HEDG

Health, Econometrics and Data Group

The University of York

WP 22/19

Team composition and productivity: evidence from nursing teams in the English National Health Service

Elaine Kelly; Carol Propper and Ben Zaranko

July 2022

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

Team composition and productivity: evidence from nursing teams in the English National Health Service

Elaine Kelly, Carol Propper and Ben Zaranko*

May 2022

Abstract

We study the impact of team composition on productivity in a setting where team production is particularly important: nursing teams in the English National Health Service (NHS). Composition is measured both in terms of the quantity of staff and the quality of staff, as measured by qualifications, rank and experience. We use a panel dataset that links daily staffing rotas with inpatient mortality records for a single NHS Trust that includes 3 large hospitals and 52 wards. Our results show that the probability of a patient death is lower for teams with a greater number of qualified and senior nursing staff, but find no statistically significant impacts of increased numbers of support staff or agency workers. There are returns to experience for qualified staff, with a lower probability of a patient death in teams where nurses have more experience in the Trust, and returns to both team- and ward (physical location)-specific experience, with a lower probability of death for patients treated by staff who regularly work together and on the ward in question. Our results also provide evidence of the value of bosses, with higher mortality rates when there is an unexpected absence of a senior nurse who leads the team.

JEL classification: I11, J24, J45, M50.

*The research was enabled by the Imperial Clinical Analytics Research and Evaluation (iCARE) environment and used the iCARE team and data resources. Data management was provided by the Big Data and Analytical Unit (BDAU) at the Institute of Global Health Innovation (IGHI). Thanks are extended to seminar participants at the Institute for Fiscal Studies, University of York, and the Royal Economic Society 2022 conference for helpful comments. This paper has been screened to ensure no confidential information is revealed. Any errors are the authors' own. Author affiliations and contacts: Kelly (Health Foundation and Institute for Fiscal Studies, elaine.kelly@health.org.uk); Propper (Imperial College Business School, Centre for Economic Policy Research and Institute for Fiscal Studies, c.propper@imperial.ac.uk, corresponding author); Zaranko (Institute for Fiscal Studies, ben.zaranko@ifs.org.uk).

1 Introduction

Teams play an essential role in the world of work. Teamwork, collaboration and co-ordination is central to the production process in a broad range of sectors and industries, from construction and manufacturing to software development and corporate law. In all of these settings, teams form because they make possible gains from specialisation, knowledge sharing, and complementarities between the skills of different workers (Lazear and Shaw, 2007). Team production can be more productive than individuals working alone, but the size, structure, composition, experience and incentives of the team will determine whether and to what extent this is the case.

Given the pervasiveness of teams and team production in the workplace (Deloitte, 2016, 2021), understanding the determinants of team productivity is of considerable economic importance. Yet despite this, the academic literature on team production and the determinants of team productivity remains surprisingly sparse. Previous studies have often focused on the impacts of team composition, team incentives and peer effects on individual workers' performance in relatively low-skilled settings, such as teams of garment plant workers (Hamilton et al., 2003), supermarket cashiers (Mas and Moretti, 2009; Friebel et al., 2017) and fruit pickers (Bandiera et al., 2009, 2013). In these settings, although work is organised in teams, and incentives may be offered to the team as a whole, the measured output is typically individual rather collective. Other studies have examined settings where output is collective, but these have either focused on highly specialised settings with limited applicability to larger and more general settings (Arcidiacono et al., 2017; Jones, 2021) or have focused on issues of task reallocation and financial incentives (Burgess et al., 2010, 2017) rather than team composition.

In this paper, we study the impact of team composition on productivity in a large, teamwork-intensive industry where outputs are collective: nursing teams in the English National Health Service (NHS). Productivity is measured by the inpatient mortality rate, which is both a high stakes outcome and measured with minimal error. Nurses are the largest single clinical staffing group in the English NHS, with 316,000 full-time equivalents employed in October 2021, supported by a further 277,000 nursing support staff (Digital, Digital). Internationally, healthcare workers account for more than 10% of the workforce in several developed countries, and nurses are the largest profession within that group (OECD, 2016).

Nursing teams, comprising both registered (degree qualified) nurses and nursing support staff, play a critical role in the delivery of healthcare, including monitoring patients, implementing and adjusting treatment plans, and the co-ordination of overall care. Collaboration is essential, as patients are clinically vulnerable and require round the clock care, and some tasks cannot be carried out by a single member of staff. Collaboration is potentially easier for teams with more experience – whether that be through qualifications, general experience working in nursing teams, experience working in the specific hospital or ward, or experience working with fellow team members. The composition of the team is therefore likely to be an important determinant of productivity and the quality of patient care.

We employ a panel dataset that links daily staffing rotas with inpatient mortality records for a single NHS hospital group (known as an NHS Trust) that includes 3 large hospitals and 52 wards. We identify daily fluctuations in the size, skill-mix and work history of nursing teams, and link these to the outcomes for patients under their care.[1] In our empirical framework, we control for both time-varying patient characteristics (such as age and clinical diagnoses) and hospital ward fixed effects, such that our identification comes from within-ward variation in staffing over time. We address concerns about the potential endogeneity of team composition to patient severity based on the institutional structure of how shifts are allocated and by controlling for patient severity. For robustness, we also examine the impact of short-term staff absences due to sickness, which are plausibly unrelated to patient case mix, and find consistent results.

We find evidence that both the size and composition of nursing teams matters for their productivity. For the average team, an additional Registered Nurse (RN) reduces the odds of a patient death by approximately 10%. In contrast, the addition of an extra Nursing Assistant (NA), who do not have the formal training of their RN counterparts, has no impact on patient mortality. Teams with higher levels of general human capital – as measured by having a greater share of RNs rather than NAs – are more productive. We also show evidence of substantial returns to firm-specific experience (in this setting, experience working within the NHS Trust). Conditional on the quantity and skill-mix of the team, increasing the average firm-specific experience among RNs by one year reduces the odds of a patient death by 7.2% (equivalent to roughly two-thirds of the impact of adding an extra nurse). We no find no evidence of such an effect for NAs, which indicates the existence of complementarities between general and firm-specific human capital. Our results are also suggestive of returns to both ward- and team-specific human capital, with a lower probability of death for patients treated by staff who regularly work together and on the ward in question. Finally, we find that the most senior nursing staff within

[1] This is unlike other contexts where the size of the team is fixed and only the composition changes, such as professional basketball (Arcidiacono et al., 2017) or two-person physician teams within hospitals (Chen, 2021).

the team are, on average, around 2.2 times more productive than their newly qualified counterparts. Teams in which a senior nurse is absent due to a short-term sickness have a 63% increase in the odds of a patient death. Thus managers are important in team production in a healthcare setting.

The implications of our findings are that under-staffing by qualified staff matters for patient outcomes, but that even holding the total volume of healthcare inputs fixed, reorganising nursing teams based on work histories could improve patient survival.

This work contributes to a number of academic literatures. First, we contribute to the literature on team production and the relationship between human capital and team productivity in healthcare. Our paper is most closely related to Bartel et al. (2014), who examine the impacts of month-to-month variations in general and ward-specific human capital on the productivity of nursing teams in the US. The authors find that experience working in the specific hospital unit (ward) is more important than general experience. We add to this work by exploiting the granularity and higher frequency of our data to additionally examine the pivotal role of senior nurse managers ('bosses') and team-specific human capital in determining nursing team performance. Our paper also relates to Chen (2021), who examines the impact of team-specific human capital on the performance of two-person doctor teams, finding that higher levels of shared work experience between the doctor performing a heart procedure and the doctor who provides subsequent care is associated with reduced patient mortality. In a non-healthcare setting, Jaravel et al. (2018) show that the premature death of an inventor significantly lowers the subsequent innovation and earnings of their co-inventors, pointing to an important role for team-specific human capital. We extend these papers to examine the role of team-specific human capital and complementarities between different types of human capital for nurses, who represent a much larger fraction of the overall workforce. Our paper relates to previous studies into the role of peer effects (Mas and Moretti, 2009; Guryan et al., 2009; Cornelissen et al., 2017), learning from co-workers (Jarosch et al., 2021), credit-sharing within teams (Jones, 2021), productivity spillovers (Arcidiacono et al., 2017) and team incentives (Hamilton et al., 2003; Bandiera et al., 2009, 2013; Burgess et al., 2010, 2017; Friebel et al., 2017).

Secondly, we contribute to the literature on the role of nurses in health care production, building on papers such as Friedrich and Hackmann (2021), who exploit the labour supply effects of a parental leave program in Denmark to quantify the impacts of nurse employment on patient outcomes; Gruber and Kleiner (2012), who examine the impacts of nursing strikes; Propper and Van Reenen (2010), who exploit variation in outside wage options for nurses induced by centralised pay regulation to examine the impacts on hospital performance; and Lin (2014), who exploits legislative changes to minimum staffing requirements in nursing homes. Our data, which is both more granular and more high frequency than that used in most previous studies, provides new evidence on the impacts of both the quantity and quality of nurses on patient outcomes.

Finally, our paper contributes to the literature on the importance of management (Bloom et al., 2013) and the 'value of bosses' (Lazear et al., 2015). Of particular relevance is Fenizia (2020), who exploits the rotation of public sector managers across offices of the Italian Social Security Agency to examine the impact of managerial talent on office productivity. We similarly find an important role for senior managers in a public sector setting.

The paper proceeds as follows. Section 2 describes the institutional setting and introduces the data used in our analysis. Section 3 outlines a simple model of team production in a nursing setting and defines various measures of human capital. Section 4 presents descriptive statistics. Section 5 presents our empirical strategy. Section 6 sets out our results, looking first at the impact of the overall level of staffing, before turning to the human capital of the team and the impact of unexpected absences. Section 7 concludes.

2 Institutional background and data

2.1 The role of nursing teams in healthcare production

Nursing teams play a crucial role in healthcare delivery. These teams are responsible for monitoring patients, administering medicine, implementing treatment plans and co-ordinating the delivery of care more generally. This pivotal role relies on effective teamwork, communication, knowledge sharing and co-ordination. Collaboration is required for the simple reason that some tasks cannot be carried out by a single member of staff. In addition, while a typical shift lasts 12 hours, nursing care needs to provided 24 hours a day, 7 days a week, and so the information on patients' conditions and treatments shared by nurses on one shift with nurses on another is a crucial ingredient to team production in this setting.

Nursing teams are made up of two broad groups. Nursing assistants (NAs) are personnel without formal training or registration requirements, who are typically employed as health care assistants or other support workers, with responsibility only for basic patient tasks. Registered nurses (RNs) are fully qualified nurses on the Nursing and Midwifery Council register, who have completed formal training and hold a university diploma or degree-level qualification. Within the broad groups of NAs and RNs, there are multiple levels of seniority and responsibility, organised and paid according to a national set of pay bands. Promotion between these pay bands is based on experience and may require specific training or qualifications. Each ward is led by a senior nurse manager. NAs and RNs are typically contracted to work a set number of hours in a particular ward, though many choose to work additional shifts either in their usual ward or elsewhere, and hospitals can also employ staff via an external agency.

2.2 Data sources and sample construction

This study exploits a novel data linkage between electronic staff roster data and electronic patient records for a large National Health Service (NHS) Trust in England. We combine routinely recorded administrative information on the size and composition of nursing teams with information on the characteristics and outcomes of patients under their care. Our data covers the period between 1 January and 31 December 2017.

The NHS Trust used in our study includes three large hospitals with a total of 98 wards. To reduce heterogeneity we focus on inpatient wards responsible for treating adult patients. We exclude: all maternity and paediatric wards (which employ very different staffing models); wards that regularly closed (defined as having an entire day with no patients in the ward 30 times or more over the year); wards that employed no registered nurses; and wards that had zero patient deaths over the calendar year. For each of the remaining 52 hospital units (corresponding to one or sometimes two wards), we construct various measures of staffing, patient characteristics and patient outcomes at the daily level. The unit of analysis is the hospital ward-day.[2] The final sample was 18,922 observations.[3] Each of these can be thought of as a distinct team: the staff members who worked together on a given calendar day (including the handover between those doing the night shift and those who take over the following morning). 4,484 unique staff members worked across these teams, working 3,533,583 hours and 294,044 shifts over the course of the year. These teams were responsible for treating 44,485 unique patients with 66,662 separate hospital spells.

Nursing shifts are generated automatically by the e-rostering system several (generally 3) months ahead of time, in order to provide staff with at least 8 weeks notice of their shift patterns. The roster is generated so as to ensure that each team contains the

[2] In what follows we refer inter-changeably to unit and ward.

[3] Note that the sample does not contain 365 observations for each of the 52 wards (18,980 observations) because on 58 days (across 26 wards) no patients were treated, and these days are excluded from our sample.

appropriate number and mix of staff, with the appropriate or 'target' level of staffing determined by hospital managers.[4] These shifts are then allocated to individual staff members either by the system or manually by managers. The mean length of a shift is 11.5 hours; more than 70% of shifts are 12 hours long. Not all planned shifts are ultimately worked, because of staff absences (due to sickness or annual leave, for instance), because there is a staff vacancy, or for another reason. We construct the hours worked in each team and compare this to the planned (or rostered) number of hours.[5] Staff absences are recorded in a separate dataset, with information on the start date, end date and reason for absence.

For those shifts that are worked, they can be worked by a 'local' staff member (one who is directly employed by the NHS Trust, working their contracted hours in the ward to which they are attached), a 'bank' staff member (one who is employed by the NHS Trust but doing extracontractual or overtime work via the NHS 'staff bank', in their usual ward or elsewhere) or an agency worker (who is working in the Trust but employed via an external agency and is generally contracted at short notice). Student nurses are treated as supernumerary and excluded from our analysis.

NHS employees are paid according to a national pay structure, known as 'Agenda for Change' (AfC). The electronic staffing records include information on the AfC pay band of the staff member who worked each shift. Staff in AfC pay bands 2–4 are identified as NAs; those in pay bands 5–8 are identified as RNs. Individual pay bands also identify staff of different levels of seniority within each group. Within the category of RNs, Band 5 includes newly qualified and less experienced nurses; Band 6 includes more senior and experienced nurses, including deputy ward managers; and Band 7 and 8 includes the most senior nurses and ward managers with the most responsibility. For staff members employed by the Trust, the staff records include the month and year in which their employment commenced, which we use to construct a measure of experience within the NHS Trust. Agency workers, who are not employed by the Trust, are given a value of 0 on this measure.

To capture team performance and productivity, we focus on an important and high-stakes outcome: inpatient mortality. Death at discharge is recorded in electronic patient records, which we link to the team responsible for treating them at the point of death. The outcome is treated as binary, with an indicator coded as 1 if a team (ward-day)

[4] There are no mandated national nurse to patient staffing ratios in the UK.

[5] Note that because we define a team as a 'hospital ward-day', a night shift that spans midnight will contribute to the staffing of more than one team. For instance a shift that starts at 20:00 on day t and ends at 08:00 on day t+1 will contribute 4 hours to the staffing of the first team and 8 hours to the staffing of the second.

had a patient death occur, and coded as 0 otherwise. Patient mortality is a commonly used performance measure in the medical literature (Needleman et al., 2011), and has the advantage of being unambiguous and of being accurately and consistently recorded across wards. Deaths occur at all hours of the day (Appendix Figure A1), with the only noticeable spike occurring between 19:00 and 20:00 (when the handover between day and night shifts takes place) which suggests that there is no systematic misallocation of patient deaths to workers whose shifts span more than one calendar day.

3 Human capital in a nursing setting

3.1 A model of nursing team production

In this section, we present a simple model of team production to motivate and structure the empirical analysis which follows. In our setting, a team is a group of nursing staff (two or more) who work together in a particular location (hospital ward) with the same group of patients; the final output of the team is the medical care provided for those patients. Teams are ultimately made up of individuals. We begin by outlining a model of individual productivity in a nursing setting, before aggregating up to the team.

Let T be a team consisting of n members $T = \{1, 2, ..., n\}$, which in our setting is the group of nurses working in a ward (k) on a particular day (t), such that a specific team can be denoted as T_{kt}. $|T_{kt}|$ is the number of staff in the team, which is not fixed and varies across both wards and time.[6]

Each team is composed of individuals. We assume that the productivity of an individual i depends on their innate ability (denoted by θ_i) and four types of human capital, each of which is accumulated through different types of experience: general, firm-specific, task-specific and team-specific capital. Specifically, let the productivity P of individual i, working in firm (hospital) h, in ward k on day t be equal to:

$$P_{ihkt} = f(\theta_i, W_{it}, X_{iht}, Y_{ihkt}, Z_{-ihkt}) \tag{1}$$

where:

- W_{it} denotes **general human capital** for worker i at date t.
- X_{iht} denotes **firm-specific human capital**: worker i's experience working in firm (hospital) h at date t.

[6] This is a key difference between nursing and other settings in which team size is fixed, such as professional sports (Guryan et al., 2009; Müller et al., 2013; Arcidiacono et al., 2017).

- Y_{ihkt} denotes **ward-specific human capital**: worker i's experience working in ward k within hospital h at date t.

- Z_{-ihkt} denotes **team-specific human capital**: worker i's shared work experience with the other individuals working in ward k within hospital h at date t (i.e. with the other team members).

Each of these variables is formally defined in Section 3.2 below.

Nursing teams are formed of individuals, who vary in their productivity. In some settings, the output of each team member can be observed and recorded separately (e.g. in the case of the teams of fruit pickers examined by Bandiera et al. (2009, 2013)). But in many other settings – such as health care or professional sports – the output is a team output and cannot be directly attributed to individuals: providing high-quality patient care is a team effort, as is winning a basketball match. What matters, therefore, is *team* productivity, which will depend on the size and composition of the team, and on interactions between team members.

In many team settings, there is an 'optimal' team size. In football, for example, it is optimal to have 11 players, and teams with fewer players (due to red cards or injuries) tend to perform worse. In a kitchen, a team with too few chefs may struggle to prepare meals of adequate quality in the time available, while a team with too many cooks may spoil the broth. In nursing, the 'optimal' or 'target' team size is determined by hospital managers based on factors like the ward's size, medical specialty (because intensive care units require more staff per patient, for instance), physical layout, and so on. The size of the team, relative to this optimum, will affect productivity. Here, we denote the optimal size of team T_{kt} as $|T^*_{kt}|$.

The composition of the team will also matter. In particular, we might expect teams with higher levels of human capital – whether general, firm-specific, task-specific or team-specific – to perform better.

We model team productivity as follows. Let the productivity of team T_{kt} be given by:

$$P(T_{kt}) = \quad g\left(\frac{|T_{kt}|}{|T^*_{kt}|}, \overline{\theta}_{kt}, \overline{W}_{kt}, \overline{X}_{kt}, \overline{Y}_{kt}, \overline{Z}_{kt}\right) \tag{2}$$

where the first term inside function g captures the impact of the size of the team. $|T_{kt}|$ / $|T^*_{kt}| \in [0, 1]$ represents the ratio between *actual* team size and *optimal* team size, and thus captures the size of the team relative to 'target'. We impose that $|T_{kt}| \leq |T^*_{kt}|$. If short-staffed teams are less productive, this implies that $\partial g \; / \; \partial \frac{|T_{kt}|}{|T^*_{kt}|} > 0$. The remaining variables inside g capture the average characteristics of team members, where:

$$\begin{aligned}
\overline{\theta}_{kt} &= \frac{1}{|T_{kt}|}\sum_{i\in T_{kt}} \theta_i \quad , \quad \overline{W}_{kt} = \frac{1}{|T_{kt}|}\sum_{i\in T_{kt}} W_{it} \ , \\
\overline{X}_{kt} &= \frac{1}{|T_{kt}|}\sum_{i\in T_{kt}} X_{iht} \quad , \quad \overline{Y}_{kt} = \frac{1}{|T_{kt}|}\sum_{i\in T_{kt}} Y_{ihkt} \ , \\
\overline{Z}_{kt} &= \frac{1}{|T_{kt}|}\sum_{i\in T_{kt}} Z_{-ihkt}
\end{aligned} \tag{3}$$

Of these variables, θ_{kt} is unobservable to the researcher, because it represents the average innate ability of team members. The remaining variables are empirically calculable and observable, and are defined below. the relationship between these human capital measures and team performance is theoretically ambiguous, and therefore an empirical question, which we return to later in the paper.

3.2 Human capital definitions

3.2.1 General human capital

In nursing, as in many other settings, general-purpose human capital - such as overall education and experience - will contribute to individual productivity (Becker, 1964; Mincer, 1974). As discussed in Section 2.1, nursing teams can be split into two broad groups: nursing assistants (NAs) and registered nurses (RNs). RNs, who have completed formal training and hold a university diploma or degree-level qualification, can be considered to have more general human capital.[7] Similarly, those in a higher pay band – who are promoted based on experience and in many cases undergo advanced training and hold additional qualifications – can be thought of as possessing more general human capital.

In this study, we proxy for general human capital W_{it} using the pay band of each team member. This allows to separately identify NAs and RNs (NAs are in NHS Agenda for Change pay band 2–4, while all RNs are in pay bands 5 and above) and also to distinguish between qualified nurses of different levels of seniority and experience (a newly qualified nurse would be in pay band 5, while the most senior nurses and managers would be in

[7] Bartel et al. (2014) proxy for nurses' general human capital with their education level, and find that greater amounts of general human capital in nursing teams improves patient outcomes. Distinguishing between NAs and RNs is a similar approach, as only the latter are required to have a degree-level qualification. Studies in the nursing and medical literature have examined the impacts of substituting RNs with NAs (Rafferty et al., 2007; Griffiths et al., 2016, 2019) and typically find that a greater share of RNs is associated with improved patient outcomes.

pay band 7 or 8).

3.2.2 Firm-specific human capital

Human capital theory typically distinguishes between general and specific human capital, the latter being skills that are not portable across jobs (Parsons, 1972). The idea is that with experience at a particular firm, workers develop firm-specific skills and knowledge that make them more productive at that firm, but not necessarily at other firms.

There are good reasons to suppose the existence of returns to firm-specific human capital in a nursing context. Different hospitals (firms) often employ their own systems, processes and protocols. The longer an individual has worked at a particular hospital, the more familiar they will be with those systems, processes and protocols.[8] If they were to move to another hospital, it may take time to build up a similar amount of hospital-specific knowledge.

In this study, firm-specific human capital, is denoted as X_{iht} and represents the experience of individual i in firm (hospital) h at time t. We define this simply as the amount of time an individual has been employed in the firm, which in this context is the NHS Trust (which contains 3 large hospitals).[9]

3.2.3 Ward-specific human capital

Hospital-specific experience may yield productivity benefits, but within a hospital, wards are far from uniform. Experience in one ward may be less applicable to others. It is useful to distinguish between location-specific and task-specific human capital. The former comes from familiarity with one's physical surroundings: a nurse accustomed to the layout of a particular intensive care ward may find it initially more difficult to monitor patients if she moves to a different, less familiar intensive care ward in another hospital. The latter comes from task-specific learning by doing, where some of the experience and human capital that an individual acquires on the job may be specific to the task being performed, rather than specific to the firm as a whole (Gibbons and Waldman, 2004). This can be thought of as task-specific learning by doing (Levitt et al., 2013; Haggag

[8] Huckman and Pisano (2006) provide evidence of returns to hospital-specific experience for surgeons carrying out cardiac surgery.

[9] For 89% of individuals in our sample (who work 87% of all shifts) tenure is directly observable in staff records, as these contain the date at which the individual's employment at the Trust started. For the remaining 11% of individuals, for whom this information is missing, experience in the Trust is imputed based on: their pay band; the % of shifts they work as overtime via the staff 'bank'; the % of shifts they work at night; and whether they are an agency worker (agency workers are assigned a value of zero, as they are not employed by the Trust).

et al., 2017), and these accumulated skills may not be transferable if a worker moves to a different part of the firm where they perform a different task. For example, a nurse familiar with the treatment protocols on the haemotology ward may not be any more productive if she moves to the neurology ward.

In this study, we cannot observe the tasks performed by each member of the nursing team and so cannot disentangle task- and location-specific experience. Instead, we construct a measure of ward-specific experience, which will capture both of these factors (and is distinct from *team*-specific human capital, which is explored below). This approach also follows Bartel et al. (2014), who provide evidence of returns to hospital unit-specific human capital for nurses in a US setting.

We define task-specific human capital as follows. First, let $K(h)$ be the set of wards in hospital h. Then for all $k \in K(h)$ we define Y_{ihkt} as the task-specific human capital for worker i in ward k on day t as:

$$Y_{ihkt} = \sum_{\tau=t-90}^{t-1} \mathbb{1}(i \in T_{\tau k}) \quad \forall k \in K(h) \tag{4}$$

where $\mathbb{1}(i \in T_{\tau k})$ is an indicator equal to one if individual i was part of team $T_{\tau k}$ and zero otherwise. Y_{ihkt} therefore represents the number of times the individual has worked in ward k in the previous 90 days.[10]

We construct several further measures for use in our empirical analysis. We define:

$$WardShifts^{5}_{ihkt} = \mathbb{1}(Y_{ihkt} \geq 5) \quad \text{and} \quad WardShifts^{10}_{ihkt} = \mathbb{1}(Y_{ihkt} \geq 10) \tag{5}$$

as binary variables equal to one if the individual has worked at least 5 and 10 shifts in the ward in the past 90 days, respectively. We additionally define:

$$\begin{aligned} FirstShift_{ihkt} &= \mathbb{1}(Y_{ihkt} = 0 \wedge i \in T_{kt}) \\ NewJoiner_{ihkt} &= \mathbb{1}(\sum_{\tau=t-30}^{t} FirstShift_{ikh\tau} > 0 \wedge i \in T_{kt}) \end{aligned} \tag{6}$$

where $\mathbb{1}(Y_{ihkt} = 0 \wedge i \in T_{kt})$ is an indicator equal to one if an individual is working in team

[10] We measure ward-specific experience based on the past 90 days for two reasons. One, one might expect the effects of experience to decay over time. Two, our sample covers a single calendar year and in order to construct a backwards-looking measure of experience, we have to discard a portion of the data at the start of the period (for which such a backwards-looking measure cannot be calculated). Using shared work experience over the previous 90 days strikes a balance between capturing how familiar workers will be with the ward, and having to discard no more than a quarter of our sample.

T_{kt}, having not worked in ward k in the previous 90 days. $\mathbb{1}(\sum_{\tau=t-30}^{t} FirstShift_{ikh\tau} > 0 \wedge i \in T_{kt})$ is therefore an indicator equal to one if an individual in team T_{kt} did their first shift (in at least 90 days) in this ward on date $\tau \in [t-30, t]$ – i.e. at some point in the last 30 days. That is, it is equal to one if an individual is within their first 30 days on the ward: we define these individuals as 'new joiners'.

3.2.4 Team-specific human capital

Collaboration, communication and co-ordination are inherent to team production. The costs associated with each of these may fall with shared experience (Lazear and Shaw, 2007). In a nursing setting, many tasks cannot be done by a single person and require multiple team members to work together. In addition, patients require round-the-clock care and so the sharing of information when nurses are handing over between shifts is of critical importance. Such collaboration and information sharing may get easier the more times two individuals have worked together. This is distinct from experience working in a particular location.

We define team-specific human capital as follows. First, let $K(h)$ be the set of wards in hospital h. Let $E(i, j, t)$ represent the (recent) shared work experience between workers i and j, as of date t, where:

$$E(i, j, t) = \sum_{k \in K(h)} \sum_{\tau=t-90}^{t-1} \mathbb{1}(i \in T_{\tau k} \wedge j \in T_{\tau k}) \tag{7}$$

where $\mathbb{1}(i \in T_{\tau k} \wedge j \in T_{\tau k})$ is an indicator that equals one if both workers i and j worked in ward k on day $\tau \in [t-90, t-1]$ (i.e. equals one if both i and j were in team $T_{\tau k}$). $E(i, j, t)$ therefore represents the number of shifts i and j have worked together, in any ward, over the past 90 days prior to day t.[11]

We can then define an individual's average shared work experience with fellow team members (team-specific human capital) as:

$$Z_{-ihkt} = \frac{1}{|T_{kt}| - 1} \cdot \sum_{j \in T_{kt}, j \neq i} E(i, j, t) \tag{8}$$

where T_{kt} is the set of team members (in ward k on date t), $|T_{kt}|$ is the size of the team, and $E(i, j, t)$ is defined as above. Z_{-ihkt} therefore captures the average number of shifts that individual i has worked with their team members in the most recent 90 days.

[11] As above, we measure shared work experience based on the past 90 days to allow for the effects of experience to decay over time, and to strike a balance between defining a suitably backwards-looking measure and having to discard a substantial portion of our sample.

We define a further variable for use in empirical analysis:

$$SharedExp^5_{-ihkt} = \mathbb{1}(Z_{-ihkt} \geq 5 \wedge i \in T_{kt}) \tag{9}$$

which is a binary variable equal to 1 if an individual in team T_{kt} has worked with their fellow team members 5 or more times, on average, in any ward, over the previous 90 days.

4 Summary statistics

4.1 Staffing and team composition

Table 1 presents summary statistics for the quantity and composition of team staffing. The average team (unit-day) had 194.8 rostered hours. Within that, an average 53.4 hours were rostered for NAs, and 141.4 for RNs. This is equivalent to around 16 staff members working 12-hour shifts, with around 4 NAs and 12 RNs in the average team. Note that not all of these staff members will be working at any one time; shifts overlap in order to ensure continuous care over the full 24 hours.

In just over half (51.2%) of teams, the actual number of hours worked was less than the number of planned/rostered hours. In the average team, 8 hours of planned staffing was 'unfilled', equivalent to two-thirds an average shift. This is equivalent to saying that in the average team, 95.7% of planned hours were actually worked.[12] This is slightly lower for NAs (94.6%) than for RNs (96.4%).

Table 1 also shows the share of planned hours worked by staff of different contract type and seniority. The majority of hours – 67.9% of all those planned – were worked by local staff in their regular ward to which they are attached and in which they do their contracted hours. A further 20.6% were worked by bank staff, and a further 7.2% by agency workers.

Nurses in NHS AfC pay band 5 are the largest staffing group. These are recently qualified RNs in the lowest seniority band. Band 5 nurses work almost half (47.1%) of all hours and more than two-thirds (68.4%) of rostered RN hours. Agency work is concentrated in band 5. Almost all hours worked by (the more senior) Band 6–8 nurses are in their regular ward as local staff. Band 7 and 8 staff – the most senior nurses responsible for managing their ward – work around 5% of all rostered RN hours.

A little over a tenth (12.2%) of all planned hours are worked by 'new joiners': those

[12] This measure – the actual number of hours worked divided by the number of rostered hours – is routinely collected and published by the NHS Trust as the 'fill-rate'.

who are within their first month on a ward, having not worked there for the previous 90 days or more. In the average team, the average staff member had 6.3 years of experience within the NHS Trust (5.6 years for NAs; 6.7 for RNs); the average team member had done 30.3 shifts in the ward in the past 90 days (27.8 for NAs; 31.5 for RNs); and the average team member had worked 14.5 shifts with their fellow team members in the previous 90 days.

Importantly, there is considerable day-to-day variation in both the level and composition of staffing. This includes variation in the degree of firm (Trust)-, ward- and team-specific human capital amongst the team. This within-ward variation is key to our identification strategy and is documented in Table 3. In part, this variation is because of staff rotations, arrivals and departures which contribute to turnover. But in addition, most staff members work across multiple wards (Figure 1). More junior staff, in particular, tend to work across multiple hospitals and wards within the Trust. The average Nursing Assistant worked 76.3 shifts across 6.8 different wards over the course of the year. The average Band 5 RN worked 51.6 shifts across 4.5 unique wards.[13] In contrast, the most senior nurses in Band 7 and 8 move around little, and did 96.7% of their shifts in their usual unit (versus 72.4% for Band 5s).

4.2 Patients and patient outcomes

The average team in our sample was responsible for treating 20.6 patients (Table 2). As well as the number of patients, the clinical acuity of those patients is an important contributor to a team's workload. Our analysis therefore controls for time-varying patient characteristics (discussed in more detail in Section 5). The average patient was 64.1 years old, 46% were female, and 52% were recorded with an ethnicity other than White (including 'unknown'). The average Elixhauser Comorbidity Score, a well-established measure of clinical severity (Elixhauser et al., 1998), was 28.53.[14] 6.3% of the teams in our sample recorded a patient death, with a mean mortality rate of 3.58 per 1,000 patients.

[13]Note that the average Band 5 works fewer shifts because they are more likely to be part-time, and more likely to be an agency worker (who could appear as little as once in our sample).

[14]We calculated the Elixhauser Cormorbidity Score for each patient using their recorded diagnoses, with coding from the International Classification of Diseases, tenth edition (ICD-10).

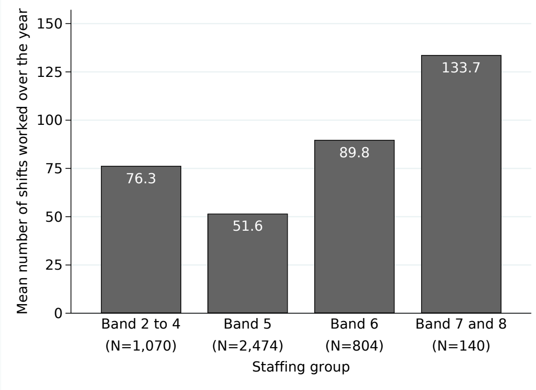
Table 1: Summary statistics: ward staffing levels and team composition

	All nursing staff		**Nursing Assistants**		**Registered Nurses**	
	Mean	SD	Mean	SD	Mean	SD
Planned (rostered) hours	194.8	89.8	53.4	30.7	141.4	91.4
Actual hours worked	186.7	88.8	50.2	29.1	136.6	90.6
Unfilled hours	8.0	10.1	3.2	6.1	4.8	7.6
Share of planned hours worked (%), *of which:*	95.7	5.4	94.8	10.9	96.4	5.8
Local/regular staff	67.9	15.7	63.9	26.4	70.5	16.9
Bank staff	20.6	12.7	28.8	23.8	16.3	12.7
Agency staff	7.2	8.2	2.0	8.4	9.5	11.0
Band 2 staff	23.9	14.6	78.0	25.5	–	–
Band 3 staff	3.7	5.4	15.7	23.6	–	–
Band 4 staff	0.2	1.0	0.9	3.8	–	–
Band 5 staff	47.1	11.5	–	–	68.4	15.8
Band 6 staff	17.0	12.5	–	–	22.8	13.3
Band 7 and 8 staff	3.8	4.5	–	–	5.2	5.8
Band 5 local staff	30.7	12.0	–	–	44.0	16.0
Band 5 bank staff	10.1	8.5	–	–	15.1	13.0
Band 5 agency staff	6.2	7.6	–	–	9.2	11.0
Band 6 local staff	15.6	10.6	–	–	21.2	11.9
Band 6 bank staff	1.1	3.3	–	–	1.2	3.7
Band 6 agency staff	0.3	2.0	–	–	0.3	2.0
Band 7 and 8 local staff	3.8	4.5	–	–	5.2	5.8
Band 7 and 8 bank staff	0.0	0.0	–	–	0.0	0.1
Band 7 and 8 agency staff	0.0	0.0	–	–	0.0	0.0
New joiners to the ward (%) †	12.2	9.4	16.4	19.7	10.7	10.6
Non-new joiners (%) †	83.5	10.7	78.4	21.9	85.6	11.9
Years of experience in the NHS Trust	6.3	2.0	5.6	3.2	6.7	2.5
Shifts in the ward in the past 90 days	30.3	5.2	27.8	9.7	31.5	5.9
Average shared work experience (shifts) with other team members (in any ward) in the past 90 days	14.5	5.0	13.5	6.3	14.9	5.1
Average shared work experience (shifts) with other RNs in the team (in any ward) in the past 90 days	–	–	–	–	15.2	5.7
Observations	18,922		18,922		18,922	
Hospitals	3		3		3	
Wards	52		52		52	

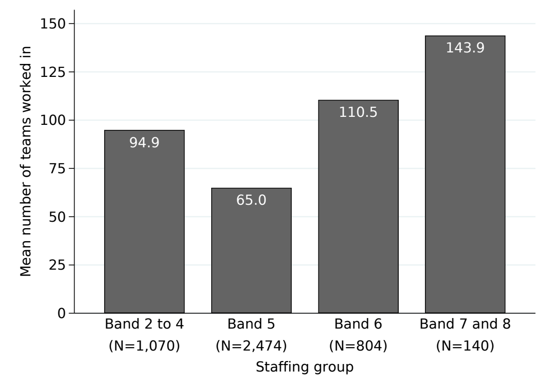
† New joiners are defined as those who are within 30 days of starting on the unit for the first time, having not done so in (at least) the past 90 days.
Note: Unit of analysis is the hospital unit-day. Nursing support staff are personnel without formal training or registration requirements, identified as those in NHS Agenda for Change pay bands 2–4), and typically employed as health care assistants or other support workers. Registered Nurses (RNs) are fully qualified nurses on the Nursing and Midwifery Council register, who have completed formal training and hold a university diploma or degree-level qualification, identified in our data as those in NHS Agenda for Change pay bands 5–8, with bands 5 and 8 representng the least and most senior nurses, respectively. Mean characteristics of team members are weighted by the number of hours worked.

Figure 1: Staff movements across teams, wards and hospitals

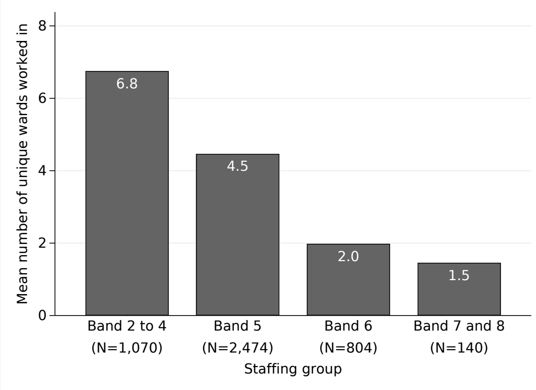
(a) Number of shifts (mean)



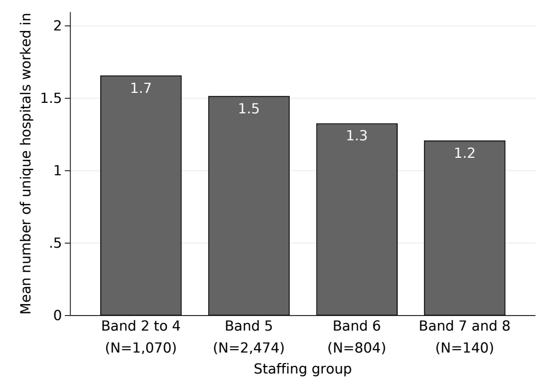
(b) Unique teams (mean)



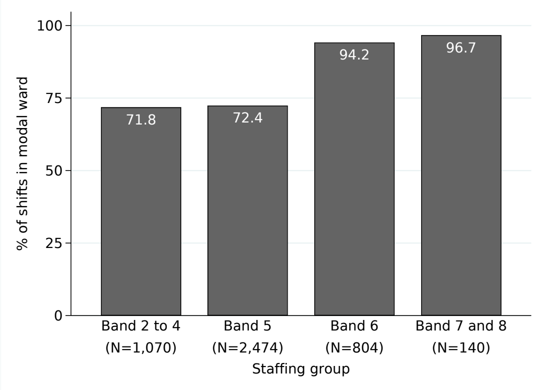
(c) Unique wards (mean)



(d) Unique hospitals (mean)



(e) Share (%) of shifts in usual (modal) ward



(f) Share (%) of shifts worked by agency staff

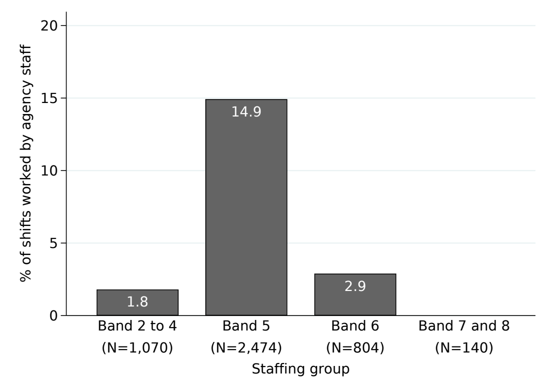


Table 2: Summary statistics: patient outcomes and characteristics

	Mean	Std. Dev.
Number of patients treated in the unit	20.61	8.46
Age	64.18	9.86
Female (%)	0.46	0.18
Non-White (%) †	0.52	0.16
Elixhauser Comorbidity Index score	3.69	1.17
Average length of hospital stay (days) ‡	28.53	17.08
Patient death (binary)	0.063	0.243
Death rate per 1,000 patients	3.58	16.20
Observations	18,922	
Hospitals	3	
Wards	52	

Note: Unit of analysis is the hospital unit-day. Patient characteristics weighted by the hours spent in the unit on the day in question.
† Non-white includes those patients for whom ethnicity was recorded as unknown.
‡ Calculated as the average for the patients treated in a given unit on a given day, rather than the average for the universe of patients.

Table 3: Summary statistics: within-ward and between-ward standard deviation (SD)

	Mean	SD	Within SD	Between SD
Share (%) of all planned hours worked	95.7	5.4	4.9	2.2
Share (%) of planned NA hours worked	94.8	10.9	10.3	3.8
Share (%) of planned RN hours worked	96.4	5.8	5.3	2.3
Share (%) of all planned hours worked by:				
Band 5 staff	47.1	11.5	8.2	8.1
Band 6 staff	17.0	12.5	6.3	10.8
Band 7 and 8 staff	3.8	4.5	3.3	3.1
Local staff	67.9	15.7	11.7	10.6
Bank staff	20.6	12.7	10.4	7.4
Agency staff	7.2	8.2	6.5	5.1
Patient death (binary)	0.06	0.24	0.24	0.06

5 Empirical strategy

5.1 Baseline model

We estimate the following baseline fixed-effects logit model:

$$\begin{aligned} y_{it} &= \mathbb{1}(y^*_{it} > 0) \\ y^*_{it} &= \beta_1 FillRateNA_{it} + \beta_2 FillRateRN_{it} + \delta PatientChars_{it} + \lambda_t + \eta_i + \epsilon_{it} \end{aligned} \tag{10}$$

where y_{it} is a binary indicator of a patient death in ward i on day t. The ward-day – the team – is the unit of analysis, to reflect the centrality of teams to healthcare production: patient outcomes are the product of the efforts of the team as a whole and cannot be attributed to any individual team member.

In our baseline specification, we measure team composition by the share of planned NA and RN hours that were actually worked, denoted by $FillRateNA_{it}$ and $FillRateRN_{it}$, respectively. These capture both the size of the team relative to 'optimal' (corresponding to $|T_{kt}|/T^*_{kt}|$ in equation 2) and, because it's is defined separately for NAs and RNs, the skill-mix and level of general human capital of the team. They are defined as:

$$\begin{aligned} FillRateNA_{it} &= 100 * \frac{\text{Hours worked by NAs in ward } i \text{ on day } t}{\text{Planned NA hours in ward } i \text{ on day } t} \\ FillRateRN_{it} &= 100 * \frac{\text{Hours worked by RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t} \end{aligned} \tag{11}$$

β_1 and β_2 are the coefficients of interest, and represent the impact of a change in the level of NA and RN staffing on the odds of a team experiencing a patient death, respectively. We present our results as odds ratios.

$PatientChars_{it}$ captures time-varying characteristics of patients in ward i on day t, weighted by the amount of time that each patient spent under the care of the team. These include: the mean age of patients; the mean age squared; the female share; the share of patients who are non-white; the mean patient Elixhauser Comorbidity Index score (a standard measure of clincial severity); pairwise interactions between each of these variables; the average length of hospital stay for the patients in the ward; and the number of patients treated in the ward that day (a proxy for nurse workload). λ_t captures time effects (day of week; month; and a dummy variable indicating a public holiday).

We include ward fixed effects (η_i) to capture time-invariant differences across hospital wards (such as their medical specialty, patient mix, Trust and hospital management quality, and physical layout). Our results are therefore identified from within-ward variation in staffing levels and team composition. The extent of this within-ward variation is illustrated in Table 3.

ϵ_{it} is an error term, assumed to be logistically distributed, with standard errors clustered at the ward level.

One concern is that nurse staffing is endogenous to patient severity: when a ward has an influx of sicker patients (making a patient death more likely), the ward manager may respond by increasing the number of staff on the ward, or by adjusting the skill mix of the team. As discussed in Section 2, nurse rosters are planned months in advance, but some last-minute adjustments may still be possible. This would lead to an upwards bias in our estimates of the relationship between nurse staffing and patient mortality.[15] Where we estimate a negative association between nurse staffing and mortality, this would mean that we are *underestimating* the 'true' benefits of higher nurse staffing and/or higher levels of human capital.

While such endogenous staffing decisions are theoretically possible, staff shortages are endemic within the English NHS and within the hospitals used in our study. Even following an influx of sick patients, additional nurses may simply not be available. There certainly is no pool of experienced nurses lying idle in case they are needed. Furthermore, the primary means of finding an additional nurse at short notice is via an external agency, but due to budgetary concerns and constraints, this requires approval from a manager external to the ward. This approval may not be granted in time to fill an unexpected vacancy – or may not be granted at all. In any case, agency staff are almost exclusively Band 5 nurses (Figure 1), and so cannot be used as a like-for-like replacement when a more senior nurse is absent.

We take three main steps to further alleviate this concern. First, to the extent that such changes in patient severity are observable (e.g. a change in patient age structure, or in recorded diagnoses) this will be captured in $PatientChars_{it}$, and any change in the volume of patients is directly controlled for. Second, any differences in unobservable patient severity that are time-invariant across wards will be soaked up by our inclusion of ward fixed effects. Third, in addition to our main results, we directly examine the impact of plausibly unexpected staff absences – those caused by a short-term sickness – to estimate the impact of staffing changes that cannot be related to any changes in patient mix, and find consistent results.

[15]Indeed, many cross-sectional studies into the impact of nurse staffing in the medical literature suffer from this shortcoming – see Griffiths et al. (2016) for a discussion.

5.2 Extensions

The baseline model examines the separate effects of NA and RN staffing on team performance. Differences between the coefficients on these variables would reflect the differential impacts of staff with more or less general human capital. We employ a number of other specifications to examine different aspects of team composition and human capital. These include, for example, the average amount of firm-specific experience in the team, and measures of the proportion of the team who have recent ward- and team-specific experience. Precise definitions for each of these variables is provided in Appendix Section A.1.

6 Results

We start by presenting the estimated impacts of overall staffing levels on team performance, including how this impact varies according to the skill mix and general human capital of the team. To explore the returns to different types of human capital we examine different aspects of team composition. Finally, we examine the impact of unexpected staff absences, with a particular focus on that of the senior nurse managers.

6.1 Overall staffing and skill-mix

Table 4 reports our baseline results. The first column regresses a binary indicator of a patient death on the share of planned Nursing Assistant (NA) and Registered Nurse (RN) hours that were actually worked, along with the controls discussed above. A one-unit (one percentage point) increase in each of these variables is equivalent to an additional 0.53 and 1.41 hours, respectively, for the average team (as per Table 1), though this will vary according to the size of the ward.

We find that an increase in NA staffing has no statistically significant impact on the odds of a patient death. In contrast, higher levels of RN staffing are associated with lower patient mortality: a one percentage point increase in the RN fill-rate reduces the odds of a patient death by 1.3% (with an odds ratio of 0.987). These results suggest that for the average team, an extra RN doing a 12-hour shift would reduce the odds of experiencing a patient death by around 10%.[16] The size of the team therefore matters. But just as important is the composition of the team. There are significant returns

[16]The average team has 141.4 rostered RN hours (Table 1). A one percentage point increase would therefore add approximately 1.4 hours, and an extra staff member working a 12-hour shift would increase staffing by $12/1.4 \approx 8.6$ percentage points of planned RN hours. Using the results from Table 4, $0.9874^{8.6} \approx 0.9$, equivalent to a 10% reduction.

to qualifications and experience: teams with higher levels of general human capital (as measured by a greater share of RNs rather than NAs in the team) are more productive.

The second column distinguishes between nurses of different seniority within the broad category of RNs. Again, our results provide evidence of significant returns to skill and general human capital. A one percentage point increase in the share of planned RN (band 5–8) hours worked by a band 5 nurse reduces the odds of a patient death by 1.1%, increasing to 1.6% for band 6, and 2.4% for band 7 and 8. This means that for the average team, adding an extra nurse in the most senior pay bands reduces the odds of a patient death by more than twice as much as adding a newly qualified nurse: our central estimates suggest that the average band 7–8 nurse is about 2.2 times as productive as a band 5 nurse.

The third column of Table 4 distinguishes between RNs of different contract types: local, bank and agency. The results show that only RNs directly employed by the Trust – local and bank staff – have a statistically significant impact on patient mortality. Agency RNs are also almost exclusively in Band 5 so this result could just be reflecting the skill and seniority mix. The fourth column therefore controls for Band 6, 7 and 8 staffing, but separates Band 5 staffing into agency and non-agency. The results provide some weak suggestive evidence that agency RNs are less productive than their non-agency (local and bank) counterparts, but the general human capital of the team (as measured by seniority) appears to be more important than contract type.

6.2 Firm-specific, ward-specific and team-specific human capital

We now turn to an examination of the impact of different types of human capital and the returns to different types of experience, over and above the returns to seniority.

Table 5 focuses on the impact of firm-specific (in our case, NHS Trust-specific) experience, after controlling for the quantity and seniority mix of staffing. The first column shows that a greater amount of firm-specific experience – as measured by mean years of experience working in the NHS Trust – is associated with better team performance. The second column shows that there are returns to firm-specific experience only for RNs, with no impact for NAs. Increasing the average firm-specific experience among RNs in the team by one year reduces the odds of a patient death by 7.2% (equivalent to roughly two-thirds of the impact of adding an extra nurse). In contrast, a greater level of firm-specific experience among the (less highly skilled) NAs has no statistically significant impact. The third column of Table 5 shows that the returns to firm specific experience are increasing with years of experience more or less monotonically.

Table 4: Impact of nurse staffing levels, contract type and seniority on patient mortality

	Outcome: patient death			
	(1)	(2)	(3)	(4)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.003 (0.004) [0.360]	1.003 (0.004) [0.356]	1.003 (0.004) [0.348]	1.003 (0.004) [0.348]
Share (ppt) of planned Registered Nurse (RN) hours filled	0.987** (0.006) [0.038]			
Share (ppt) of planned Registered Nurse (RN) hours filled by:				
Band 5 nurses		0.989* (0.006) [0.087]		
Band 6 nurses		0.984** (0.007) [0.020]		0.984** (0.007) [0.020]
Band 7 and 8 nurses		0.976** (0.011) [0.025]		0.976** (0.011) [0.026]
Local (regular) nurses			0.987** (0.006) [0.037]	
Bank nurses			0.986** (0.007) [0.038]	
Agency nurses			0.991 (0.006) [0.140]	
Band 5 Local and Bank nurses				0.989* (0.006) [0.084]
Band 5 Agency nurses				0.991 (0.006) [0.139]
Patient volume and characteristics	✓	✓	✓	✓
Time controls	✓	✓	✓	✓
Hospital ward fixed effects	✓	✓	✓	✓
N	18,922	18,922	18,922	18,922
Clusters	52	52	52	52

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward fixed effects. Robust standard errors, clustered at the hospital unit level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. All regressions control for the mean patient age; the mean patient age^2; the female share of patients; the non-white share of patients; the mean Elixhauser Comorbidity Index; pairwise interaction terms between age, female share, non-white share and Elixhauser Cormorbidity Index; the mean hospital length of stay of patients treated in the unit that day; the number of patients treated in the unit that day; a dummy for each day of the week; a dummy for month of the year; and a dummy indicating whether the day was a bank holiday.

Table 5: Impact of firm-specific experience on patient mortality

	Outcome: patient death		
	(1)	(2)	(3)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.003 (0.003) [0.386]	1.003 (0.003) [0.331]	1.003 (0.003) [0.365]
Share (ppt) of planned Registered Nurse (RN) hours filled by:			
Band 5 nurses	0.989* (0.006) [0.082]	0.989* (0.006) [0.062]	0.988* (0.006) [0.067]
Band 6 nurses	0.986** (0.007) [0.037]	0.986** (0.007) [0.036]	0.987** (0.007) [0.049]
Band 7 and 8 nurses	0.979* (0.011) [0.066]	0.980* (0.011) [0.078]	0.980* (0.011) [0.088]
Average experience in the Trust (years)	0.939* (0.034) [0.079]		
Average experience in the Trust for NAs (years)		1.017 (0.015) [0.246]	
Average experience in the Trust for RNs (years)		0.928*** (0.021) [0.001]	
Percent of Registered Nurses (RNs) with: †			
1-3 years Trust experience			0.991** (0.004) [0.047]
3-7 years Trust experience			0.990** (0.005) [0.034]
7-11 years Trust experience			0.987*** (0.004) [0.003]
11-15 years Trust experience			0.988** (0.005) [0.016]
15+ years Trust experience			0.985*** (0.005) [0.005]
Patient volume and characteristics	✓	✓	✓
Time controls	✓	✓	✓
Hospital ward fixed effects	✓	✓	✓
N	18,922	18,922	18,922
Clusters	52	52	52

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward fixed effects. Robust standard errors, clustered at the hospital unit level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. See notes to Table 4 for a full list of controls.

† Reference group is those with less than one year of experience in the Trust.

These results suggest that, consistent with Huckman and Pisano (2006), teams with workers with more firm-specific human capital perform better in a healthcare setting. This indicates that familiarity with hospital-specific systems and processes can yield substantial benefits. But within a hospital, wards are far from uniform. For example, experience in monitoring patients on a cardiology ward may be of less use in an intensive care ward. A nurse familiar with the treatment protocols on the haemotology ward may not be any more productive if she moves to the neurology ward. Therefore ward-specific experience may be important.

To examine this, we split out RNs into those who have newly joined the ward[17] and those who have worked on the ward for longer and thus have more ward-specific experience. The results in the first column of Table 6 indicate that teams with more ward-specific experience are more productive. An additional 1% of planned RN hours worked by a new joiner (who by definition has little-to-nothing in the way of recent ward-specific experience) has no statistically significant impact on the odds of a patient death, while there is a statistically significant 1.6% reduction following the addition of a RN who is not new to the ward.

More senior nurses (band 6 and above) move around less than band 5 nurses (Figure 1) and the estimated reduction in the odds from death from additional filled shifts is larger for more senior nurses (Table 4). To avoid the estimation of familiarity effects being confounded by seniority effects, we next focus just on Band 5 RNs. The second column shows reductions in mortality when a higher share of Band 5s have recent experience in the ward (non-new joiners), although the estimated coefficient is only statistically significant at the 10% level. The estimated coefficients remain unchanged when we condition on working together for at least 5 shifts (column 3) and 10 shifts (column 4) in the last 90 days. This suggests that any effect of ward specific experience is not increasing in the extent of that experience.

As well as familiarity with the ward in which a nurse is working, there may be returns to greater familiarity with a nurse's team members. Collaboration, communication and co-ordination – all crucial ingredients to a successful nursing team – may be easier when individual nurses have experience working with one another. This is distinct from familiarity with one's physical surroundings: two nurses may have experience working together elsewhere in the hospital.

To address this question, we construct a measure of shared work experience for each pairing of RNs within a team, which measures the number of times the two individuals

[17] As per Table **??**, we define someone as a new joiner if they are within their first 30 days on the ward, having not worked there in the previous 90 days.

Table 6: Impact of ward-specific experience on patient mortality

	Outcome: patient death			
	(1)	(2)	(3)	(4)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.001 (0.004) [0.835]	1.001 (0.004) [0.823]	1.001 (0.004) [0.819]	1.001 (0.004) [0.826]
Share (ppt) of planned Registered Nurse (RN) hours filled by:				
RN new joiners to the unit †	0.989 (0.008) [0.147]			
RNs who are not new joiners	0.984** (0.008) [0.037]			
Band 5 new joiners †		0.990 (0.008) [0.202]		
Band 5 nurses who are not new joiners		0.985* (0.008) [0.059]		
Band 5 nurses with <5 shifts in unit in past 90 days			0.990 (0.008) [0.222]	
Band 5 nurses with ≥5 shifts in unit in past 90 days			0.985* (0.008) [0.057]	
Band 5 nurses with <10 shifts in unit in past 90 days				0.989 (0.008) [0.160]
Band 5 nurses with ≥10 shifts in unit in past 90 days				0.985* (0.008) [0.058]
Band 6 nurses		0.982** (0.008) [0.023]	0.982** (0.008) [0.023]	0.982** (0.008) [0.023]
Band 7 and 8 nurses		0.977* (0.012) [0.059]	0.977* (0.012) [0.059]	0.977* (0.012) [0.058]
Patient volume and characteristics	✓	✓	✓	✓
Time controls	✓	✓	✓	✓
Hospital ward fixed effects	✓	✓	✓	✓
N	14,290	14,290	14,290	14,290
Clusters	52	52	52	52

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

† New joiners are defined as those who are within 30 days of starting on the unit for the first time, having not done so in (at least) the past 90 days.

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward fixed effects. Robust standard errors, clustered at the hospital unit level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. See notes to Table 4 for a full list of controls.

have worked together in the past 90 days (in any ward).[18] We use this as our proxy for team-specific human capital, and look separately at the impact of RNs with more and less shared work experience (and thus more or less team-specific human capital). The results in Table 7, column 1, show that after controlling for the seniority mix of the team, the average amount of shared experience in the team does not have a statistically significant effect on team productivity. However, without controls for seniority, having more RNs with shared work experience of over 5 shifts is statistically significant associated with reductions in patient mortality (column 2). Column 3 shows this is also the case for Band 5 nurses conditional on seniority mix, although the coefficient in column 3 on higher shared experience is less precisely estimated. As with the results in Table 7, this is because: (i) senior RNs (Band 6 and above) work in fewer wards, resulting in higher levels of team familiarity; and, (ii) senior RNs also have greater impacts – and in the case of Band 6 RNs, better defined impacts – on mortality rates.

6.3 Unexpected absences

Variation in staffing levels and team composition can be caused by staff absences. Some forms of absences are likely to result in a greater degree of disruption to a team than others. When absences are known about in advance (such as a pre-agreed period of holiday or training leave), rosters can be re-arranged in advance with little disruption. Unexpected absences, such as those due to short-term sick leave, may be harder to adjust to, as managers may struggle more to find an appropriate replacement at short notice.

In Table 8, we examine the impact of staff absences on the productivity of the team. We construct a dummy for an absence lasting ≤ 7 days due to sickness, and one for an absence lasting ≤ 7 days due to any other reason. The only difference between these two should be that the former is more likely to be unexpected and thus harder to adapt to. The column shows that, conditional on staffing levels and seniority mix, a short-term absence of an RN for a reason other than sickness is not associated with a statistically significant increase in patient mortality. The second column shows that the same is true for a non-sickness absence of a Band 7 or 8 nurse. The third column shows no impact of having an RN absent due to short-term sickness. The final column, though, shows that teams in which a senior nurse (in Band 7 or 8) is absent due to a short-term sickness perform substantially worse: the odds of a patient death is 63% greater. This points to the important role played by the senior nurses who manage the ward in which they work.

[18] This is similar to the measure used for doctors in Chen (2021).

Table 7: Impact of shared work experience on patient mortality

	Outcome: patient death		
	(1)	(2)	(3)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.001 (0.004) [0.821]	1.001 (0.004) [0.839]	1.001 (0.004) [0.843]
Share (ppt) of planned Registered Nurse (RN) hours filled by:			
Band 5 nurses	0.986* (0.008) [0.073]		
Band 6 nurses	0.982** (0.008) [0.022]		0.986** (0.007) [0.046]
Band 7 and 8 nurses	0.977* (0.012) [0.056]		0.980* (0.012) [0.094]
RNs with average shared work experience of <5 shifts †		0.989 (0.008) [0.147]	
RNs with average shared work experience of ≥5 shifts †		0.983** (0.008) [0.033]	
Band 5s with average shared work experience of <5 shifts †			0.994 (0.007) [0.389]
Band 5s with average shared work experience of ≥5 shifts †			0.988* (0.007) [0.085]
Mean shared work experience among RNs †	0.998 (0.009) [0.791]		
Patient volume and characteristics	✓	✓	✓
Time controls	✓	✓	✓
Hospital ward fixed effects	✓	✓	✓
N	14,290	14,290	14,290
Clusters	52	52	52

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

† Shared work experience is defined as the number of times two RNs worked together in the same team over the previous 90 days, in any unit. The average is calculated with respect to all other RNs in the team.

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward fixed effects. Robust standard errors, clustered at the hospital unit level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. See notes to Table 4 for a full list of controls.

Table 8: Impact of staff absences on patient mortality

	Outcome: patient death			
	(1)	(2)	(3)	(4)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.003 (0.004) [0.345]	1.003 (0.004) [0.346]	1.003 (0.004) [0.349]	1.003 (0.003) [0.357]
Share (ppt) of planned Registered Nurse (RN) hours filled by:				
Band 5 nurses	0.989* (0.006) [0.081]	0.989* (0.006) (0.006)	0.989* (0.006) [0.073]	0.990* (0.006) [0.099]
Band 6 nurses	0.984** (0.007) [0.017]	0.984** (0.007) [0.021]	0.984** (0.007) [0.014]	0.978** (0.011) [0.040]
Band 7 and 8 nurses	0.975** (0.011) [0.024]	0.977* (0.012) [0.056]	0.975** (0.011) [0.025]	0.978** (0.011) [0.040]
Absence for a reason other than sickness, lasting $\leq$ 7 days:				
RN of any band	1.041 (0.073) [0.565]			
Band 7–8 nurse		1.030 (0.085) [0.717]		
Absence due to sickness, lasting $\leq$ 7 days:				
RN of any band			0.966 (0.076) [0.656]	
Band 7–8 nurse				1.632*** (0.239) [<0.001]
Patient volume and characteristics	✓	✓	✓	✓
Time controls	✓	✓	✓	✓
Hospital ward fixed effects	✓	✓	✓	✓
N	18,922	18,922	18,922	18,922
Clusters	52	52	52	52

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward fixed effects. Robust standard errors, clustered at the hospital unit level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. See notes to Table 4 for a full list of controls.

7 Conclusion

This paper examines the role of team production in healthcare, a labour- and teamwork-intensive sector that accounts for a substantial fraction of employment in developed economies. We focus on teams of nurses, for whom collaboration, communication and knowledge sharing are crucial. Employing a novel, high-frequency dataset that links electronic staffing rotas to inpatient mortality records in a large NHS hospital Trust in England, we examine the impact of both the size and composition of nursing teams on team productivity, as measured by inpatient mortality rates among patients under their care.

We use qualifications and rank as a proxy for general human capital, and find that teams with higher levels of general human capital are more productive. An additional Nursing Assistant (NA) has no impact on the likelihood of a patient death, but a greater number of hours worked by Registered Nurses (RNs) is associated with lower inpatient mortality, with the magnitude of these effects increasing with qualifications and experience. The most senior nurses, who are responsible for managing their ward, are around 2.2 times as productive as their newly qualified counterparts. These results demonstrate that staffing shortages – endemic to the English NHS – have adverse consequences for patient care, but suggest that efforts to substitute less highly skilled NAs for RNs are unlikely to boost team performance.

We also find evidence that teams perform better when its constituent members are more familiar with their surroundings and each other. A greater amount of firm-specific human capital – as proxied by years of employment within the NHS Trust – is associated with better team performance. This effect exists only for RNs and not for NAs, indicating a complementarity between firm-specific and general human capital. There is suggestive evidence of separate returns to recent experience working in the ward (ward-specific human capital) and with other team members (team-specific human capital) which can partially offset a lack of general human capital. These findings suggest substantial benefits associated with continuity and limiting the disruptions to teams from high levels of staff turnover. If shared work experience were taken into account in the rostering of nursing staff, patient outcomes could improved even while holding the total volume of healthcare inputs fixed. More broadly, this work demonstrates that the overall size and skill mix of teams matters, but that location- or team-specific human capital can also improve team performance.

References

Arcidiacono, P., J. Kinsler, and J. Price (2017, January). Productivity Spillovers in Team Production: Evidence from Professional Basketball. Journal of Labor Economics 35(1), 191–225.

Bandiera, O., I. Barankay, and I. Rasul (2009). Social Connections and Incentives in the Workplace: Evidence From Personnel Data. Econometrica 77(4), 1047–1094.

Bandiera, O., I. Barankay, and I. Rasul (2013). Team Incentives: Evidence from a Firm Level Experiment. Journal of the European Economic Association 11(5), 1079–1114.

Bartel, A. P., N. D. Beaulieu, C. S. Phibbs, and P. W. Stone (2014, April). Human Capital and Productivity in a Team Environment: Evidence from the Healthcare Sector. American Economic Journal: Applied Economics 6(2), 231–259.

Becker, G. S. (1964). Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, First Edition. NBER.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013, February). Does Management Matter? Evidence from India. The Quarterly Journal of Economics 128(1), 1–51.

Burgess, S., C. Propper, M. Ratto, S. v. H. Kessler Scholder, and E. Tominey (2010, September). Smarter Task Assignment or Greater Effort: The Impact of Incentives on Team Performance. The Economic Journal 120(547), 968–989.

Burgess, S., C. Propper, M. Ratto, and E. Tominey (2017, October). Incentives in the Public Sector: Evidence from a Government Agency. The Economic Journal 127(605), F117–F141.

Chen, Y. (2021, December). Team-Specific Human Capital and Team Performance: Evidence from Doctors. American Economic Review 111(12), 3923–3962.

Cornelissen, T., C. Dustmann, and U. Schönberg (2017, February). Peer Effects in the Workplace. American Economic Review 107(2), 425–456.

Deloitte (2016). Global Human Capital Trends 2016. https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2016.html.

Deloitte (2021). 2021 Global Human Capital Trends: Special report. https://www2.deloitte.com/us/en/insights/focus/human-capital-trends.html.

Digital, N. NHS Workforce Statistics - October 2021.

Elixhauser, A., C. Steiner, D. R. Harris, and R. M. Coffey (1998, January). Comorbidity Measures for Use with Administrative Data. Medical Care 36(1), 8–27.

Fenizia, A. (2020). Managers and Productivity in the Public Sector. Working Paper, 22.

Friebel, G., M. Heinz, M. Krueger, and N. Zubanov (2017, August). Team Incentives and Performance: Evidence from a Retail Chain. American Economic Review 107(8), 2168–2203.

Friedrich, B. U. and M. B. Hackmann (2021, October). The Returns to Nursing: Evidence from a Parental-Leave Program. The Review of Economic Studies 88(5), 2308–2343.

Gibbons, R. and M. Waldman (2004, April). Task-Specific Human Capital. American Economic Review 94(2), 203–207.

Griffiths, P., J. Ball, J. Drennan, C. Dall'Ora, J. Jones, A. Maruotti, C. Pope, A. Recio Saucedo, and M. Simon (2016, November). Nurse staffing and patient outcomes: Strengths and limitations of the evidence to inform policy and practice. A review and discussion paper based on evidence reviewed for the National Institute for Health and Care Excellence Safe Staffing guideline development. International Journal of Nursing Studies 63, 213–225.

Griffiths, P., A. Maruotti, A. Recio Saucedo, O. C. Redfern, J. E. Ball, J. Briggs, C. Dall'Ora, P. E. Schmidt, and G. B. Smith (2019, August). Nurse staffing, nursing assistants and hospital mortality: Retrospective longitudinal cohort study. BMJ Quality & Safety 28(8), 609–617.

Gruber, J. and S. A. Kleiner (2012, February). Do Strikes Kill? Evidence from New York State. American Economic Journal: Economic Policy 4(1), 127–157.

Guryan, J., K. Kroft, and M. J. Notowidigdo (2009, September). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. American Economic Journal: Applied Economics 1(4), 34–68.

Haggag, K., B. McManus, and G. Paci (2017, January). Learning by Driving: Productivity Improvements by New York City Taxi Drivers. American Economic Journal: Applied Economics 9(1), 70–95.

Hamilton, B. H., J. A. Nickerson, and H. Owan (2003, June). Team Incentives and Worker Heterogeneity: An Empirical Analysis of the Impact of Teams on Productivity and Participation. Journal of Political Economy 111(3), 465–497.

Huckman, R. S. and G. P. Pisano (2006, April). The Firm Specificity of Individual Performance: Evidence from Cardiac Surgery. Management Science 52(4), 473–488.

Jaravel, X., N. Petkova, and A. Bell (2018, April). Team-Specific Capital and Innovation. American Economic Review 108(4-5), 1034–1073.

Jarosch, G., E. Oberfield, and E. Rossi-Hansberg (2021). Learning From Coworkers. Econometrica 89(2), 647–676.

Jones, B. F. (2021, May). The Rise of Research Teams: Benefits and Costs in Economics. Journal of Economic Perspectives 35(2), 191–216.

Lazear, E. P. and K. L. Shaw (2007, December). Personnel Economics: The Economist's View of Human Resources. Journal of Economic Perspectives 21(4), 91–114.

Lazear, E. P., K. L. Shaw, and C. T. Stanton (2015, October). The Value of Bosses. Journal of Labor Economics 33(4), 823–861.

Levitt, S. D., J. A. List, and C. Syverson (2013, August). Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant. Journal of Political Economy 121(4), 643–681.

Lin, H. (2014). Revisiting the relationship between nurse staffing and quality of care in nursing homes: An instrumental variables approach. Journal of Health Economics, 12.

Mas, A. and E. Moretti (2009, February). Peers at Work. American Economic Review 99(1), 112–145.

Mincer, J. A. (1974). Schooling, Experience, and Earnings. NBER.

Müller, J., T. Upmann, and J. Prinz (2013). Individual Team Productivity - A Conceptual Approach. Tinbergen Institute Discussion Paper TI 2013-183/I.

Needleman, J., C. L. Leibson, and M. Harris (2011). Nurse Staffing and Inpatient Hospital Mortality. The New England Journal of Medicine, 10.

OECD (2016). Health Workforce Policies in OECD Countries: Right Jobs, Right Skills, Right Places. https://www.oecd.org/publications/health-workforce-policies-in-oecd-countries-9789264239517-en.htm.

Parsons, D. O. (1972, November). Specific Human Capital: An Application to Quit Rates and Layoff Rates. Journal of Political Economy 80(6), 1120–1143.

Propper, C. and J. Van Reenen (2010, April). Can Pay Regulation Kill? Panel Data Evidence on the Effect of Labor Markets on Hospital Performance. Journal of Political Economy 118(2), 222–273.

Rafferty, A. M., S. P. Clarke, J. Coles, J. Ball, P. James, M. McKee, and L. H. Aiken (2007, February). Outcomes of variation in hospital nurse staffing in English hospitals: Cross-sectional analysis of survey data and discharge records. International Journal of Nursing Studies 44(2), 175–182.

A Appendix

A.1 Additional definitions

Staffing variables used in Table 4

$$FillRateNA_{it} = 100 * \frac{\text{Hours worked by NAs in ward } i \text{ on day } t}{\text{Planned NA hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it} = 100 * \frac{\text{Hours worked by RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Band5} = 100 * \frac{\text{Hours worked by Band 5 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Band6} = 100 * \frac{\text{Hours worked by Band 6 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Band7and8} = 100 * \frac{\text{Hours worked by Band 7 and 8 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Local} = 100 * \frac{\text{Hours worked by Local (regular) RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Bank} = 100 * \frac{\text{Hours worked by Bank RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{Agency} = 100 * \frac{\text{Hours worked by Agency RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{LocalBand5} = 100 * \frac{\text{Hours worked by Local Band 5 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{BankBand5} = 100 * \frac{\text{Hours worked by Bank Band 5 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

$$FillRateRN_{it}^{AgencyBand5} = 100 * \frac{\text{Hours worked by Agency Band 5 RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

Additional staffing variables used in Table 5:

$$\text{Average experience in the Trust} = \overline{X}_{kt} = \frac{1}{|T_{kt}|} \sum_{i \in T_{kt}} X_{iht}$$

$$\text{Average experience in the Trust for RNs} = \overline{X}_{kt}^{RN} = \frac{1}{|T_{kt}|} \sum_{i \in T_{kt}^{RN}} X_{iht}$$

$$\text{Average experience in the Trust for NAs} = \overline{X}_{kt}^{NA} = \frac{1}{|T_{kt}|} \sum_{i \in T_{kt}^{NA}} X_{iht}$$

where T_{kt} is the team working in ward k on day t, T_{kt}^{RN} is the set of RNs working in ward k on day t, and T_{kt}^{NA} is the set of NAs working in ward k on day t. X_{iht} is defined (as per Section 3) as the amount of time (in years) that individual i has been employed in the NHS Trust at date t.

Additional staffing variables used in Table 6:

In Section 3, we define:

$$Y_{ihkt} = \sum_{\tau=t-90}^{t-1} \mathbb{1}(i \in T_{\tau k}) \forall k \in K(h)$$
$$WardShifts_{ihkt}^{5} = \mathbb{1}(Y_{ihkt} \geq 5) \text{ and } WardShifts_{ihkt}^{10} = \mathbb{1}(Y_{ihkt} \geq 10)$$
$$FirstShift_{ihkt} = \mathbb{1}(Y_{ihkt} = 0 \wedge i \in T_{kt})$$
$$NewJoiner_{ihkt} = \mathbb{1}(\sum_{\tau=t-30}^{t} FirstShift_{ikh\tau} > 0 \wedge i \in T_{kt})$$

where Y_{ihkt} represents the number of times the individual has worked in ward k in the previous 90 days. We define a 'new joiner' as any member of staff with $NewJoiner_{ihkt} = 1$. We can then define the following staffing variables:

$$FillRateRNNewJoiner_{it} = 100 * \frac{\text{Hours worked by new joiner RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNnonNewJoiner_{it} = 100 * \frac{\text{Hours worked by non-new joiner RNs in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNShiftsMore5_{it} = 100 * \frac{\text{Hours by RNs with } WardShifts_{ihkt}^{5} = 1 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNShiftsMore10_{it} = 100 * \frac{\text{Hours by RNs with } WardShifts_{ihkt}^{10} = 1 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNShiftsLess5_{it} = 100 * \frac{\text{Hours by RNs with } WardShifts_{ihkt}^{5} = 0 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNShiftsLess10_{it} = 100 * \frac{\text{Hours by RNs with } WardShifts_{ihkt}^{10} = 0 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

Additional staffing variables used in Table 7:

In Section 3, we define:

$$E(i,j,t) = \sum_{k \in K(h)} \sum_{\tau=t-90}^{t-1} \mathbb{1}(i \in T_{\tau k} \wedge j \in T_{\tau k})$$

$$Z_{-ihkt} = \frac{1}{|T_{kt}| - 1} \cdot \sum_{j \in T_{kt}, j \neq i} E(i,j,t)$$

$$\overline{Z}_{kt} = \frac{1}{|T_{kt}|} \sum_{i \in T_{kt}} Z_{-ihkt}$$

$$SharedExp^{5}_{-ihkt} = \mathbb{1}(Z_{-ihkt} \geq 5 \wedge i \in T_{kt})$$

where Z_{-ihkt} represents average shared work experience with other team members over the past 90 days (in any ward). We can then define:

$$FillRateRNSharedMore5_{it} = 100 * \frac{\text{Hours by RNs with } SharedExp^{5}_{ihkt} = 1 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNSharedLess5_{it} = 100 * \frac{\text{Hours by RNs with } SharedExp^{5}_{ihkt} = 0 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNSharedMore5^{Band5}_{it} = 100 * \frac{\text{Hours by Band 5s with } SharedExp^{5}_{ihkt} = 1 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$
$$FillRateRNSharedLess5^{Band5}_{it} = 100 * \frac{\text{Hours by Band 5s with } SharedExp^{5}_{ihkt} = 0 \text{ in ward } i \text{ on day } t}{\text{Planned RN hours in ward } i \text{ on day } t}$$

A.2 Additional results

Table A1: Robustness of main results to inclusion of unit-month fixed effects

	Outcome: patient death			
	(1)	(2)	(3)	(4)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.002 (0.004) [0.533]	1.002 (0.004) [0.532]	1.002 (0.004) [0.525]	1.002 (0.004) [0.525]
Share (ppt) of planned Registered Nurse (RN) hours filled	0.988* (0.007) [0.065]			
Share (ppt) of planned Registered Nurse (RN) hours filled by:				
Band 5 nurses		0.990 (0.007) [0.117]		
Band 6 nurses		0.984** (0.008) [0.040]		0.984** (0.007) [0.038]
Band 7 and 8 nurses		0.975** (0.011) [0.022]		0.975** (0.011) [0.021]
Local (regular) nurses			0.987* (0.007) [0.053]	
Bank nurses			0.987* (0.007) [0.063]	
Agency nurses			0.993 (0.007) [0.304]	
Band 5 Local and Bank nurses				0.989 (0.007) [0.100]
Band 5 Agency nurses				0.992 (0.007) [0.278]
Patient volume and characteristics	✓	✓	✓	✓
Time controls	✓	✓	✓	✓
Hospital ward – month fixed effects	✓	✓	✓	✓
N	13,362	13,362	13,362	13,362
Clusters	440	440	440	440

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward – month fixed effects. Robust standard errors, clustered at the hospital unit – month level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. All regressions control for the mean patient age; the mean patient age^2; the female share of patients; the non-white share of patients; the mean Elixhauser Comorbidity Index; pairwise interaction terms between age, female share, non-white share and Elixhauser Cormorbidity Index; the mean hospital length of stay of patients treated in the unit that day; the number of patients treated in the unit that day; a dummy for each day of the week; and a dummy indicating whether the day was a bank holiday.

Table A2: Robustness of main results to inclusion of unit-quarter fixed effects

	Outcome: patient death			
	(1)	(2)	(3)	(4)
Share (ppt) of planned Nursing Assistant (NA) hours filled	1.003 (0.004) [0.454]	1.003 (0.004) [0.450]	1.003 (0.004) [0.445]	1.003 (0.004) [0.444]
Share (ppt) of planned Registered Nurse (RN) hours filled	0.987** (0.006) [0.041]			
Share (ppt) of planned Registered Nurse (RN) hours filled by:				
Band 5 nurses		0.988* (0.007) [0.080]		
Band 6 nurses		0.984** (0.007) [0.029]		0.984** (0.007) [0.029]
Band 7 and 8 nurses		0.975** (0.011) [0.019]		0.975** (0.011) [0.019]
Local (regular) nurses			0.986** (0.006) [0.034]	
Bank nurses			0.986** (0.007) [0.041]	
Agency nurses			0.991 (0.007) [0.210]	
Band 5 Local and Bank nurses				0.988* (0.007) [0.069]
Band 5 Agency nurses				0.991 (0.007) [0.206]
Patient volume and characteristics	✓	✓	✓	✓
Time controls	✓	✓	✓	✓
Hospital ward – quarter fixed effects	✓	✓	✓	✓
N	17,398	17,398	17,398	17,398
Clusters	191	191	191	191

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Coefficients shown are odds ratios from a fixed-effect logit regression, with hospital ward – quarter fixed effects. Robust standard errors, clustered at the hospital unit – month level, are shown in parentheses; p-values are shown in square brackets. The unit of analysis is the hospital unit-day. All regressions control for the mean patient age; the mean patient age^2; the female share of patients; the non-white share of patients; the mean Elixhauser Comorbidity Index; pairwise interaction terms between age, female share, non-white share and Elixhauser Cormorbidity Index; the mean hospital length of stay of patients treated in the unit that day; the number of patients treated in the unit that day; a dummy for each day of the week; and a dummy indicating whether the day was a bank holiday.

Figure A1: Distribution of time of recorded patient death

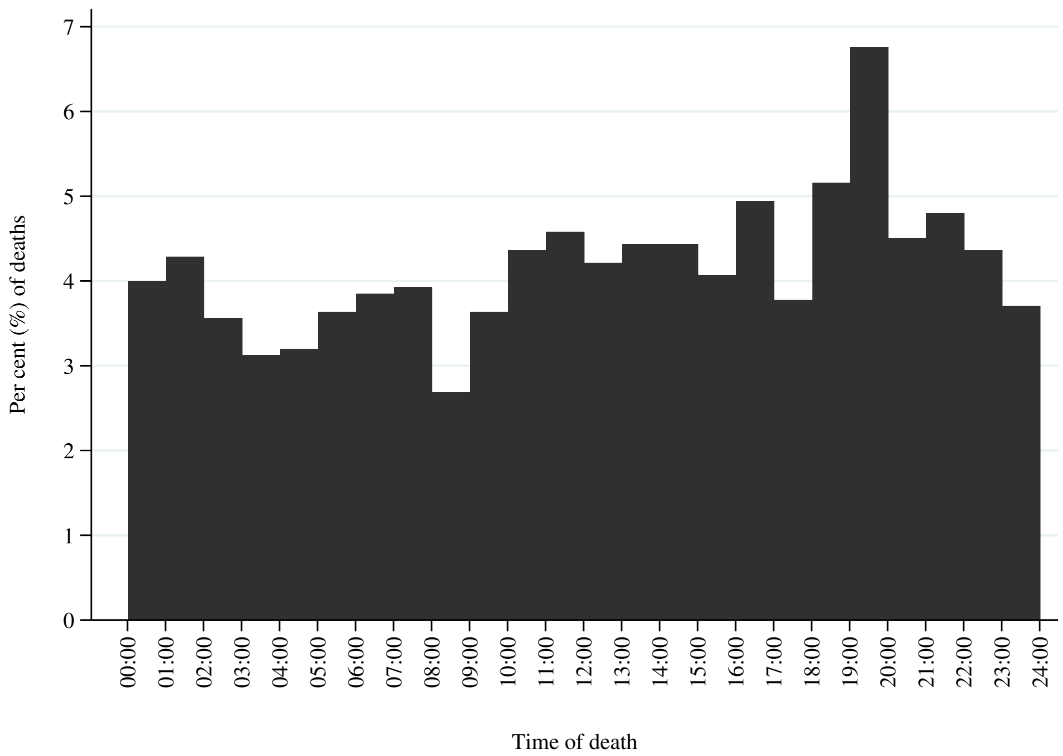
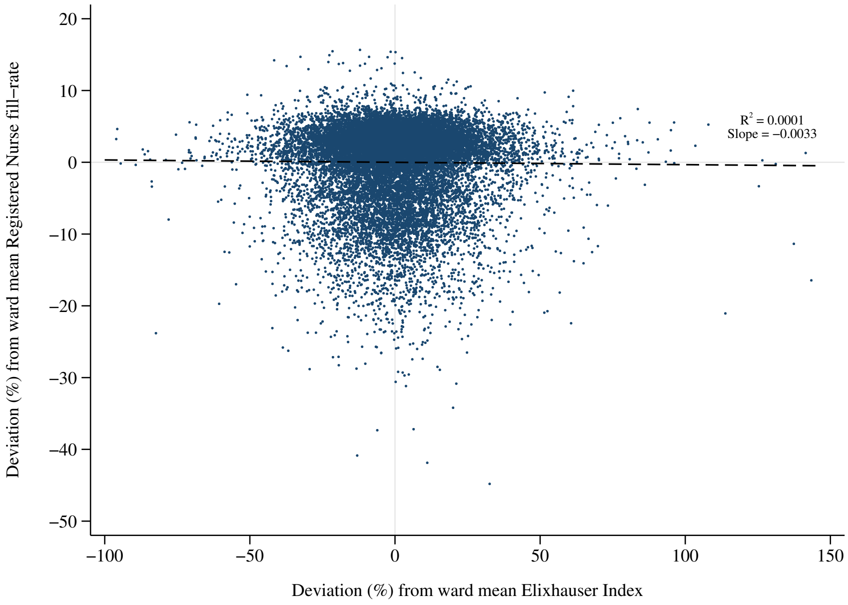
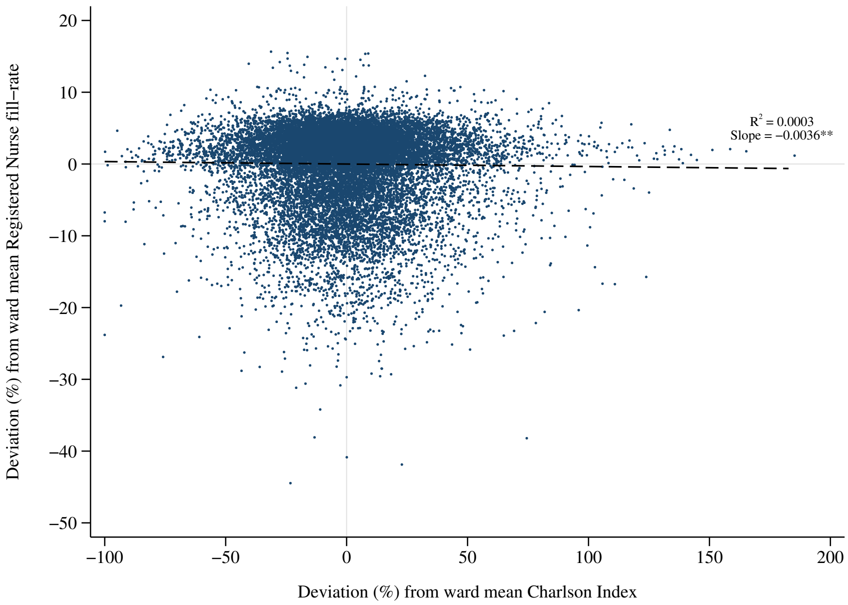


Figure A2: Relationship between Registered Nurse staffing levels and patient comorbidity

(a) Elixhauser Comorbidity Index



(b) Charlson Comorbidity Index



Note: each point denotes an observation (i.e. a team, defined as a hospital unit-day). Values are calculated relative to the unit mean, as our baseline specification includes unit fixed effects, and so all results are identified from within-unit variation.