) Temporary (12 months)



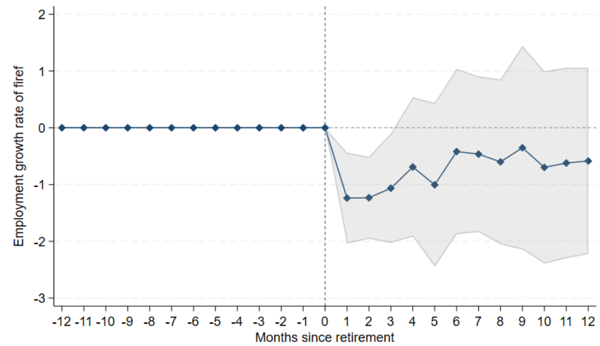
(b) Cumulative (12 months)

Note: FTE volunteer is equal to the number of days worked by the volunteer in the month divided by the standard number of days worked in a month by a firefighter (15). Data provided by INPS.

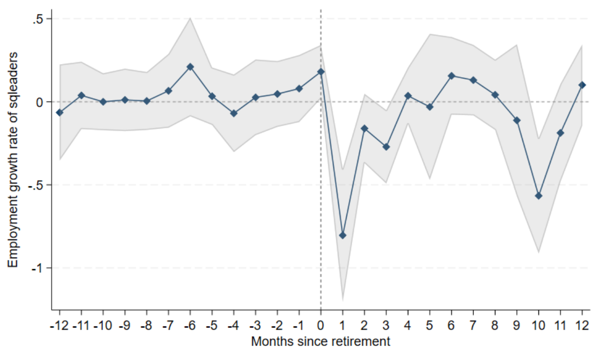
Figure A14: Effect of age-related retirements on employment growth by position, basic firefighters and middle managers



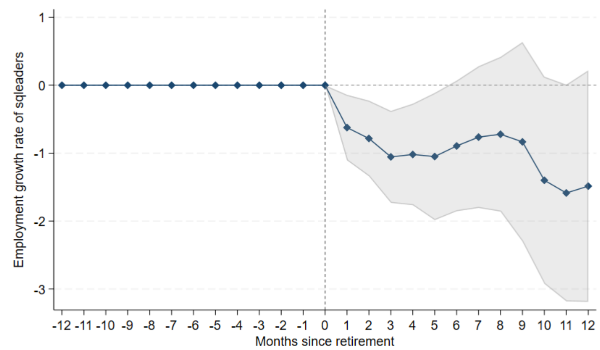
(a) Basic Firefighters, temporary (12 months)



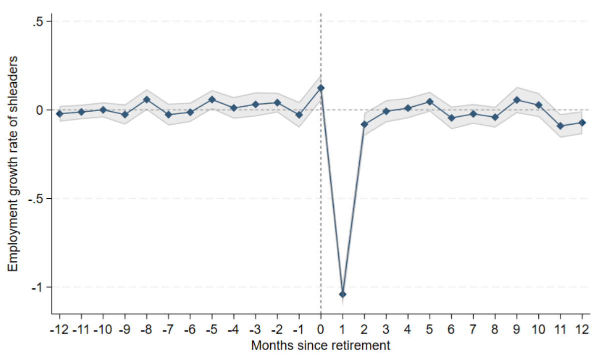
(b) Basic Firefighters, cumulative (12 months)



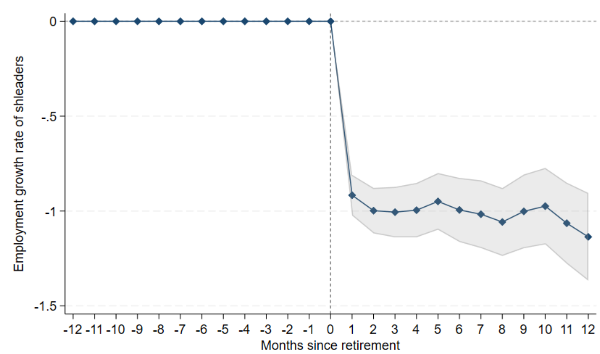
(c) Squad leaders, temporary (12 months)



(d) Squad leaders, Cumulative (12 months)



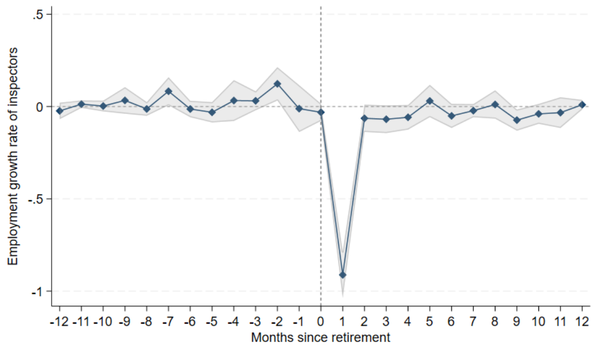
(e) Shift leaders, temporary (12 months)



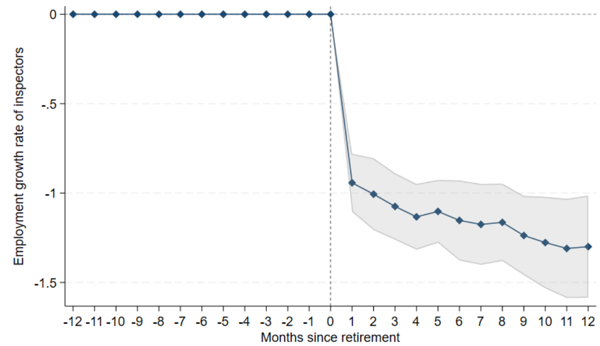
(f) Shift leaders, Cumulative (12 months)

Note: We restrict the sample to firefighters that have a permanent contract. Data provided by INPS.

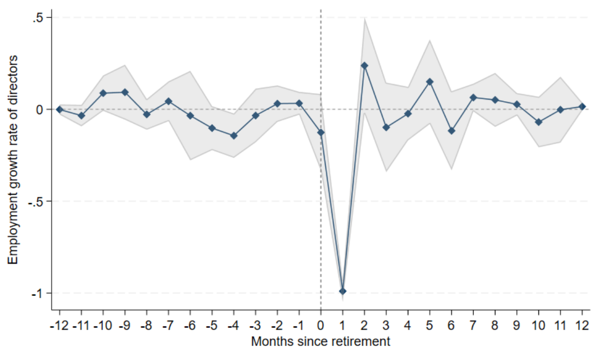
Figure A15: Effect of age-related retirements on employment growth by position, top managers



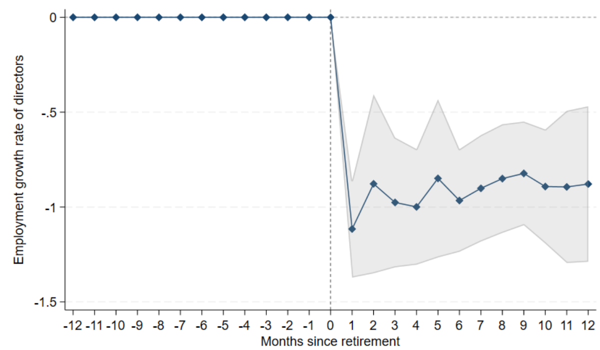
(a) Inspectors, temporary (12 months)



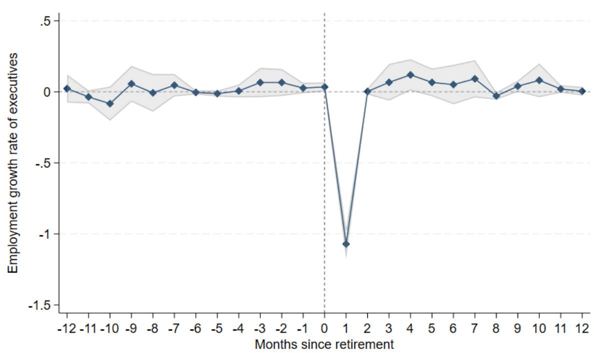
(b) Inspectors, cumulative (12 months)



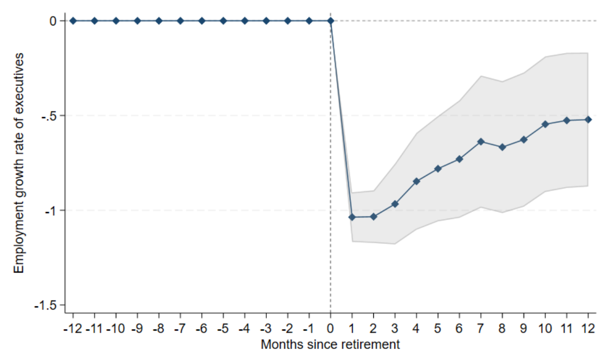
(c) Directors, temporary (12 months)



(d) Directors, Cumulative (12 months)



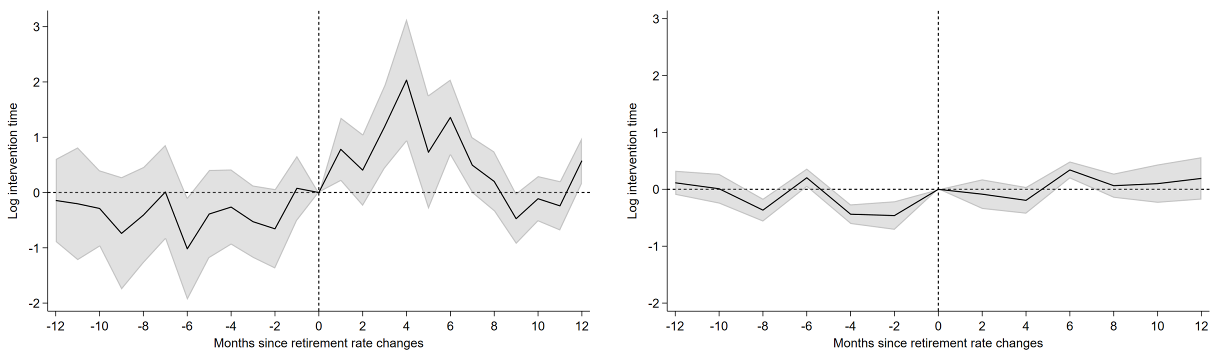
(e) Executives, temporary (12 months)



(f) Executives, Cumulative (12 months)

Note: We restrict the sample to firefighters that have a permanent contract. Data provided by INPS.

Figure A16: Dynamic effects of retirements of middle managers on total intervention time

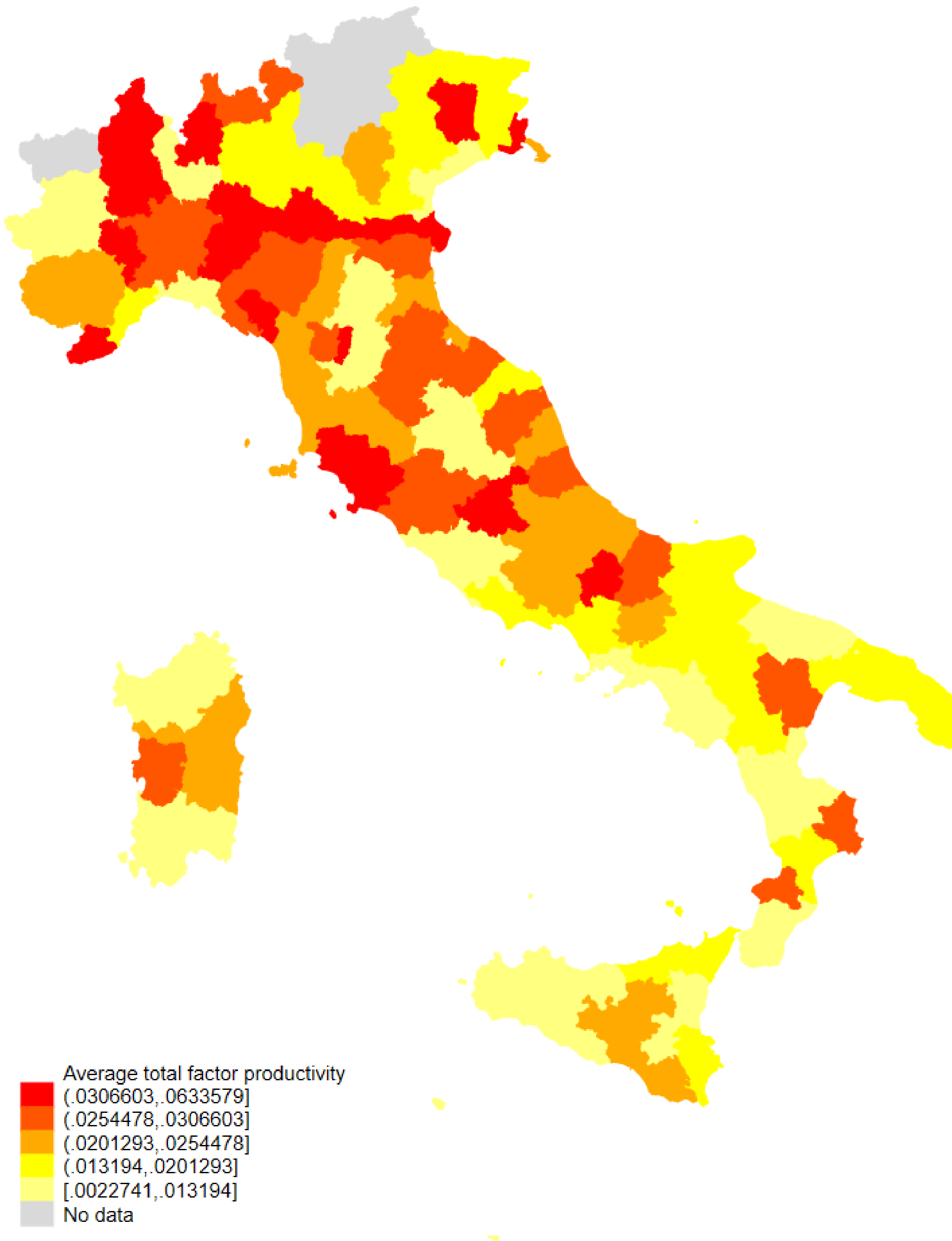


(a) Middle managers

(b) Top managers

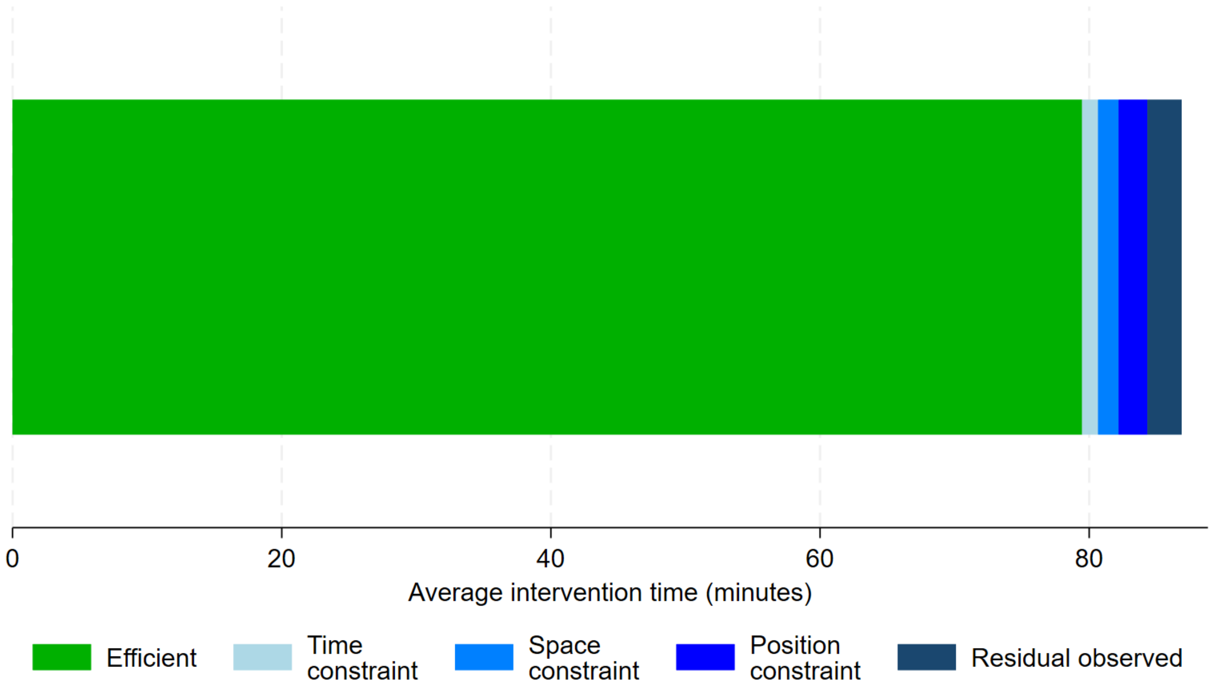
Note: This figure shows the placebo and dynamic effects of retirements of middle managers (a) and top managers (b) on the logarithm of total intervention time in the year prior to and after an increase in the retirement rate. The effects are estimated using the estimator by de Chaisemartin et al. [2024], which is robust to heterogeneous treatment effects. The red lines indicate 95 percent confidence intervals.

Figure A17: Average total factor productivity by province



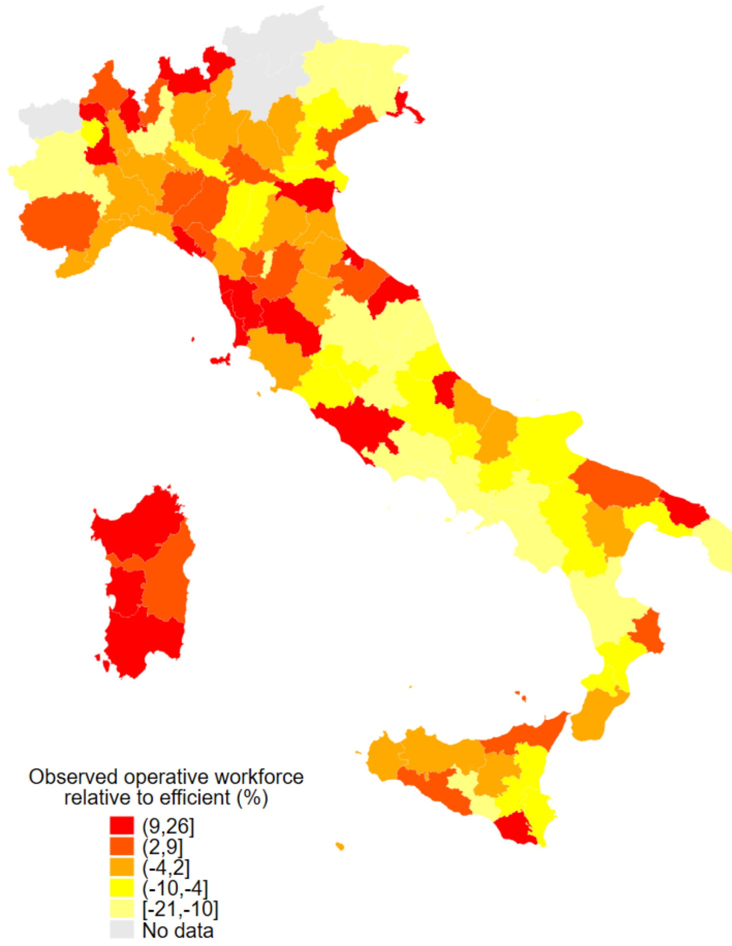
Note: The figure shows the average TFP for the interventions occurred in each province from 2014 to 2022. The TFP of each intervention is obtained by inverting the model production function $A_{idt} = \frac{1}{h^o_{idt} \prod_p (L^o_{pdt})^{\psi_p}}$ where h^o_{idt} and plugging the observed hours of intervention, the observed labor force of each position and the estimated ψ_p.

Figure A18: Average intervention time, observed and counterfactuals



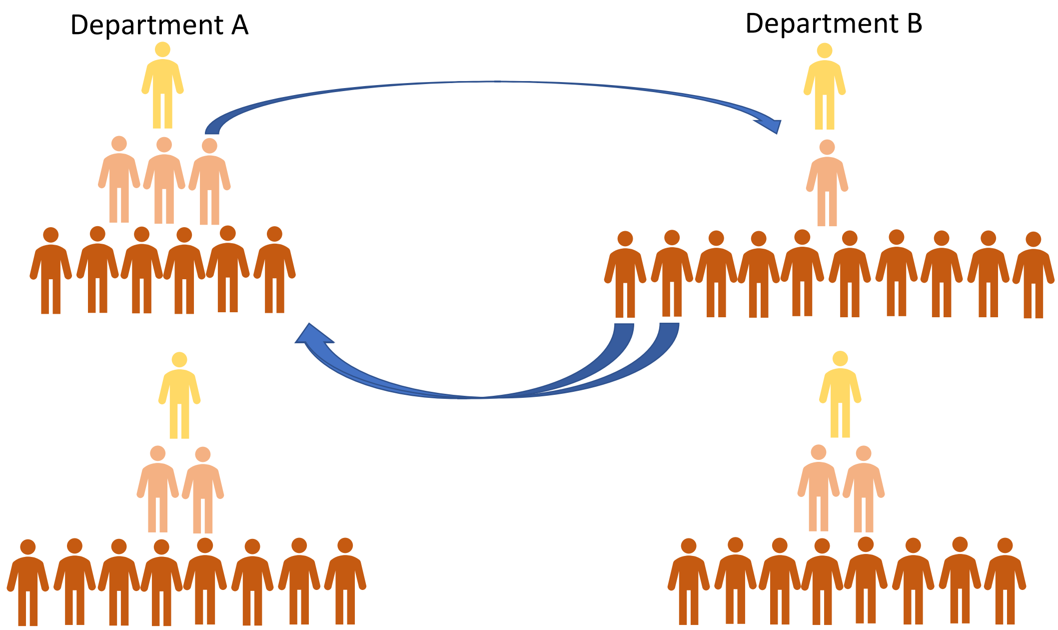
Note: This figure shows the average intervention time (in minutes) that is: simulated under an efficient labor allocation (in green); simulated under a constrained efficient labor allocation adding time constraints (light blue); adding space constraints (mid-blue); adding position constraints (dark blue); adding the residual time necessary to obtain the observed average time (navy).

Figure A19: Observed vs efficient distribution of firefighters by fire department



Note: This figure shows the percentage change in the fire department labor force in the observed data relative to the efficient labor allocation. Red (yellow) means the observed labor force is higher (lower) than efficient. Data provided by INPS.

Figure A20: Example of residual misallocation



Note: This figure shows an example of residual misallocation while holding the amount of resources allocated to each department, month and job position constant. Basic firefighters are in red, squad leaders are in orange and shift leaders in yellow. The efficient allocation is presented in the second row. In this example we assume that the wage of a squad leader is twice as much as the wage of a basic firefighter. The reallocation does not affect the total amount of resources over space, because each department continues to have the same wage expenditures. The reallocation does not affect the total amount of resources over time, because it simply moves workers across departments within the same period. The reallocation does not affect the total amount of resources across job positions, because the total number of basic firefighters and the total number of squad leaders are unchanged.

A.6 Additional Tables

Table A1: Seniority, education requirements and exams by position and level

Position	**Level**	**Seniority**	**Education**	**Exam**
Basic Firefighter	Firefighter	Being under 37 years of age	High school diploma	Yes, open
	Expert Firefighter	4 years as Firefighter		No
	Coordinator Firefighter	8 years as Expert Firefighter		No
Squad Leader	Squad Leader	Being a Coordinator Firefighter		Yes, internal
	Expert Squad Leader	5 years as Squad Leader		No
Shift Leader	Shift Leader	5 years as Expert Squad Leader		Yes, internal
	Expert Shift Leader	5 years as Shift Leader		No
Inspector	Inspector	15 years as firefighter or being a Platoon or Shift Leader	BSc Engineering or Architecture	Yes, 50 percent open
	Expert Inspector	7 years as Inspector		No
	Coordinator Inspector	16 years as Expert Inspector		No
Director	Vice-Director		MSc Economics or Master in Law	Yes, 75 percent open
	Director	2 years as Vice-Director		No
	Director Vice-Executive	5.5 years as Director		No
Executive	First Executive	2 years as Director Vice-Executive		Yes, internal
	Superior Executive	3 years as First Executive		No
	General Executive	Chosen among Superior Executives by the Minister of Interior		No

Note: This table shows the list of positions and levels for firefighters working in the Fire and Rescue Service. For each position-level it reports the required seniority, level of education and whether the promotion is conditional on successfully passing a competitive exam. Firefighters are also required to have political rights and a certified level of physical and mental fitness. Promotions are blocked if the firefighter has incurred in a disciplinary sanction equal to or more severe than a pecuniary sanction in the previous three years.

Table A2: Retirement criteria

		Firefighters		Professionals	
		Operatives	**Top managers**	**Male**	**Female**
Minimum seniority	**2014-2015**	41 years, 6 months. 5 years earlier if 57 years, 3 months old	41 years, 6 months. 5 years earlier if 57 years, 3 months old	42 years, 3 months	41 years, 3 months
	2016-2019	41 years, 10 months. 5 years earlier if 57 years, 7 months old	41 years, 10 months. 5 years earlier if 57 years, 7 months old	42 years, 10 months	41 years, 10 months
	2020-2022	42 years. 5 years earlier if 58 years old	42 years. 5 years earlier if 58 years old	42 years, 10 months	41 years, 10 months
Maximum age	**2014-2015**	61 years, 3 months	65 years, 3 months	65 years, 3 months	65 years, 3 months
	2016-2019	61 years, 7 months	65 years, 7 months	65 years, 7 months	65 years, 7 months
	2020-2022	62 years	66 years	66 years	66 years

Note: This table shows the minimum seniority and the maximum age for firefighters and professionals to obtain a pension. Professionals have technical roles such as accountants, administrators and computer engineers. We exclude them from the analysis. Operatives include the positions of Basic Firefighter, Squad Leader or Shift Leader. Top managers include the positions of Inspector, Director or Executive. All professionals can retire 12 months before the age limit without receiving a pension in those 12 months. All firefighters can retire 15 months before the seniority limit without receiving a pension in those 15 months ('finestra mobile').

Table A3: Percentage of age- and seniority-related retirements

	Frequency	Percentage
Age-related retirement	3778	95.96
Seniority-related retirement	159	4.04
Total	3937	100

Table A4: Number of operative firefighters' age-related retirements by position

	Frequency	Percentage
Director	92	2.44
Executive	70	1.85
Firefighter	146	3.86
Inspector	271	7.17
Shift Leader	2754	72.90
Squad Leader	445	11.78
Total	3778	100

Table A5: Summary statistics

	Obs.	Mean	S.D.	Min.	Max.
A. Fire and Rescue intervention data					
Intervention time	6768185	1.459	1.639	0.117	11.250
Dispatch time	5727134	0.017	0.000	0.017	0.017
Response time	5348765	0.272	0.248	0.017	1.500
On-scene time	6294140	0.886	1.264	0.017	8.567
Return time	5176205	0.346	0.338	0.017	2.067
Urgent intervention time	3783287	1.654	1.788	0.117	11.250
Non-urgent intervention time	2984898	1.212	1.390	0.117	11.250
Civilian injury (%)	6885799	2.196	14.657	0.000	100.000
Civilian casualty (%)	6885799	0.491	6.991	0.000	100.000
Firefighter injury (%)	6885799	0.036	1.887	0.000	100.000
Firefighter casualty (%)	6885799	0.000	0.093	0.000	100.000
Hectares burned	6885799	0.152	0.946	0.000	8.000
Squads per intervention	6885799	1.983	8.910	1.000	480.000
Capacity utilization (%)	6885799	35.193	61.597	0.000	1382.820
B. Personnel data					
Number of basic firefighters	10692	177	107	44	771
Number of squad leaders	10692	59	40	5	326
Number of shift leaders	10692	25	24	0	194
Number of middle managers	10692	84	54	14	429
Number of inspectors	10692	5	6	0	57
Number of directors	10692	7	5	0	29
Number of executives	10692	1	1	0	8
Number of top managers	10692	13	10	1	85
Number of all	10692	274	165	66	1155
Retirement rate (%) basic firefighters	10692	0.008	0.077	0.000	1.899
Retirement rate (%) squad leaders	10692	0.061	0.349	0.000	5.255
Retirement rate (%) shift leaders	10692	0.930	2.419	0.000	28.235
Retirement rate (%) middle managers	10692	0.317	0.753	0.000	8.311
Retirement rate (%) inspectors	10692	0.414	3.387	0.000	91.525
Retirement rate (%) directors	10692	0.086	1.249	0.000	45.957
Retirement rate (%) executives	10692	0.248	4.365	0.000	121.348
Retirement rate (%) top managers	10692	0.236	1.512	0.000	27.481
Retirement rate (%) all	10692	0.115	0.258	0.000	2.698

Notes: This table reports the number of observations, mean, standard deviations, minimum and maximum of the outcome variables in 2014-2022. Panel A shows data on the interventions of the Fire and Rescue Service at squad-intervention level. Panel B show personnel data on the labor force and the retirement rates by position at province-month level. Times are in hours. Squads per intervention are the number of squads involved in an intervention. Capacity utilization is the percentage of total operative firefighters involved in interventions in a province-hour. Retirement rates are monthly retirement rates (in percent) obtained by dividing the number of monthly retirements by the average number of firefighters of the same position in the fire department during the period 2014-2022. Injuries and casualties are the percentage of interventions that involved an injury or a casualty. Times, hectares burned and capacity utilization are windsorized at the 1^{st} and 99^{th} percentiles.

Table A6: Effect of age-based retirement rate on the logarithm of firefighters, by position

	Middle managers	Top managers	Basic firefighters	Squad leaders	Shift leaders	Inspectors	Directors	Executives
Retirement rate	-1.255***	-0.551***	-1.873**	-0.234	-0.548***	-0.354***	-0.822***	-0.491***
	(0.211)	(0.115)	(0.774)	(0.678)	(0.197)	(0.099)	(0.274)	(0.136)
F-statistic	35.519	23.043	5.858	0.119	7.718	12.741	8.975	13.052
Observations	10593	10593	10593	10593	10587	9301	10592	9483
Mean	4.281	2.384	5.034	3.902	2.843	1.418	1.691	0.267

Notes: This table shows the estimate for the effect of the retirement rate of firefighters of the position indicated in the column head lagged by one month on the logarithm of the number of operative firefighters of the same position and fire department. All regressions include province and month fixed effects. Standard errors are clustered at department level. *F-statistic* is the F-statistic testing the null hypothesis that the cofficient for lagged retirement is 0. *Mean* is the average of the dependent variable in the regression sample.

Table A7: Effect of age-based retirement rate on volunteers growth rate, by position of retirees

	Middle managers	Top managers	Basic firefighters	Squad leaders	Shift leaders	Inspectors	Directors	Executives
Retirement rate	0.029	-0.004	-0.236	0.051	0.008	0.001	0.006	-0.003
	(0.042)	(0.020)	(0.273)	(0.100)	(0.011)	(0.007)	(0.011)	(0.006)
F-statistic	0.483	0.034	0.747	0.254	0.499	0.033	0.323	0.172
Observations	10593	10593	10593	10593	10593	10593	10593	10593
Mean	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000

Notes: This table shows the estimate for the effect of the retirement rate of firefighters of the position indicated in the column head lagged by one month on the change in the number of volunteers divided by the number of average firefighters in the fire department. The last column uses retirements from all operative firefighters. All regressions include province and month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

	Reduced form		
	(1)	(2)	(3)
	Firefighter injury	Civilian injury	Log hectares burned
Middle manager retir. rate at t-1	0.002*	-0.005	1.746*
	(0.001)	(0.011)	(1.014)
Top-manager retir. rate at t-1	-0.000	0.007	-0.305
	(0.001)	(0.006)	(0.455)
Observations	7341321	7341321	481977
	Two-stage least squares		
	(1)	(2)	(3)
	Firefighter injury	Civilian injury	Log hectares burned
log(middle managers)	-0.002*	0.006	-1.737*
	(0.001)	(0.009)	(0.951)
log(top managers)	0.001	-0.014	1.145
	(0.001)	(0.011)	(0.996)
Observations	7341321	7341321	481977
Mean	0.000	0.021	-0.789

Table A8: Effect of age-based retirement rate on injuries and hectares burned, by hierarchical position.

	(1) Firefighter injury	(2) Civilian injury	(3) Log hectares burned
Middle manager retirement rate	0.002	-0.002	1.681
	(0.002)	(0.010)	(1.645)
Top-manager retirement rate	-0.000	0.007	-0.337
	(0.001)	(0.006)	(0.523)
Observations	6800728	6800728	454790
Mean	0.000	0.022	-0.753

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers and top managers on the outcome variable indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A9: Effect of age-based retirement rate on the probability an observed intervention is urgent, by hierarchical position.

	Urgent intervention
Middle manager retirement rate	0.084
	(0.155)
Top-manager retirement rate	0.061
	(0.053)
Observations	6843237
Mean	0.557

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers and top managers on the outcome variable indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A10: Effect of age-based retirement rate by position on intervention time, by mid and top managers. Heterogeneity by urgent and non-urgent interventions.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
	Non-urgent interventions			
Middle manager retirement rate	0.114	-0.073	0.386**	-0.087
	(0.113)	(0.174)	(0.152)	(0.162)
Top-manager retirement rate	0.021	-0.022	-0.084	0.098*
	(0.045)	(0.068)	(0.063)	(0.058)
Observations	2942131	2298002	2767590	2207302
Mean	-0.140	-1.652	-0.967	-1.571
	Urgent interventions			
Middle manager retirement rate	0.415**	0.119	0.545**	0.130
	(0.209)	(0.179)	(0.253)	(0.181)
Top-manager retirement rate	-0.030	-0.018	-0.001	0.062
	(0.066)	(0.064)	(0.086)	(0.066)
Observations	3741329	2971407	3443133	2890905
Mean	0.151	-1.625	-0.507	-1.322

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate and the logarithm of the number of firefighters indicated in each row on the outcome variables indicated in each column, by urgent and non-urgent interventions. Urgent interventions include fires, explosions, gas leaks, transport accidents, landslides, earthquakes, floods, people searches and rescues. Non-urgent interventions include recovery of goods, removal of debris, leaning trees, pest control, animal rescues, elevator rescues, door/window openings, safety checks. We exclude for the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A11: Effect of age-based retirement rate on average years of age and tenure of middle managers.

	(1) Avg age of mid managers	(2) Avg tenure of mid managers
Middle manager retirement rate	-2.802***	-0.848
	(0.731)	(2.630)
Observations	6800728	6800728
Mean	53.912	27.977

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers on the outcome variable indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. Age and tenure are in years. All regressions control for the top-manager retirement rate, fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A12: Effect of age-based retirement rate by position on intervention time, by mid and top managers. Heterogeneity by hours already worked during the shift.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
Mid manager retir. rate	0.405*	-0.050	0.628**	0.249
	(0.222)	(0.164)	(0.274)	(0.215)
Mid manager retir. rate*hours worked	-0.022	0.015	-0.028	-0.036
	(0.029)	(0.017)	(0.039)	(0.024)
Hours worked	-0.008***	-0.001	-0.009***	0.002***
	(0.001)	(0.000)	(0.001)	(0.001)
Observations	6683472	5269420	6210737	5098218
Mean	0.023	-1.637	-0.712	-1.430

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers interacted with hours already worked during the shift on the outcome variables indicated in each column. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A13: Effect of age-based retirement rate by position on intervention time, by mid and top managers. Heterogeneity by tenure.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
Middle manager retirement rate	0.345	-1.736	0.957	-0.218
	(1.327)	(1.676)	(1.473)	(1.413)
Middle manager retirement rate*Tenure	-0.002	0.060	-0.016	0.009
	(0.046)	(0.057)	(0.051)	(0.049)
Tenure	-0.001	-0.001	-0.001	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Observations	6683472	5269420	6210737	5098218
Mean	0.023	-1.637	-0.712	-1.430

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers interacted with tenure on the outcome variables indicated in each column. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A14: Effect of age-based retirement rate by position on intervention time, by mid and top managers. Heterogeneity by age.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
Middle manager retirement rate	-12.381	-17.160*	-12.902	-9.149
	(8.837)	(9.038)	(11.223)	(8.211)
Middle manager retirement rate*Age	0.230	0.313*	0.243	0.167
	(0.161)	(0.165)	(0.205)	(0.150)
Age	-0.008	-0.003	-0.011*	-0.002
	(0.006)	(0.009)	(0.006)	(0.008)
Observations	6683472	5269420	6210737	5098218
Mean	0.023	-1.637	-0.712	-1.430

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers interacted with age on the outcome variables indicated in each column. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. Age is in years. *Mean* is the average of the dependent variable in the regression sample.

Table A15: Effect of age-based retirement rate on intervention time. Heterogeneity by capacity.

	(1) Log intervention time	(2) Log response time	(3) Log on-scene time	(4) Log return time
		Below median capacity utilization		
Basic firefighters retirement rate	1.308	1.582	1.323	-0.474
	(1.155)	(1.274)	(1.528)	(1.047)
Squad leaders retirement rate	0.052	0.132	0.067	-0.056
	(0.158)	(0.246)	(0.213)	(0.220)
Shift leaders retirement rate	0.013	-0.002	0.024	-0.000
	(0.032)	(0.045)	(0.043)	(0.042)
Inspectors retirement rate	-0.012	-0.011	-0.023	0.018
	(0.019)	(0.023)	(0.024)	(0.023)
Directors retirement rate	0.029	0.091	-0.052	0.101
	(0.056)	(0.058)	(0.079)	(0.077)
Executives retirement rate	-0.010	-0.015	-0.025	-0.015
	(0.016)	(0.021)	(0.020)	(0.018)
Observations	3334772	2868067	3121574	2703527
Mean	-0.076	-1.706	-0.838	-1.520
		Above median capacity utilization		
Basic firefighters retirement rate	-1.270	-0.138	-0.592	-2.460**
	(1.365)	(1.194)	(1.878)	(1.208)
Squad leaders retirement rate	0.650*	0.645*	0.757**	0.234
	(0.331)	(0.354)	(0.358)	(0.289)
Shift leaders retirement rate	0.114**	-0.008	0.198***	0.066
	(0.055)	(0.054)	(0.063)	(0.049)
Inspectors retirement rate	-0.014	-0.016	-0.014	0.014
	(0.026)	(0.026)	(0.033)	(0.024)
Directors retirement rate	0.024	-0.044	0.012	0.076
	(0.073)	(0.076)	(0.104)	(0.075)
Executives retirement rate	0.007	0.006	0.002	0.037**
	(0.016)	(0.026)	(0.020)	(0.018)
Observations	3320293	2374269	3061353	2367881
Mean	0.120	-1.536	-0.589	-1.319

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of firefighters indicated in each row on the outcome variables indicated in each column, by below and above median capacity utilization. We exclude for the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A16: Effect of age-based retirement rate on the number of squads involved, by hierarchical position.

	(1) Multiple squads	(2) Log number of squads per interventions
Middle manager retirement rate	-0.129	-0.007
	(0.095)	(0.210)
Top-manager retirement rate	-0.005	0.034
	(0.043)	(0.066)
Observations	6800728	6800728
Mean	0.272	0.273

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers and top managers on the outcome variable indicated in each column. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A17: Effect of age-based retirement rate on work fatigue, by hierarchical position.

	(1) Capacity utilization	(2) Finishing overtime	(3) Hours overtime	(4) Log hours overtime
Middle manager retirement rate	35.844*	0.035	0.001	-1.242
	(20.194)	(0.033)	(0.050)	(1.247)
Top-manager retirement rate	-3.589	-0.004	0.002	-0.479
	(8.224)	(0.014)	(0.016)	(0.466)
Observations	6800728	6800728	6800728	470590
Mean	35.325	0.072	0.060	-1.180

Notes: This table shows the estimate for the effect of the lagged monthly retirement rate of middle managers and top managers on the outcome variable indicated in each column. Hours overtime are windsorized at the 99th percentile. We exclude from the sample interventions made by squads of volunteers and false alarms, and interventions that were no longer necessary. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level. *Mean* is the average of the dependent variable in the regression sample.

Table A18: Top-manager characteristics

	(1) Full sample	(2) Movers
A. Demographics		
Female	0.041	0.058
Age	56.907	57.274
Tenure	29.051	26.694
B. Macroareas of birth		
South	0.423	0.457
Center	0.237	0.167
North	0.133	0.145
Islands	0.195	0.210
Abroad	0.012	0.022

Notes: This table reports the summary statistics of top manager characteristics. Column (1) includes the full sample of top managers. Column (2) includes only the subsample of movers, that is top managers that worked in at least two departments over the sample period. Age and tenure are in years. Tenure is the number of years from the first month of work.

Table A19: Top-manager characteristics

	(1) Full sample	(2) Movers
A. Demographics		
Female	0.000	0.000
Age	58.752	58.406
Tenure	41.853	42.517
B. Macroareas of birth		
South	0.273	0.417
Center	0.195	0.083
North	0.365	0.500
Islands	0.161	0.000
Abroad	0.005	0.000

Notes: This table reports the summary statistics of middle manager characteristics. Column (1) includes the full sample of middle managers. Column (2) includes only the subsample of movers, that is middle managers that worked in at least two departments over the sample period. Age and tenure are in years. Tenure is the number of years from the first month of work.

Table A20: Middle-manager characteristics

	(1) All departments	(2) Departments with ≥ 1 long-term switches
	A. Demographics	
# Middle managers	771	579
# Middle managers in > 1 department	12	12
# Departments	100	79
# Departments with ≥ 1 movers	20	17
# Connected sets	88	72
# Middle-manager switches	770	119

Notes: This table shows the structure of the full sample of departments (column 1) and for the sample of departments with at least one long-term switch (column 2). A long-term switch is a change in middle management where the outgoing manager held the position for at least one year and the incoming manager remains in the role for at least one year. Number of switches in middle managers is the number of all switches in column 1 and the number of long-term switches in column 2.

Table A21: Correlation between baseline department characteristics and incoming top-manager FE

	(1)	(2)
South and islands	-0.011	0.018
	(0.008)	(0.009)
$Ln(D)_{2014q1}$	-0.082	-0.049
	(0.043)	(0.030)
$Ln(D)_{q-1}$	0.025	-0.018
	(0.035)	(0.040)
$Ln(D)_{q-2}$	0.012	-0.016
	(0.037)	(0.036)
$Ln(D)_{q-3}$	0.044	0.010
	(0.034)	(0.030)
$Ln(D)_{q-4}$	0.008	-0.018
	(0.039)	(0.047)
$Ln(\dot{D})_{q-1}$	0.000	0.000
	(0.001)	(0.001)
$Ln(\dot{D})_{q-2}$	-0.000	0.001
	(0.000)	(0.000)
$Ln(\dot{D})_{q-3}$	0.001	0.000
	(0.001)	(0.001)
N	113	113
R-squared	0.088	0.148
P-value	0.219	0.722

Notes: This table analyzes whether baseline court characteristics predict the incoming top-manager fixed effect and the difference between the incoming and the outgoing top-manager fixed effects. Each observation is an incoming top-manager in a department experiencing a long-term switch. The dependent variable in column (1) is the top-manager effect estimated using equation (5). The dependent variable in column (2) is difference of incoming and outgoing top-manager effects estimated using equation (5). q indexes the quarter of the event. Ln(D) is the average logarithm of total intervention time in the quarter-department cell. The variables with a dot above with subscript q-x represent growth rates from quarter q-(x+1) to quarter q-x. *N* represents the number of long-term switches. The P-value is the p-value of the null hypothesis that all lagged average log intervention times and their growth rates are jointly zero. Standard errors are clustered at the department level and are reported in parentheses.

Table A22: Elasticities of total time of intervention with respect to labor, by position

	Middle managers	Top managers	Basic firefighters	Squad leaders	Shift leaders	Inspectors	Directors	Executives
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(middle managers)	-0.203*							
	(0.107)							
Log(top managers)		0.021						
		(0.080)						
Log(basic firefighters)			-0.379					
			(1.483)					
Log(squad leaders)				-1.480				
				(2.971)				
Log(shift leaders)					-0.112*			
					(0.061)			
Log(inspectors)						0.034		
						(0.056)		
Log(directors)							-0.025	
							(0.061)	
Log(executives)								0.001
								(0.044)
Observations	6683472	6683472	6683472	6683472	6681309	6198120	6682831	6133957

Notes: This table shows estimates of the elasticities of total time of intervention with respect to the number of firefighters in each position. We regress the logarithm of total time of intervention on the logarithm of the number of firefighters of each position, instrumented by the lagged monthly retirement rate of the corresponding position. All regressions include fire station and type-by-month fixed effects. Standard errors are clustered at department level.

Table A23: Average intervention time, observed and counterfactual

	(1) Mean
Observed	86.874
Space constraints	80.998
Position constraints	81.615
Time constraints	80.661
Efficient	79.474

Notes: This table shows the average intervention time (in minutes) in the observed data and in the counterfactual scenarios. The counterfactual scenario are the efficient labor allocation and the constrained efficient labor allocation with space, position and time constraints.