HOW TEAMS SUBSTITUTE WORKERS: EVIDENCE FROM THE HEALTHCARE SECTOR

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Abstract

I study how temporary absences of workers due to a health shock affect individual working hours, team organization and team production using a personnel dataset from a large hospital in Italy. Using an event study design, I present three key findings: (i) in teams with less skill-intensive tasks, such as in teams of nurses, young co-workers increase their working hours, but old co-workers do not (internal substitution); (ii) small teams of nurses include outsiders to cover temporary absences (external substitution); (iii) in teams with skill-intensive tasks, such as in teams of doctors, co-workers neither increase their working time nor are temporary outsiders hired. I find that, when affected by health shocks, teams of doctors experience a greater decline in the services they provide than teams of nurses. The results suggest that health shocks affect team organization, co-workers and service provision.

Keywords: Team production; Health shocks; Worker absences; Work substitution; Healthcare; Hospital work.

JEL Classification: I12; I18; J22; J24; J81; M54.

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1 Introduction

Work teams are a key organizational unit in contemporary firms, therefore understanding their functioning is central to explain how firms organize production activities. From small innovative start-ups to large multinational conglomerates, business operations are increasingly organized around teams where workers share responsibilities (Ahmady et al., 2016; Ford and Randolph, 1992). While in the early 20^{th} century, during the rise of mass production, it was more common for workers to complete tasks in isolation with minimal interaction (Hounshell, 1984; Scranton, 2018), most modern firms have flexible structures and they are organized in teams where workers collaborate to produce an output (Jerab and Mabrouk, 2023; Milgrom and Roberts, 1990).

Prolonged absences from work are a significant challenge for firms, workers and organizations. Verbrugghe et al. (2018) shows that 10% of the Belgian workforce considers themselves at risk of experiencing medium- or long-term absence. Koopmans et al. (2008) find that more than 7% of employees are affected by absences longer than 6 weeks. Prolong absences, although less frequent than short ones, represent the major part of costs of sick absences for companies and firms (van Amelsvoort et al., 2017). Therefore, it is important to study what are the effects of prolonged health-related absences on work teams.

While there exists extensive literature on the negative and persistent effects of health shocks on individual wages, career prospects, education, bankruptcies, and household outcomes (Halla and Zweimüller, 2013; Parro and Pohl, 2021; Dobkin et al., 2018; Decker and Schmitz, 2016; Sundmacher, 2012; Jäger and Heining, 2022), much less is known about how co-workers are affected. I study how the management of an Italian public hospital adjusts work teams when a team member experiences a prolonged absence due to health shocks. I define health shocks as sick leaves lasting more than 30 consecutive days among workers without chronic conditions, in this way I aim to exclude long absences that are expected and less disruptive to team operations, which helps ensure the exogeneity of the shocks. I analyze doctors and nurses separately, given differences in task complexity. I examine teams of varying sizes to assess how team size influences substitution decisions, as larger teams may have greater flexibility to reassign tasks and absorb absences.

In this paper, I show that young nurses work longer when a co-worker is absent for a prolonged period due to health shocks, that teams of nurses rely on outsiders to cover such absences and that absences affect service provision. I find that young nurses[1] increase their time worked by around 2/3% when a co-worker is affected by a prolonged absence, with a persistent effect even thereafter, while older nurses do not. This effect is driven by larger teams[2]. I also find that teams of nurses cover more than half of prolonged absences with outsiders joining the team temporarily. This finding is driven by smaller teams. In contrast, teams of doctors do not include outsiders nor do they increase working time during a prolonged absences of a co-worker. Absences negatively affect services provided, especially by doctors. I estimate that health shocks in a team of doctors decrease hospitalizations and ambulatory visits by 10% while I find smaller effects on services delivered caused by health shocks affecting nurses.

I contribute to the ongoing debate on how health shocks affect workers and organizations in three main ways. First, I provide new empirical evidence on how co-workers are affected by health shocks of a co-worker, while prior literature has primarily focused on individual- or household-level outcomes. For instance, Dobkin et al. (2018) studied the individual and household consequences of hospitalization on earnings, out-of-pocket expenditures, and bankruptcy. Bradley et al. (2012) examined how health shocks affect the likelihood of losing health insurance, depending on the type of insurance coverage. Halla and Zweimüller (2013) used unexpected commuting accidents as a quasi-experimental setting to study the medium-term effects of health shocks on earnings and employment. García-Gómez et al. (2013) documented large negative effects on employment, around 7%, two years after acute hospitalization, as well as substantial spillover effects on household income in the Netherlands. Similarly, Lenhart (2019) analyzed comparable outcomes in the UK, offering a detailed discussion of heterogeneous effects of health shocks by gender and job qualification. Cook et al. (2019) studied how early-life exposure to parental health shocks affects children's later educational and economic outcomes. I extend this literature by showing that health shocks can also affect co-workers who are not directly impacted.

I use precise measure of teams compared to the previous literature on work teams. I adopt a metric similar to Emanuel et al. (2023), which allows me to directly observe work units. My unique data enable me to identify teams by precisely observing who works in the same hospital department, with the same job level, in a given month. Prior studies on workplace teams, such as Jäger and Heining (2022); Jarosch et al. (2021); Caicedo et al. (2019);

[1] I define young nurses as those below 30 years old in January 2016, in the robustness checks I change this arbitrary threshold and the main findings hold

[2] I define large teams as those with a size over the 85^{th} percentile of the size distribution of teams within a job category (doctor or nurses) as of January 2016. The threshold is 15 members for nurses and 10 members for doctors. Results do not change when I slightly change this threshold.

Cornelissen et al. (2017), examine interactions and spillover effects among co-workers. These studies typically define teams by combining occupation and firm identifiers. However, workers with the same occupation and employer may be assigned to different units within the organization, causing potential misclassifications. My approach improves on this literature by offering a more granular and accurate definition of teams, based on actual unit-level assignments.

Second, I investigate how workers affected by prolonged absences affect team composition and structure. I provide new evidence on the topic from a critical and widespread sector such as healthcare. Previous literature studied how firms substitute their sick workers using qualitative methods and theoretical models. Nicholson et al. (2006) used survey data interviewing firm managers to understand how replacements of absent workers are different across occupations, finding that for most of them the cost of the absence for firms is higher than the wage paid to the worker. Pauly et al. (2002) provides theoretical predictions on the consequences of absenteeism for the employers and the employees when perfect substitute workers are not available and how this could affect production outcomes of teams. Compared to the previous literature, I show new evidence on this topic by using a natural experimental setting to estimate how team managers adjust team composition if a worker is affected by a prolonged absence.

Third, I assess how health shocks in teams affect production outcomes and services delivered in the healthcare sector. Other studies on this topic estimated how absences of individuals affect team production, but focused on smaller and narrower sectors compared to the healthcare. Hoey et al. (2023) study the impact of temporary absences on co-workers' productivity in the National Hockey League using individual unexpected prolonged injuries as health shocks affecting teammates. Azoulay et al. (2010) and Khanna (2021) focused on academia estimating the effect of premature deaths of prominent researchers on the output of their co-author estimating a productivity drop of 5% to 8% of their quality adjusted publications in the following years. Compared to them, I focus on a more general setting like healthcare showing new findings on how absences affect output.

I use the personnel database of one of the largest public-sector hospital in Italy. This dataset includes monthly observations from January 2016 to October 2022 and it contains records of key variables such as hours worked, hierarchical level, job type, sick and maternity leaves, worker characteristics, team membership, and team-level production outcomes. The hospital is made of multiple health departments located in different buildings. I define teams as groups of workers who, in a given month, share the same job type (doctor or nurse), hierarchical level, and department. I consider workers to be in the same team if they share these variables. In contrast, data on hours worked are obtained from the administrative records of the hospital, based on workers scanning their ID badges upon entering and exiting each shift.

I use event study models with two-way fixed effects (TWFE), with an approach similar to that used in Schmieder et al. (2023) and Halla et al. (2020), to estimate the effects of prolonged absences on co-workers and team composition. This method allows me to assess the short term impact of absences on co-workers and output, check for pre-treatment trends or anticipatory effects that could threaten identification and detect potential longer term effects during the post-treatment months. To study the effect of sick leaves on services delivered, I use an Ordinary Least Squares (OLS) model.

I support my findings with several robustness and falsification checks that confirm the estimates from the main specification. First, I exclude the first years of the dataset and I remove the COVID years from the analysis on hours worked. Second, I change the threshold for defining young workers. Third, I estimate the regressions with the outcome variable in levels. Fourth, I use only observations part of teams affected by health shocks exploiting different timing of health shocks to implicitly control for unobservable differences between teams affected or not by health shocks. Fifth, I study the effect of maternity leaves on team organization to observe whether anticipated absences have a different effect. Sixth, I exclude COVID periods from the analysis on services delivered. Seventh, I exclude temporary workers. To conclude, I check whether my results are robust to a different definition of large and small teams.

I present a simple theoretical model to interpret my empirical results. I provide different cases on how working time, team structure and production are affected by prolonged absences of team members. I use a Constant Elasticity of Substitution (CES) production function with a cost function defined with payroll expenditures and the burden associated with the different replacement options. I compare the different replacement options to understand which one is selected by each type of team. The decision of the management responsible for the organization of the teams is between no replacement, internal replacement increasing incumbent colleagues working time or external replacement using new temporary hirings. Replacement decisions are dependent on team specific replacement costs, size and the substitutability between different workers. I show that teams employed in tasks in which workers are costly to replace do not respond to the absence, while teams in tasks with high replaceability among co-workers and low costs for substitutions, either hire external replacements or redistribute duties among incumbent employees, depending on the initial team size.

To summarize, I find that individual health shocks and absences affect other co-workers and team organization while, at the same time, decreasing output. Temporary absences in teams are tackled by including temporary substitutes or by increasing working time of other co-workers and I find the replacement strategy to depend on the structure of the team and on the job. I find that in nurse teams, workers increase their working hours and the team structure adjusts, whereas this behavior is not observed in doctor teams. My estimates suggest that young nurses work longer during a co-worker's prolonged absence, with this effect persisting afterward. This persistence may stem from nurses keeping the informal responsibilities they assumed during a colleague's prolonged absence, even thereafter. The different behavior between nurses and doctors might be driven by the difference in task complexity among the two occupations. The effect is driven by large teams, which can more easily spread an absent worker's tasks across a larger workforce. Similarly, I estimate that teams of nurses, especially small ones, cover prolonged absences by including outsiders. This likely occurs because small teams cannot easily rearrange an absent co-worker's tasks, making a temporary team member necessary. Moreover, health shocks, especially those affecting doctors, negatively affect hospitalizations and ambulatory services. This matters for patient well-being, as missed services can harm recovery and reduce service satisfaction, as shown in Prentice and Pizer (2007).

The remainder of the paper is structured as follows. Section 2 describes the Hospital-level data with the institutional setting. In section 3 and 4, I present the empirical strategy and the summary statistics. In section 5, I show the main results of the paper with robustness and sensitivity checks. In Section 6, I present a model on how teams react to individual absences to provide a framework to interpret my results. In section 7 I discuss the results. Finally, section 8 contains a brief discussion on the applicability of my findings to other contexts, lists the possible avenues for future research and concludes the paper.

2 Setting and Data

In this section, I present the institutional setting I am analyzing and the data sources I use for the empirical analysis.

2.1 Institutional Setting

I study the labor and production outcomes of a major public sector hospital situated in Florence, Italy. With an average workforce of around 6000 employees over different months, the hospital provides nearly 1 million hospitalization days annually. As per the decentralized structure of the Italian healthcare system, the hospital is administered by the regional health authority. It is composed of 53 different sections ranging from typical healthcare services, like orthopedics and cardiology, to research departments operated in collaboration with the University of Florence.

The Italian healthcare system operates on a decentralized Beveridge model, with regional governments managing hospitals that are structured in a hierarchical manner, with major and subsidiary hospitals. Smaller hospitals typically provide general healthcare services, while major hospitals provide more specialized and complex services such as cancer treatments or transplants, as well as research departments. Hospitals within the same health districts engage in cooperative efforts to ensure a consistent level of service, effectively meeting the demand for urgent healthcare services. This collaboration becomes crucial in situations where a hospital may face challenges in providing sufficient services due to various reasons. By working together, they bolster their ability to address the healthcare needs of the community, ensuring that critical services remain available even if one hospital encounters limitations in its service provision.

The hierarchical management structure is composed of a Chief Executive Officer (CEO) and two directors responsible for administrative and healthcare performance, respectively (Costumato et al., 2021). The appointment of doctors and nurses follows a competitive process through public open applications where candidates are evaluated based on their knowledge, education, and experience although in case of necessity nurses can be hired forgoing this process[3]. The doctors are organized into teams that are divided between senior and junior doctors, with the former responsible for overseeing the healthcare performance of each department. Similarly, nurses are structured into teams, with selected senior nurses coordinating and organizing the daily work activity within each department.

Workers are employed with public sector contracts according to the national payment scheme and job protection rules. These jobs are highly protected and unionized as are most of the Italian public employees (Bordogna, 2012) and it is impossible for the management to fire employees discretionally. In accordance with the national contract, workers receive

[3] D.Lgs. 165/2001

a fixed monthly salary based on their job level. To increase their monthly income, workers can request additional hours on top of their regular shifts. These additional hours are compensated at a higher rate than normal shifts, typically ranging from 15% to 50% depending on the time and festivities. For instance, extra hours worked during nights and national holidays are compensated at the highest rate.

According to national public insurance regulations for employees, sick leave is provided to workers upon presenting certified proof of illness from their doctors. This documentation specifies the expected duration of the absence based on a worker's illness and their health conditions. During the entire period indicated by the doctor, the worker's job is protected, and they receive their base contract salary. Additionally, to determine the legitimacy of an employee's claim for insurance payment, the national institute of social security may send doctors to the ill worker house to evaluate the worker during their sick leave period. This is done to ensure that payments are not made for fraudulent claims.

The hospital I analyze in this paper is structured in different health departments and in each department there are teams of doctors and nurses responsible for the delivery of health services. In every department, like cardiology or orthopedics, has a group of doctors that deliver services inside the department and there is a group of nurses that collaborate with each different department. Each group of nurses is composed by two or three different teams that differ for their hierarchical level and responsibilities.

2.2 Data

I use personnel data from a large public hospital in Florence. The dataset covers a period from January 2016 to October 2022 and is composed of six different parts: job data, hours worked, sick leaves, production, maternity leaves, and demographics. To investigate the impact of sick leaves on hours worked, team structure, and production, I merge the datasets together using workers' anonymized ID numbers to obtain a balanced monthly panel of workers employed in the hospital. This allows me to analyze the effects of sick leaves on various aspects of the workplace environment like work hours, team structure and output.

Jobs Data: This dataset reports the job codes of each employee working in the hospital for the period from January 2016 to October 2022, recorded on a monthly basis. It provides a comprehensive overview of employee qualifications, including job titles such as doctor, nurse, or administrative personnel, as well as their job levels and the health department in which they operate. The combination of those three information together with the reporting month allows me to build a unique team membership identifier for each of the workers in every month in my dataset. In each health department, there is a group of nurses and a group of doctors. Within a group of nurses there are two or three teams that differ for their responsibility at work while a group of doctors forms a team by its own. From now on, I will call a group of doctor always as a team of doctors since they are the same thing.

Hours Worked: The second dataset I use provides information on hours worked by employees at the firm. The data is of high quality, as it is based on the time of arrival and departure recorded by the employees scanning their work ID cards ensuring a high level of accuracy and reliability. The time worked variable is recorded both in minutes and hours.

Sick Leaves: The third dataset contains information on sick leaves taken by each employee in the firm. These absences show the numbers of days of work missed due to illnesses certified by the worker's physician and exclude absences for holidays, maternity leaves, or permits. The dataset records the number of sick leave absences taken by each employee on a monthly basis.

Production: The fourth dataset contains information on healthcare service production from 2016 to 2022. Services are recorded at the health department level based on the team of doctors responsible for providing care. For example, production is tracked separately for departments such as cardiology, dermatology, or orthopedics. In addition to the doctors, the dataset also records the group of nurses who supported the delivery of each service. Each nurse group includes all nursing staff assigned to a specific department, regardless of their individual team membership or job level. This structure produces a panel dataset of doctor team and nurse group pairs, with monthly observations of the number of ambulatory services and hospitalizations they jointly delivered. Ambulatory services include activities such as medication administration and patient checkups, while hospitalizations are measured as the total number of inpatient days in a given month during which both the doctor team and nurse group contributed to patient care. For the empirical analysis, I assign to each team of doctors and group of nurses the total number of ambulatory services and hospitalizations they were involved in delivering each month. This results in a panel dataset where the units of observation are doctor teams and nurse groups, and the outcome variables are the total number of monthly ambulatory services and hospitalizations they provided.

Maternity Leaves: The fifth dataset in this study provides information on official maternity leaves taken by each employee in the firm between January 2016 and October 2022, recorded on a monthly basis. The methodology for recording this dataset is similar to that described for sick leaves, days of absence due to certified maternity leave are recorded here, while other types of leave such as sick leave, holidays, or permits are excluded.

Demographic Variables: The sixth dataset in this study contains demographic information pertaining to employees of the hospital. The variables include the municipality of birth, province of residence, education level, age, and tenure of the employees.

3 Empirical Strategy

In this section, I present my empirical strategy. First, I discuss identification threats and how I tackled possible identification issues highlighted in the literature of difference-in-differences and event study design. Second, I discuss definitions and thresholds used in the empirical analysis. Then, I present the empirical equations for analyzing individual, team and production outcomes.

3.1 Identification

To evaluate the effects of prolonged absences, I exploit a quasi-experimental setting comparing outcomes across the occurrence of a health shock between a treatment group of teams affected by a co-workers' prolonged absence to a control group of not yet or never affected teams. The health shocks I consider last on average 47 days with no significant difference between doctors and nurses for the duration of health shock periods. I use a balanced dataset of month-employee observations that allows me to estimate the effect of prolonged absences over time on teams and co-workers using an Event Study model with individual/team and time fixed effects.

For the estimation of the regressions model using an event study design with two ways fixed effects, I assume the absence of anticipatory effects and I support this assumption by finding no pre-trends in the event study regressions. In doing so, I follow Marcus and Sant'Anna (2021) and Roth and Sant'Anna (2021). Moreover, I assume uncorrelatedness between the error term and treatment events conditional on individual/team and time fixed effects I included in the regression to correctly identify the parameters of interest in the empirical analysis, following Borusyak and Jaravel (2018) and Roth et al. (2023). I also provide suggestive evidence, in the robustness checks, that my results are unlikely to be substantially affected by the biases highlighted in Callaway and Sant'Anna (2021), as the estimates remain stable and robust with the main specification when either the early years of the dataset or the post-COVID period are excluded from the analysis.

I follow Schmidheiny and Siegloch (2020) in defining the event study window and to tackle possible threats to identification. I use binned endpoints for my event study dummy variables, this means that my last period in the event window pools together all future the periods. This study provides evidence that using binned endpoints in an Event Study model is a reliable method to identify the parameters of interest in case units are treated multiple times.

I avoid possible threats to identification from "forbidden comparisons" when a control group of already treated units is used. This issue is highlighted in Borusyak et al. (2021) and Goodman-Bacon (2021) and it is common in event study estimations. Throughout my analysis, individuals and teams are either in the treatment or in the control groups and they do not switch from one to the other, alleviating this issue. Moreover, I include a comparable control group of never treated in my regression that further mitigates this threat (Borusyak et al., 2021). These conditions allow me to rely on less strict assumptions for the identification of the parameters, specifically those requiring homogeneous treatment effects across treated units.

Another possible threats to the identification of the causal effect of co-worker absences on team could be a correlation between individual health shock and absences of other co-workers. If this would be the case, the effect I estimate would derive also from the higher likelihood of other team members of being sick and not only from unexpected health shocks. I find that workers of teams in the treatment group do not report more sick leaves days in the months after being affected by a co-worker health shock. Moreover, in the summary statistics section, I show that teams of doctor and nurses in the treatment group do not report, on average, more absences per worker per month compared to the control group. Another additional threat could be if the results are driven by some particular years, I find that my empirical results are robust when I exclude from my analysis the COVID period or the two initial years in my data.

3.2 Measurements and Definitions

I analyze the effects of extended absences across different job categories in the hospital. I focus on teams of doctors and teams of nurses given the different tasks content of both jobs. Nurses in a team perform more homogeneous tasks and duties performed by a worker are easily substitutable. In contrast, substitution of doctors is more difficult since their skill sets are more heterogeneous within a single team. In defining the difficulty of substitutions I follow the healthcare management literature (Hatfield et al., 2012; Beil-Hildebrand, 1996). In my dataset, I observe in almost every department a team of doctor and three teams of nurses with each of this team responsible for more or less complex tasks from helping doctors in surgeries to taking care well-being of patients. Although task complexity varies across different teams of doctors and nurses, to simplify my analysis, I estimate the regressions for doctors and nurses separately as they group together workers with similar characteristics and similar levels of complementarity/substitutability.

I investigate heterogeneous effects between small and large teams or departments. I classify teams as small in size if they are below the 85^{th} percentile of the team size distribution specific to each job in January 2016. Following this, I define small teams as those with fewer than 10 doctors or fewer than 15 nurses, and large teams as the opposite. I vary this threshold in the robustness checks. For teams created later than January 2016, I classify them based on the size they have when they are created according to the definition used for other teams.

I examine heterogeneity in replacement behavior among co-workers across different age cohorts. I classify young nurses as those under 30 years old and young doctors as those under 35 years old as of January 2016. On average, workers in these age groups have five or fewer years of tenure. This difference reflects the fact that doctors spend, on average, additional years in training before entering the hospital, resulting in lower tenure compared to same-aged nurses. I focus on the behavior of young and older workers because anecdotal evidence from the hospital suggests that the burden of substitutions disproportionately falls on younger staff.

I define a health shock if an individual experienced a long absence exceeding 30 days, excluding workers affected by chronic conditions. For example, if an absence of 40 days starts on the 10^{th} of March and finishes on the 20^{th} of April, I consider March and April as the health shocks periods for the affected worker with February as the first lead and May as the first lag of my event study model. I do not consider a month to be treated if a sick leave due to health shock lasts less than three days during a month. This means that if a worker starts to be sick on the 29^{th} of October and the absence lasts until the 20^{th} of December, I consider treated only November and December and October would be the first month before the health shock. While if the absence would have started on the 20^{th} of October also this month would be consider treated according to my definition and September would be, in this case, the first month before the health shock. I define a team to be in the treatment group if that team has been affected at least once by a health shock during the period of my dataset. Conversely, a team is in the control group if it workers in the team never experienced a health shock in that period of time.

3.3 Regression Equations

To investigate individual outcomes, I use an event study design, which compares individuals working in teams affected by a health shock in different periods to a control group of workers part of teams never affected by a health shock during the time period of my dataset. I have a balanced panel of individuals that allows me to control for unobserved individual characteristics and time fixed effects. I exclude from the analysis the individual directly affected by the health shock and workers in teams with less than three members as smaller units do not work in teams but more likely the perform their tasks individually.

I investigate the effect of an exogenous shock, specifically a long absence, on monthly working time. I use a two-way fixed effects event study design that is presented below:

$$y_{it} = \beta_0 + \sum_{k=-7,k\neq-1}^{k=7} \gamma_k D_{it}^k + \lambda_t + \theta_i + \epsilon_{it} \tag{1}$$

In the above equation, y_{it} represents the main outcome variables: log time worked by an individual, team size, log ambulatory visits or log hospitalizations by observation i at time t. When I study time worked the observation is the individual, when I study team size the observation is the team and when I study services delivered it is the department. The variables $D_{it}^{-6,-5,-4,-3.-2}$ denote the event study indicators, which capture the effects within a time window of six months before the occurrence of health shocks in the team/department to check for pre-treatment trends with $t = -1$ as my baseline period. D_{it}^0 is the the indicator equal to 1 for all the periods during which a co-worker is affected by health shocks. $D_{it}^{1,2,3,4,5,6}$ are the indicators equal to 1 for the each of the 6 months following the come back of the absent colleague. D_{it}^{7} and D_{it}^{-7} contain respectively all the periods before or after the event study window of 6 months used in the regressions. The terms λ_t and θ_i are month and individual/team/department fixed effects. I use a 6 months event window as interviewed employees in the hospital suggested me that temporary substitution with outside workers last maximum few months after a prolonged absence. I cluster the standard errors at the individual level.

In the empirical analysis, I also use a simplified version of equation 1, where I pool together all the dummy variables in the six month event window after the health shock of a co-worker. The equation is:

$$y_{it} = \beta_0 + \sum_{k=-7,k\neq -1}^{k=0} \gamma_k D_{it}^{k} + \gamma_1 D_{it}^{post} + \gamma_2 D_{it}^{7} + \lambda_t + \theta_i + \epsilon_{it} \tag{1.1}$$

In this equation, D_{it}^{post} is one for the six months after the worker affected by a health shock comes back to work.

4 Summary Statistics

To provide a description of my setting I provide summary statistics on demographic variables at the individual and team levels and on production outcomes. I present summary statistics on teams with more than three workers as smaller units are not considered as team but individual workers in the hospital.

In Table 1, I present the main summary statistics regarding individual demographics and job data of employees working in the hospital between January 2016 and October 2022 for the two major occupations: doctors and nurses. Nurses are younger but doctors are more likely to be men compared to nurses and vice-versa. Doctors work around 12% more time while nurses have, on average, more absences per month. Absences per month are measured as total days of absences due to sick leaves in a month. Moreover, nurses are slightly more affected by health shocks than doctors.

In Table 2, I present the summary statistics at the team level for gender composition, tenure, team members, health shocks and age. The statistics are similar to Table 1 for age and gender. In addition, I show that nurses are employed for more time, with around 6 years more tenure and that teams of nurses are bigger than teams of doctors. To conclude, I show that the share of teams affected by a member health shock is similar between doctors and

Table 1: Summary Statistics - Workers

	Doctors		**Nurses**	
Age in 2022	51.01	(11.63)	48.05	(11.29)
Women	0.47	(0.50)	0.77	(0.42)
Minutes Worked per Month	9878.76	(902.00)	8716.43	(820.53)
Absence Days per Month	0.39	(0.82)	1.19	(1.75)
Share City Residents	0.58	(0.49)	0.31	(0.46)
Health Shock	0.08	(0.27)	0.13	(0.33)
N	1192		4688	

Notes: I present individual averages for variable of interest for doctors and nurses. Age is defined as age in 2022 to have an homogeneous measure of age. Minutes worked per month is the average across workers within a doctors or nurses of each individual average working time per month between 2016 and 2022. Absences per month is a variable measuring the number of absences per month of an individual. Standard deviations in parenthesis. Health shock measures the share of workers affected by health shocks. I exclude workers in team with less than three members.
Data: Individual level records from the personnel dataset of the hospital.

nurses with 39% of doctor and 33% of nurse teams affected by a health shock of a member between 2016 and 2022.

Table 2: Summary Statistics - Teams

	Doctors		**Nurses**	
Share of Women in Team	0.41	(0.28)	0.80	(0.21)
Age in 2022	51.40	(4.31)	49.34	(5.08)
Tenure	10.97	(4.42)	16.76	(6.66)
Members	8.89	(7.80)	11.33	(11.19)
Health Shock	0.39	(0.49)	0.33	(0.47)
N	123		643	

Notes: I present the team averages for doctors and nurses for team characteristics. Share of women is the percentage of women in a team, Age is average age in 2022 of a team. Tenure is the average years team members are working in the hospital. Members is the average number of members in a team. Health Shock is the share of teams affected by a health shock of a team member during the data period. I use team characteristics from the first month of my dataset (January 2016) or from the first month a new team is established. I exclude teams with less than three members. Standard deviations in parenthesis.
Data: Individual demographic data aggregated at the team level from the personnel dataset of the hospital.

In Table 3, I present a balance table between teams never affected by a health shock and the teams in which at least a worker has been affected by a health shock between 2016 and 2022. In this table, I show that the share of women in the team, the average age, average tenure and monthly absences are similar across the two groups, with no statistically significant differences at the 10% level according to a t-test.Absence days per month are measured as the average number of sick leave days per worker in a given month within a team. In total there are 507 teams of doctors or nurses in the control group while 259 teams in the treatment group. I define a team to be in the treatment group if that team has been affected at least once by a health shock during the period of my dataset. Conversely, a team is in the control group if its workers in the team never experienced a health shock in that period of time.

Table 3: Balance Table - Teams

	No Health Shocks		**Health Shocks**		**T-test**	
Share of Women	0.74	(0.26)	0.73	(0.26)	0.02	(0.35)
Age	49.88	(5.18)	49.25	(4.68)	0.63	(0.10)
Team Experience	15.76	(6.98)	15.98	(6.14)	-0.22	(0.67)
Absence Days per Month	1.15	(1.52)	1.21	(0.92)	-0.06	(0.56)
N	507		259		766	

Notes: This Table presents a comparison between the treatment group of team affected by health shocks and control groups of teams never affected between January 2016 and October 2022. Absences Days per month is a variable measuring the average number of absences per worker in a month in given team. In the treatment group there are teams affected at least once by a health shock between January 2016 and October 2022. In the control group there are teams never affected by a health shock between January 2016 and October 2022. I exclude teams with less than three members. In the first two columns, standard deviations are in parenthesis. In the column 3, I show the t-test between group averages and its p-values in parenthesis.
Data: Individual demographic data aggregated at the team level from the personnel dataset of the hospital.

I show the distribution of health shocks throughout the solar year in the appendix, these events happen smoothly across the different months without large differences between different seasons although they are more frequent during winters. Moreover, I also show how long the events I define health shocks last, I observe that the most of the health shocks last around 30 to 40 days with some rare events lasting more than 4 months[4].

5 Results

In this section, I present the results for the three main outcomes of interest: hours worked by individuals, team size, and services provided across the two principal hospital occupations, doctors and nurses.

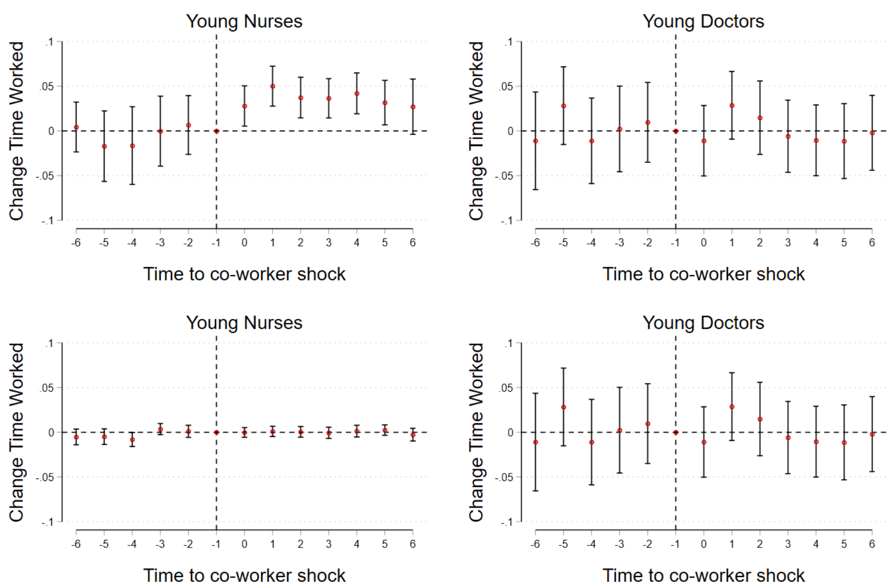
5.1 Time Worked

In this section, I estimate the effects of individual health shocks on co-workers. I examine teams composed by doctors and nurses and I explore the impact of absences by old and young workers since anecdotal stories from the hospital pointed out that most of the burden of substitution is placed on younger and less tenured workers. Additionally, I explore different effects for small and large teams.

[4]The graphical findings of this paragraph can be found in figures A14 and A15 in the appendix

In figure 1, I present the estimates of the parameters from equation 1 over the months before and after a health shock of a co-worker. I estimate the equation separately for young doctors and young nurses. I find that while a co-worker is affected by a health shock, young nurses increase their working time by around 2% to 3% compared to the pre-health shock month. Conversely, young doctors do not show any significant change in their time worked in response to health shocks. Among old workers, I do not find any effects of health shocks on working time confirming anecdotal evidence from hospital employees.

Figure 1: Effect of health shocks on time worked of young and old workers



Notes: The Figure presents the coefficient estimations of γ_t from equation 1. I show the 95% confidence intervals. The method used to estimate the event study model is an Ordinary Least Squares (OLS). Standard errors are clustered at the individual level. Baseline used is one-period before treatment. Treatment is defined as having a co-worker affected by a health shock at $t = 0$. I use individual and month fixed effects. Time to event is in month, last lag and first lead include months six month before or after the health shock. **Data**: Individual level records from the personnel dataset of the hospital.

In figure A1 in the appendix, I examine heterogeneous effects of health shocks on young workers to assess the importance of internal replacement for teams with different sizes. Among larger teams of nurses, which have a higher degree of substitutability and internal homogeneity between tasks performed by different workers, I find evidence of their tendency to use internal substitutions. I find that young nurses in large teams increase their labor supply around 4% to 5% compared to the pre-health shock month. Conversely, in small teams, I find no evidence of such effects on time worked. Young doctors, regardless of team size, do not demonstrate any significant heterogeneity, as their labor supply remains unaffected by co-worker health shocks.

In table 4, I estimate equation 1.1 to show short and long term effects of a co-worker health shock on time worked. I find that during a health shock affecting a co-worker, young nurses increase by 2% their working hours and by around 3% during the six month following the comeback of the worker affected be a health shock, compared to the months before the health shock. I find no effect on working hours among doctors or older nurses.

Table 4: Effects of health shocks on time worked

	Old Nurses	**Old Doctors**	**Young Nurses**	**Young Doctors**
D_{it}^{0}	0.002	0.004	0.019^{*}	-0.002
	(0.00)	(0.01)	(0.01)	(0.01)
D_{it}^{post}	0.001	0.004	0.032^{***}	-0.005
	(0.00)	(0.01)	(0.01)	(0.01)
N	174943	27959	18803	9001

Notes: This table presents estimates from equation 1.1. D_{it}^{0} shows the effect of health shocks on co-workers time worked while D_{it}^{post} shows the same effect during the six months following the health shock. Standard errors clustered at the individual level are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Data: Individual personnel records.

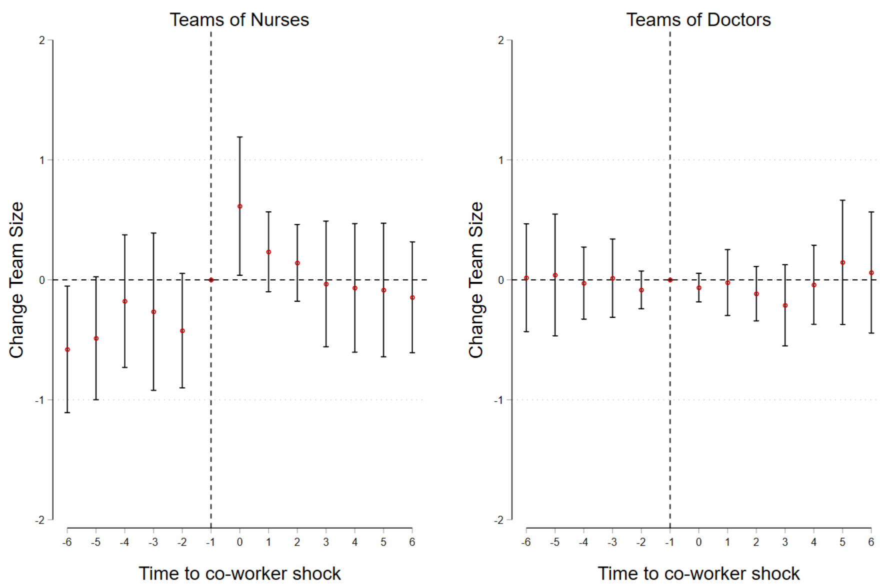
The results indicate that younger nurses perform more tasks during their shifts, leading to longer working hours when a colleague is absent for an extended period. This pattern persists in the months following the health shock, suggesting that these workers continue to handle additional tasks even after the absent colleague has returned.

5.2 Team Size

The second dimension I study is whether teams include outsider workers to cover an absence. I estimate the effect of health shocks on team size using a worker health shock as the treatment event. I use team size as the outcome since this is the only variable with which I can track movements in the workforce. Again, I estimate the equation separately for teams of doctors and nurses and for large and small teams based on their size.

In figure 2, I estimate equation 1 to study the effects of an unexpected health shock on team size for doctors and nurses over the months before and after the event. I observe that teams of nurses react after a member health shock increasing their size temporarily, hiring outsiders. The point estimate of γ_0 is around 0.6 using the month before the health shock as the baseline. From this result, I conclude that more than half of health shocks are covered by an external replacement in teams of nurses. I observe a decrease of the γ_t coefficients in the months after the absence period meaning that new workers are only temporarily in the team. The interpretation of the coefficient is that for every two health shocks, one is replaced by an outsider. I observe no pre-treatment trend or anticipatory effects that can be caused by the expected nature of health shocks. On the other hand, teams of doctors do not hire outsiders, this is probably driven by high replacement costs for hiring and installing a new doctors in the affected team just for short and temporary needs.

Figure 2: Effect of health shocks on team size



Notes: The Figure presents the coefficient estimations of γ_t from equation 1. I show the 95% confidence intervals. The method used to estimate the event study model is an Ordinary Least Squares (OLS). Standard errors are clustered at the team level. Baseline used is one-period before treatment. Treatment is defined as having a team member affected by a health shock at $t = 0$. I use team and month fixed effects. Time to event is in month, last lag and first lead include months six month before or after the health shock.
Data: Individual level records from the personnel dataset of the hospital aggregated at the team level.

Furthermore, In figure A2 in the appendix, I exploit heterogeneity across team sizes, similarly to what I do when studying individual labor supply. I find that small teams of nurses, with less possibilities of spreading tasks across co-workers with internal substitutions, replace absent workers through external substitutions. The point estimate of γ_0 is around 0.45, therefore around half of the health shocks are covered through external replacements in small teams of nurses. Large teams of nurses show a positive coefficient during the absence period but this is not significantly different from zero because the point estimates are not precisely estimated. I find no such an effect among teams of doctors.

In table 5, I estimate equation 1.1 to present short and long term effects of health shocks on time size. I find that during a health shock affecting a worker teams of nurses increase their size by 0.61 units[5] but I find no significant effects among doctors. This result shows that teams of nurses include outsiders to cover for the absence while doctors do not. Moreover, I do not find permanent effects on team size in the months after the health shock meaning that the replacements are only temporary and the team structure returns to the pre-health shock conditions almost immediately.

Table 5: Effects of health shocks on team size

	Teams of Nurses	**Teams of Doctors**
D_{it}^{0}	0.613^{**}	-0.064
	(0.29)	(0.06)
D_{it}^{post}	0.038	-0.036
	(0.20)	(0.15)
N	35181	10500

Notes: This table presents estimates from equation 1.1. D_{it}^{0} shows the effect of health shocks on team size while D_{it}^{post} shows the same effect during the six months following the health shock. Standard errors clustered at the team level are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Data: Team personnel records.

5.3 Services Delivered

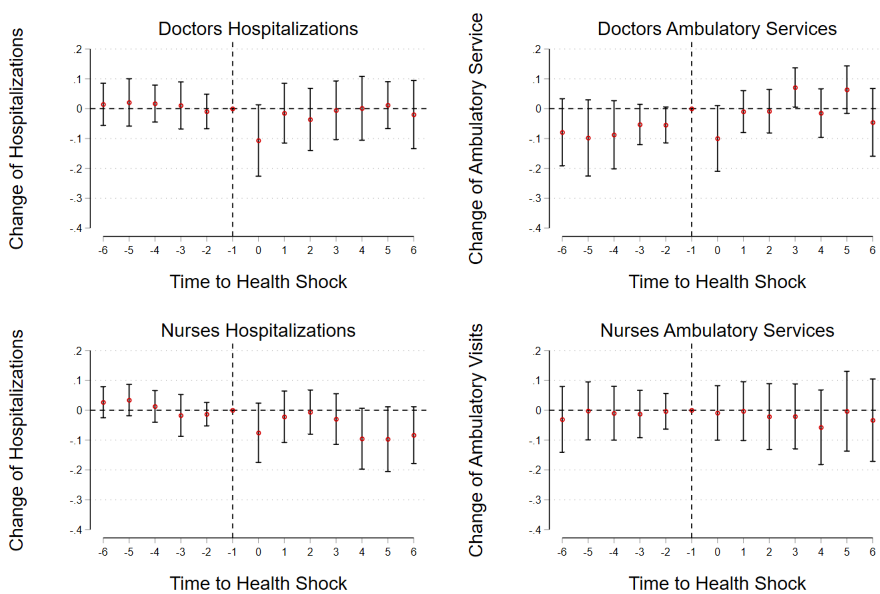
I study how production is affected by health shocks and how this effect is heterogeneous across doctors and nurses. In figure 3, I show the impact of health shocks affecting doctors and nurses on services they deliver to patients. A health shock decreases hospitalizations and ambulatory visits by around 10% among doctors compared to the month before the event. On the other hand, health shocks among nurses decrease hospitalizations around 8% although this estimate is barely not significant while the effect on ambulatory visits is null.

The results indicate that health shocks among doctors substantially reduce service provision, with a greater impact than when similar shocks affect nurses. Teams of doctors, which show no internal adjustment in working time or external replacement following a health

[5]This means that on top of absent and present workers they add on average 0.61 workers when there is a prolonged absence due to a health shock. Therefore, according to this specification, more than half of health shocks in teams of nurses are covered by workers external to the team.

shock, experience a substantial drop in hospitalizations and ambulatory visits. In contrast, when nurses are affected by such events the effect on output is similar for hospitalizations but it is not significantly different from zero for ambulatory visits. This difference in the effects of health shocks on service delivery between nurse and doctor may also be driven by the distinct nature of the two occupations. Doctors are highly specialized, and their tasks often require specific expertise that is difficult to replace in the short term. On the other hand, nurses tend to have more homogeneous skills even across different departments, making it easier for colleagues or new temporary workers to step in and cover for an absent team member during a shift.

Figure 3: Effect of health shocks on services delivered



Notes: The Figure presents the coefficient estimations of γ_t from equation 1 for doctors and nurses. I show the 95% confidence intervals. The method used to estimate the event study model is an Ordinary Least Squares (OLS). Standard errors are clustered at the department level. Baseline used is one-period before treatment. Treatment is defined as having a team member affected by a health shock at $t = 0$. I use team and month fixed effects. Time to event is in month, last lag and first lead include months six month before or after the health shock.
Data: Individual level records from the personnel dataset of the hospital aggregated at the team level.

In table 6, I present the estimates of equation 1.1 to present short and long term effects of health shocks on production. I find that during the months of a worker health shock of doctors services delivered decrease by 10%, compared to the month before the event, on both hospitalizations and ambulatory visits while the effect is negligible after the affected worker comes back on duty. The effect of health shocks on services is smaller among nurses. A health shock in a group of nurses decreases hospitalizations delivered by 8%, although this estimate is not significantly different from zero. Moreover, the effect on ambulatory visits is null. Also in this case I do not find any permanent effect after the affected worker is back on the the job.

Table 6: Effects of health shocks on services delivered

	Doctors		**Nurses**	
	Log Hosp	Log Amb	Log Hosp	Log Amb
D_{it}^{0}	-0.107*	-0.100*	-0.076	-0.009
	(0.06)	(0.06)	(0.05)	(0.05)
D_{it}^{post}	-0.011	0.009	-0.053	-0.022
	(0.04)	(0.03)	(0.04)	(0.05)
N	8810	8810	19234	19234

Notes: This table presents estimates from equation 1.1. D_{it}^{0} shows the effect of health shocks on team size while D_{it}^{post} shows the same effect during the six months following the health shock. Standard errors clustered at the department level are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Data: Records on services delivered.

5.4 Robustness and Falsification checks

In this section, I present a series of robustness and falsification tests to provide additional evidence about the strength of my findings, such as: I exclude the first and the last two years from my dataset, I vary the threshold for large and small teams, I vary the age thresholds I use, I use time worked in levels instead of logarithmic form, I include never treated in the staggered event study analysis, I estimate the effect of anticipated health shocks (maternity leaves), I check the effect of health shock on the individual directly affected in this setting and I include COVID years in the production analysis. Moreover, I change the threshold for large and small teams and I remove temporary workers from the analysis. The findings of tables and figures in this section are in the online appendix.

Excluding Years: In figure A3, I present the results obtained from equation 1, with the exclusion of the year 2016 and 2017. By removing 2016 and 2017, which are closer to the start of the dataset, I address the issue of incomplete information regarding team events and absences that occurred in the months leading up to the initial time period of the data (January 2016). The results are consistent to those presented in the main specification: young nurses increase time worked by approximately 2/4% in the months during and after a co-worker's health shock, while no such effect is observed for doctors or older nurses. Furthermore, in an additional analysis, I exclude 2021 and 2022 to examine whether the findings are influenced by organizational changes in the post-COVID period, again obtaining similar estimates although quite noisy. I report these findings In figure A4.

Change Age Threshold - Individuals: In figure A5, I show the results for young and old nurses increasing by two years the age threshold to consider young and old employees. This is important because a clear division of age cohorts is possible using an arbitrary threshold and it is valuable to show how slightly changing it does not affect the results. The estimations of equation 1 are robust after raising by two years the age cutoffs to the findings presented in table 1 and table 3. The findings do not change even for other slight changes of this age threshold

Work Time in Levels: in figure A6, I show the estimation of the parameters γ_t on hours worked using the outcome variable in level instead of logarithmic form. This specification is important to check if the estimations are robust to monotonic transformations of the dependent variable or the results are driven by particular distributional form specific to the logarithmic transformation that mitigate the effects of outliers. The results are highly robust to this change from logarithm to level of minutes (hours) worked during a month and comparable to tables 1 and 3.

Exclude Never Treated: in figure A7, I present the estimations of equation 1 using only treated observations available in my sample to identify the regression coefficients. I estimate the regression for old and young workers by different job. The results are robust to the exclusion of never treated units with estimates similar those from the main specification.

Maternity Leaves: in figure A8, I present the findings regarding the impact of maternity leaves on team size to understand how teams adjust when the health shock is expected in advance as it happens for maternity periods. I find that maternity leaves are consistently covered in all teams of nurses, regardless of their size. The estimation shows a perfect substitution, indicating that whenever expected absences due to maternity leave occur, a complete replacement takes place. This finding supports the assumption that the health shocks being considered in the previous section are unexpected and exogenous compared to expected maternity leaves. On the other hand, doctors do not demonstrate any substitution behavior for maternity leaves. This indicates the challenges associated with finding suitable replacements for doctors during maternity leaves. This highlight the difficulty in managing doctor replacements in a similar way to what I found analyzing absences of doctors related to health shocks.

Individual Health Shocks: I test the validity of my assumption that what I consider as health shocks are only temporary and the affected worker comes back on duty working the same amount of time. To do so, in figure A9, I present the estimates of equation 1 using individual health shock as the treatment on the directly affected workers. I compare their outcomes before, during and after a health shock to a control group of individuals never affected by a health shock and that are part of teams never affected by a similar event. I use time worked as the outcome variable. Workers affected by health shocks do not work during that period and I observe a drop in time worked due to their absence, when the health shock period is over these workers come back on the job working a similar amount of time compared to the pre-health shock months. This estimate confirms the reasonability of my assumption that the absences I use for identification are only temporary, since time worked by the absent worker is not permanently affected by such health shocks.

Change Threshold Team Size: in figures A10 and A11, I demonstrate that the findings on time worked and team size remain robust when varying the threshold used to define small teams. Specifically, I lower the threshold from 15 to 10 members for nurse teams and from 10 to 5 members for doctor teams to test the sensitivity of the results. Young nurses in large teams increase their working hours by approximately 2–3% during and in the months following a co-worker's health shock, whereas no comparable effect is observed for doctors or nurses in small teams. Moreover, I find that small nurse teams cover roughly half of prolonged absences using external workers, while doctor teams do not even after modifying the definition of small and large teams. These estimates mirror the estimates of the main specification presented in table 2 and 6.

Exclude Temporary Workers: in figure A12, I study the effect of co-workers' health shocks on time worked removing temporary workers. This robustness check allows to check whether by excluding temporary workers working less then 3 months in a team changes the results. This would be the case if temporary outsiders would work more than normal workers in a team when they are called to replace an absence. In this way, I consider only workers staying in the team on a longer horizon that are not included in the team just to replace the absence. I find similar results compared to the main specification, young nurses increase their working hours by 2/3% in the months of a co-worker absence and in the following periods while old nurses and doctors do not.

Service delivery excluding post COVID years: In figure A13, I estimate the effect of health shocks on output excluding post COVID years that I previously included in the main analysis reported in figure 3. Results are similar to those in the main specification with service delivery reduced compared to the month before a health shock in a team. Such events decrease hospitalizations and ambulatory visits made by doctors while the effect among nurses is smaller and concentrated only on hospitalizations. In table A1, I estimate equation 1.1 to check for short and long term effects of health shocks in production excluding post COVID years. I find that health shocks decrease hospitalizations and ambulatory visits by 13% among doctors compared to the month before such an event, with no persistent effects although the first of these coefficients it is not precisely estimated. Additionally, I find that among nurses health shocks decrease hospitalizations by 13% while there is no effect on ambulatory visits.

6 Theoretical Framework

In this section, I present a simple model of team organization to help the interpretation of my empirical findings. This model focuses on how the management of a firm can adjust teams to maximize the firm's objective function. I define the team production with a CES production function of labor input such as hours worked and number of workers employed with a substitutability parameter ρ. I define the costs as a function of team payroll. The management of the firm decides the number of workers in each team to maximize firm's output subject to their specific cost function.

The model considers the point of view of a perfectly rational management that maximizes the production of each of their teams j composed of N_j workers in every period t according to a cost constraint. The management raises the number of team members until the marginal increase in the value of production is equal to the increase in marginal cost due to the hiring of a new worker. The management decides how many workers to hire in a team. Working hours are set by workers' contracts but the management in accordance with the workers can temporarily increase them in case of staff shortages for a limited amount. I hereby define the objective function for each team that the management needs to maximize in every period when no temporary absence of a team member takes place.

$$V_{njt}(h) = A_j U\left(\left[\sum_{n=1}^{N_j} (\bar{h}_{njt})^{\rho_j}\right]\right)^{\frac{\alpha}{\rho_j}} - \sum_{n=1}^{N_j} w_j \bar{h}_{njt}$$

The first part of the objective function is the team value of production U and production is defined as CES function: for each teams j there are N_j different workers employed at time t working a number of hours defined as h_{njt}. In normal condition without staff shortages workers work their contractual hour defined as $\bar{h_{njt}}$. The implicit function U describes the monetary value of production created by the work and is increasing in h_{njt}. The production function for any team j contains a parameter of a team specific substitutability ρ_j between the N_j different workers in a team j. A_j is a scaling productivity parameter affecting production. α is the degree of homogeneity of the production function.

I assume the cost to be a function of total team salaries that are given by the product of individual contractual hourly earnings w_j, the number of employees N_j and contractual hours worked h for each period t. When there are no temporary absences the workers do their contractual hours $\bar{h_{njt}}$ without overtime work.

I focus on the analysis on how firms adjust their teams when a worker is temporarily absent. When a member is not present, he is still on the firm payroll although not working, therefore the management needs to make decisions on how to adjust the production structure following this event.

I consider that the management has three possibilities on how to replace a temporary absence. They can either include a temporary substitution in the team, use other co-workers to increase their working time due to staff shortages or do nothing and work with less employees. Hiring outsiders increases the payroll costs and places an additional burden on the team to include a new member but fully substitutes a worker. The management can increase the working hours h_{it} of other co-workers above the contractual hours $\bar{h_{it}}$ when there are staff shortages but this solution increases the payroll costs anyway due to overtime work. Additionally, other co-workers cannot increase their hours infinitely due to legal and physical constraints. Moreover, if too few co-workers can extend their working hours, or if the team is too small to cover the absence, the resulting output losses are similar to those that occur when the absence is not substituted at all. In the latter case, when no action is taken and the absence is not covered, output falls simply because fewer hours are worked with one less worker available.

I distinguish three different cases on how teams react to absences when they occur: *no replacement*, *internal replacement* and *outside replacement*. I present the objective function for each of the above states of the world when a one period absence affects a team member during a time period using N_j^* as the team size maximizing output when there is no unexpected absence. For all the cases, I present the value function for the period $t = 1$ in which a team is affected by an unexpected absence of a worker n. The management is in charge of deciding which option to select during the period in which there is an unexpected absence.

Case 1: *No substitution*

$$V_{1,t=1}(h, w) = A_j U \left[\sum_{n=1}^{N^*-1} (\bar{h}_{nj})^{\rho_j} \right]^{\frac{\alpha}{\rho_j}} - \sum_{n=1}^{N_j^*} w_j \bar{h}_{nj}$$

In this first case, the team works with a lower number of worker causing a drop in production since nobody takes the place of the absent worker.

Case 2: *Internal substitution*

$$V_{2,t=1}(h, w, S, e) = A_j U \left[\sum_{n=1}^{N^*} (h_{nj})^{\rho_j} \right]^{\frac{\alpha}{\rho_j}} - \sum_{n=1}^{N_j^*} w_j \bar{h}_{nj} - \\ - \left[S_j + \sum_{n=1}^{N_j^*} e_j (h_{nj} - \bar{h}_j) \right] \text{ s.to } h_{nj} \leq h_{max}$$

In the second case, workers can work more than the contractual hour $\bar{h}$. Internal replacement causes an increase of bureaucratic costs of arranging the new shifts denoted by S_j and an increase in payroll cost due to the additional hours paid at a higher rate e_j.

Case 3: *External substitution*

$$V_{3,t=1}(h, w, C) = A_j U \left[\sum_{n=1}^{N_j^*} (\bar{h}_{nj})^{\rho_j} \right]^{\frac{\alpha}{\rho_j}} - \sum_{n=1}^{N^*+1} w_j \bar{h}_{nj} - \theta E_j^{\frac{1}{\rho_j}} - B$$

In the third case, external replacement causes an increase of bureaucratic costs B and training costs $\theta E_j^{\frac{1}{\rho_j}}$. Training costs decrease the higher the substitutability parameter ρ_j is and there is an increase in salary costs due to an additional member in the team. θ is a scaling parameter of training costs.

When a team is affected by an unexpected absence the management needs to take a decision for the substitution based on the best state of the world between the three cases presented. The decision is made based on a comparison of the three cases. The management of the firm is assumed to be rational and to select the state of the world that maximizes the team's objective function.

State of the world 1: *No substitution* if $V_1(h) > V_2(h)$ & $V_1(h) > V_3(h)$
State of the world 2: *Internal substitution* if $V_2(h) > V_3(h)$ & $V_2(h) > V_1(h)$
State of the world 3: *External substitution* $V_3(h) > V_1(h)$ & $V_3(h) > V_2(h)$

Teams with high internal and external substitution costs due to high value of E_j and S_j decide to decrease production, working with $N^* - 1$ workforce since substitutions are costly and hard to be done. This can be the case of teams working on tasks where it is hard to find temporary substitutions or involving high costs of training if a new member would be hired. ($V_1(h) > V_2(h)$ & $V_1(h) > V_3(h)$).

Internal replacement takes place if tasks in team j are substitutable by other co-workers (high ρ_h) and substitution costs are relatively low compared to the production lost (low S_j). Hours are capped by h_{max} and h_{nj} can not be risen infinitely, therefore only large teams (with N^* relatively large) can keep the level of production constant covering the absence completely and spreading the remaining tasks across other team members. On the other hand, smaller teams have to partially decrease production if they decide for this type of substitution. The management can select internal replacements also in case this solution is not able to completely cover the absence. In case costs of external substitutions are too high, it can be better for a team to partially cover the absence using insiders and avoiding a larger drop in production instead of searching for an external worker.($V_2(h) > V_3(h)$ & $V_2(h) > V_1(h)$).

External replacement takes place when the cost of including a new employee in a team is relatively low compared to the production lost and internal replacement is not enough to sustain production (N^* is relatively small). This situation shows up when workers are similar in characteristics, easily replaceable (low E_j) and the number of co-workers is too small to spread the tasks over them to contain the losses in production. ($V_3(L) > V_1(L)$ & $V_3(L) > V_2(L)$).

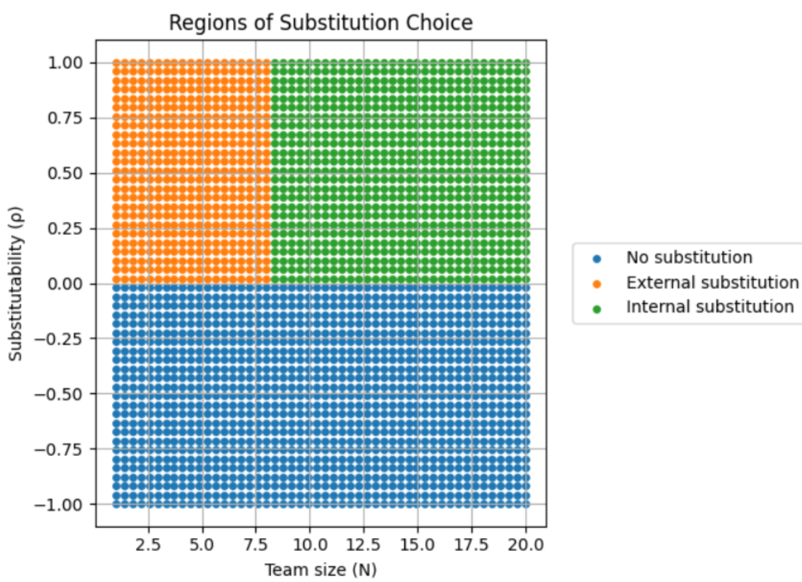
Summarizing, I present different choices of replacement when a team member is absent from work for a period t based on team characteristics:

- Teams with high replacement costs and low substitutability in the production function do not adjust their working structure, decreasing production (high E_j, high S_j, low

ρ_j)

- Small teams with relatively low substitution costs, hire outsiders in the short term reducing negative effects on production (high ρ_j, low S_j, low E_j and small L^*)
- Large teams with relatively low substitution costs and high replaceability among co-workers increase co-worker working hours using internal substitutions (high ρ_j, low S_j, low E_j and high L^*)
- Teams, where internal substitution is the most convenient replacement strategy but the number of workers N is not large enough to cover the absence completely, decrease partially their production compared to the state of the world with no unexpected absence but less than the case with no substitution.

Figure 4: Model



In figure 4, I report a graphical explanation of strategies selected by different teams by size and replaceability. Teams employed in tasks with high replaceability and low substitution costs tackle the absence through internal replacements if the team is large or with external replacements if the team is small. In teams employed in tasks with low replaceability across co-workers and high substitution costs no action is taken and it is more convenient for the management to reduce output instead of substituting the unavailable worker.

This model presents an interpretation of the main findings of the empirical analysis. For teams of nurses, where substitutability is high and training costs are low, I observe a higher attitude to modify their structure after a co-worker's temporary absence. Following the mechanisms presented in this model, small teams of nurses include outsiders because it is not possible for them to raise co-workers' hours enough to keep production levels high. By contrast, large teams of nurses manage absences through internal substitutions. In general, teams working in tasks with high ρ and low E or S are able to better adjust when they are affected by absences. On the other hand, in doctor teams I observe no adjustment to a co-worker's temporary absence, either by increasing the working hours of colleagues or by bringing in an external substitute. I also estimate a larger reduction of output caused by doctor absences compared to nurse absences in their respective teams, this can be linked to the different substitution behavior. According to this framework, such a situation arises when the training and substitution costs exceed the output gains derived by internal or external substitutions. This latter case shows up in teams working in tasks with low ρ and high S and E.

7 Discussion of the Results

In this paper, I find that during a prolonged absence of a co-worker, young nurses increase time worked 2/3% in the months of absence and thereafter. This effect persists for at least five to six months and may be explained by the fact that workers take on informal responsibilities during the absence of a colleague and continue to fulfill them even after the sick co-worker returns.

I do not estimate any significant effect on time worked among doctors or old nurses. According to interviews and anecdotal evidence with hospital workers this is due to two reasons. First, when a co-worker is sick it is young workers that take most of the burden associated with the lower workforce caused by a health shock. Second, in teams of doctors, it is hard to find another doctor with similar experience and a substitutable skill set within the team to substitute for another colleague while this is easier in teams performing simpler and more homogeneous tasks such as nurses. Moreover, I do not have any evidence of cross-team substitutions.

The effect on time worked is concentrated within teams of nurses with more than 15 workers. The reason for this might be that only teams with enough co-workers to cover part of the work time of the sick colleague are able to tackle the absence internally. Again this is true only for teams of nurses, while I do not find any change in time worked among doctors neither in large nor small teams.

I find that teams of nurses include outsiders in their teams to cover for a prolonged absence of a team member. On average, more than half of these absences are covered including outsiders in the team but the effect is concentrated during the absence and it is not permanent, therefore outsiders are included in the team only temporarily. This effect is driven by small teams, which struggle to cover absences internally due to a limited pool of co-workers that can take on some of the tasks that are usually performed by the sick co-worker, although there are some suggestive signs of internal substitutions among bigger teams as well. I find that teams of doctors do not include any outsider when a team member is affected by a health shock probably due to difficulty in finding a suitable doctor only for a short period of time.

To conclude, I observe that services delivered by a team are affected by health shocks. I estimate that when a team of doctors is affected by such an event its number of hospitalizations decreases by 10% with no permanent effects when the worker affected by the health shock comes back on duty. I find smaller effects of health shocks on production among nurses especially for ambulatory visits. The smaller effect of health shocks on services delivered by nurses is likely connected to the fact that they substitute temporary absences due to health shocks while doctors do not.

8 Conclusion

This paper contributes to the literature by providing evidence of spillover effects of health shocks on the workplace. Most previous studies on the effects of health shocks focus on individuals or their households (Dobkin et al., 2018; Halla and Zweimüller, 2013; García-Gómez et al., 2013), whereas I show that such shocks also have sizable effects also on the workplace. Health shocks affect production, hours worked by co-workers and change team structure. While previous findings on the impact of individual absences in work teams is limited to qualitative research, thanks to the detailed information collected in my dataset, I investigate this topic using a quasi-experimental design.

Using reduced form econometric models in the empirical analysis and a theoretical framework to interpret the main results, I investigate how individuals and teams of work react following a temporary absence of a co-worker. I find that teams employed in tasks with high substitutability across team members (nurses) tend to show greater flexibility. They adapt by adjusting working hours of co-workers or by hiring temporary new members to cover prolonged absences. On the other hand, teams working in tasks where substitutability across team members is low (doctors) react primarily by reducing services delivered without adjustments in the working hours of other co-workers or in the team structure. In fact, I find that temporary prolonged absences due to health shocks reduce services delivered by a team in the hospital with the effect particularly large among doctors.

The findings about the effects of absences on services provided relate to the literature studying how forgone or delayed healthcare services cause worse recovery rates among patients. Following Prentice and Pizer (2007), a delay of more than 30 days for a treatment increases individual mortality rate by around 20%. Cunningham et al. (1995) find that delayed services increase emergency treatments for initially non-serious illnesses while Lukas et al. (2004) find that postponed and foregone services decrease patient satisfaction significantly. Hence, it is crucial to emphasize the impact of absences and replacement strategies on healthcare services provided and, consequently, on patients' recovery outcomes and satisfaction.

The results of this paper can be generalized to healthcare workers in advanced countries. However, future research on this topic is key to better understand how teams and co-workers react to health shocks in other contexts. Within the healthcare sector, it may be relevant to study contexts that differ from those in advanced countries, such as healthcare providers in developing nations. It is also important to extend this research question to private firms in order to examine how they manage temporary prolonged absences and to assess whether differences exist compared to public sector organizations. Since my study focused on a public sector hospital, the findings may be driven by this specific context. Exploring other settings could provide a deeper understanding of how organizations adjust their teams and reorganize their workforce following an unexpected health shock.

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