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Learning from Many: Partner Exposure and Team Familiarity in Fluid Teams

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In services where teams come together for short collaborations, managers are often advised to strive for high team familiarity so as to improve coordination and, consequently, performance. However, inducing high team familiarity, by keeping team membership intact, can limit workers' opportunities to acquire useful knowledge and alternative practices from exposure to a broader set of partners. We introduce an empirical measure for prior partner exposure and estimate its impact (along with that of team familiarity) on operational performance using data from the London Ambulance Service. Our analysis focuses on ambulance transports involving new paramedic recruits, where exogenous changes in team membership enable identification of the performance effect. Specifically, we investigate the impact of prior partner exposure on time spent during patient pick-up at the scene and patient handover at the hospital. We find that the effect varies with the process characteristics. For the patient pick-up process, which is *less standardized*, greater partner exposure directly improves performance. For the *more standardized* patient handover process, this beneficial effect is triggered beyond a threshold of sufficient individual experience. In addition, we find some evidence that this beneficial performance impact of prior partner exposure is amplified during periods of high workload, particularly for the patient handover process. Finally, a counterfactual analysis based on our estimates shows that a team formation strategy emphasizing partner exposure outperforms one that emphasizes team familiarity by about 9.2% in our empirical context.

Key words: Fluid teams, membership change, partner exposure, team familiarity
History: July 7, 2020

1. Introduction

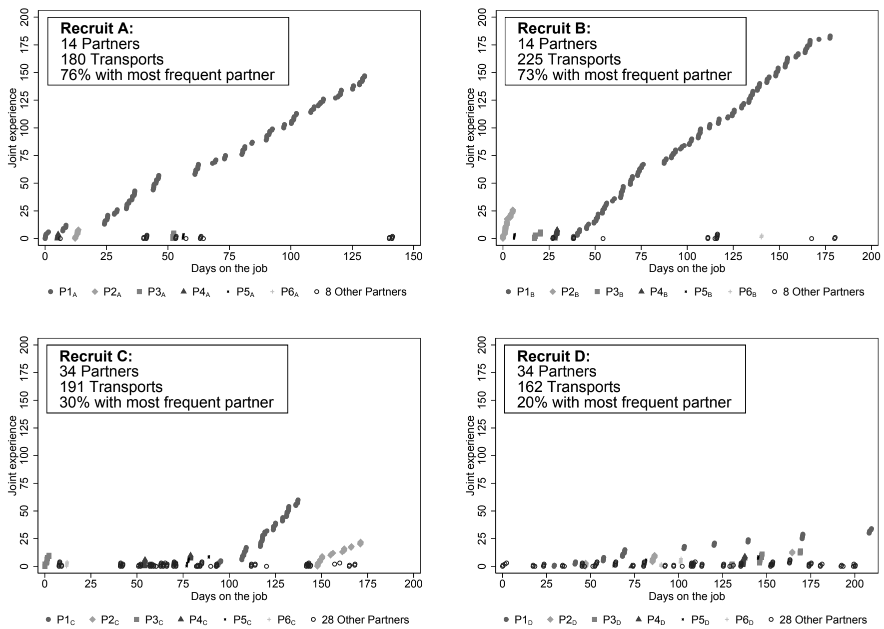
In a wide variety of operational environments such as in-flight hospitality, police patrol, ambulance transport, and surgical procedures, teams are *fluid*, i.e., assembled for short collaborations and then disbanded. In such settings, more familiar teams, comprising individuals who have worked more often with each other, yield significantly better performance due to improved coordination and shared knowledge about the task at hand (Reagans et al. 2005, Huckman et al. 2009). As a result, operations managers are advised to keep teams intact to the extent possible (Huckman and Staats 2013). In establishing these findings the literature has thus far not considered the potential benefits of being exposed to the working practices of multiple partners over time. However, existing theoretical arguments and experimental findings suggest that changes in team membership can enhance creativity and problem solving (March 1991, Arrow and McGrath 1993, Choi and Thompson 2005, Gruenfeld et al. 2000, Lewis et al. 2007, Kane et al. 2005). Knowing whether being exposed to a diverse set of partners translates into improved operational performance in field settings and how these benefits compare with those of team familiarity can help managers decide on optimal team formation strategies (Huckman and Staats 2013).

We address this question using data on ambulance transports from the London Ambulance Service (LAS) involving new paramedic recruits. Generally, ambulance transports are conducted by teams of two paramedics. In contrast to senior paramedics, who usually have stable, long-term partners, new recruits are scheduled on a *relief roster* for the first two years of their service, which provides exogenous variation in their partner assignments[1]. As an example, Figure 1 depicts how the individual experience of 4 particular new recruits is distributed across partners in their first year. The figure also highlights the distinction between team familiarity—the prior joint experience with only the partner at hand (on the Y-axis)—and the distribution of experience across all prior partners, introduced in this paper as an individual's *prior partner exposure.*

We expect the operational benefits of prior partner exposure to depend on the level of standardization of the process in which a worker is engaged. For instance, the patient pick-up process at the scene involves on-scene diagnosis, treatment and transfer to ambulance in a wide variety of physical, social, and emotional situations under limited guidelines. In a less standardized or *divergent* (Shostack 1987) process such as this, workers are likely to rely on tacit knowledge and have considerable executional latitude in applying it. Consequently, they are likely to benefit from prior

[1] See more detail about scheduling in §3.1. In addition, we conduct empirical checks to verify these aspects of relief roster scheduling in e-companion A. Based on our analysis, we do not find any evidence that new recruits are more likely to be assigned a stable senior partner or are more likely to spend longer time with him/her as their experience grows. Similarly, prior performance is not associated with frequency of partner changes or the number of senior paramedics present on new recruits' ambulance transports. This is consistent with the LAS managers' statements that the scheduling of new recruits on the relief roster is driven by operational convenience rather than considerations of the new recruits' experience or performance.

Figure 1 **Partner experience of 4 new recruits during 2011.**



Note. The x-axis is the timeline from when the new recruit joins LAS until the end of the year. Each dot is a transport, its color corresponding to a particular partner (with the most infrequent partners displayed as one color). Its y-value shows the team familiarity (number of prior joint transports) with the partner. The most frequent partner of new recruit A during the year is denoted by $P1_A$, the second most frequent by $P2_A$, etc. We observe that *Recruit* A encountered only 14 partners during the year and worked with one specific partner for 76% of her ambulance transports. In contrast *Recruit D* worked with a specific partner for at most 20% of her transports and encountered 34 distinct partners in total.

partner exposure as it offers them the opportunity to observe different ways to perform process tasks and choose the best among them. In contrast, the patient handover process at the Accident & Emergency (A&E) department of a hospital involves communication of clinical information to a triage nurse using well-defined patient report forms and physical transport of the patient to an available bed across relatively uniform physical layouts. In a more standardized or routine process such as this, team members can rely on the standard operating procedures (SOPs). They are likely to overrule those only if they expect the useful knowledge they have gained by observing a diverse set of partners to substantially improve performance. As a result, the beneficial effects of prior partner exposure may start to manifest themselves only after individual team members have accumulated sufficient experience. In addition, the magnitude of performance benefits due to prior partner exposure is likely to depend on the paramedic workload. Based on prior work demonstrating that workers adjust service rates at times of high workload (Delasay et al. 2018), we expect increased access to useful knowledge through partner exposure to result in enhanced performance improvements during periods of higher workload.

We conduct our empirical analysis on a dataset comprising operational and clinical information on 5,773 ambulance transports staffed by one of the 81 new recruits (recruited in 2011) along with one or more of 702 senior paramedics, during the 2011. We measure prior partner exposure using a Herfindahl-Hirschman Index (HHI) of a new recruit's distribution of cumulative experience over prior partners. Since the variation in partner exposure across new recruits, demonstrated in Figure 1, is due to the administrative role of the relief roster and is exogenous to performance, our data allows for a clean identification of our main effects.

Our work contributes towards understanding the joint performance impact of team familiarity and partner exposure. We develop and introduce the notion of prior partner exposure into the team productivity literature and operationalize it using an HHI measure. We jointly estimate the impact of prior partner exposure and team familiarity on operational performance, using data from a setting which allows for a clean identification of both effects. We find that the impact of prior partner exposure depends on the type of process at hand; observing a direct performance effect on a less standardized process (patient pick-up at the scene) but an experience-moderated effect on a more standardized process (patient handover at the hospital). In addition, we find some evidence that the beneficial impact of prior partner exposure on performance is amplified during periods of high workload, particularly for the patient handover process. Finally, we use our model estimates to show that a scheduling strategy favoring partner exposure would outperform one favoring team familiarity in our setting.

2. Literature review

In this section, we first review the recent literature on team productivity and distinguish prior partner exposure from prior work. Next, we discuss extant experimental studies on the impact of new team members on group creativity before reviewing the evidence on how process characteristics and team composition interact in affecting operational performance. Finally, we discuss existing results on the impact of workload on worker service rates.

2.1. Operational team productivity

Recent literature has identified team familiarity—measured by the average number of times team members have worked with each other in the past—as one of the key drivers of operational performance of fluid teams[2] (Reagans et al. 2005, Boh et al. 2007, Huckman et al. 2009, Huckman and Staats 2011). It is argued that greater experience of working with each other enables team members to learn "who knows what" thereby resulting in more effective division of labor and coordination of individual tasks and activities. Reagans et al. (2005) find that surgical teams whose members

[2] A team is considered *fluid* if team members temporarily work together to generate output, before the team is disassembled and its members move on to other tasks (Huckman and Staats 2011).

have greater experience of working with each other have shorter surgical completion times. Boh et al. (2007) and Huckman et al. (2009) find similar results in the context of software development. In contrast, in the context of stable teams, excessive team familiarity has been shown to be detrimental to team performance over the long run (Huckman and Staats 2013). Katz (1982) reports that R&D teams that remained together for more than 3.5 years on average showed a decline in performance due to reduced communication among team members and reduced interaction with external knowledge sources. Berman et al. (2002) find a similar relationship between shared team experience and team performance for professional basketball teams in the NBA. They attribute this effect to a phenomenon termed as knowledge ossification, where the body of tacit knowledge held jointly by the team starts depleting if the team is not infused with new ideas from external sources. Our contribution to this literature is twofold. On the conceptual front, we develop the notion of prior partner exposure that is distinct from team familiarity; this is also reflected in their respective quantitative definitions. On the empirical front, we show that prior partner exposure has a beneficial effect on the performance of fluid teams in the short run, which is different from the adverse effect of excessive team familiarity on performance of stable teams over the long run. Thus, our results indicate the existence of two simultaneous effects in the short run: team familiarity improves coordination among team members on a given task whereas prior partner exposure broadens the knowledge base of the team members.

A related stream of literature has documented how diversity in tasks and customers served can help teams build a diverse knowledge base and thus improve performance over time (Boh et al. 2007, Narayanan et al. 2009, Staats and Gino 2012, Narayanan et al. 2013, Huckman and Staats 2011, Clark et al. 2013). Similar questions of scope and scale have been studied at the organizational level (Clark and Huckman 2012, Freeman et al. 2018). Our results show that the benefits of a diverse knowledge base can also be accrued through diversity of prior partners for individual workers. This effect is especially relevant if there is minimal task or customer diversity but processes required to complete the tasks are divergent (Shostack 1987), i.e., the same task for the same customer can be (and is) carried out in multiple different ways.

Finally, a recent paper by Kim et al. (2019) extends our work by jointly estimating the impact of partner variety (number of prior partners) and team familiarity of physicians and nurses on time to disposition in an emergency department. In contrast to our results demonstrating the benefit of prior partner exposure, they find limited benefits of partner variety. A likely explanation is the difference in the variable definition (we also find a less pronounced performance impact of partner variety than prior partner exposure as part of our robustness checks (Table 14 in e-companion)).

2.2. Experimental studies of team membership changes

Our concept of prior partner exposure and the proposed mechanism of its impact on team performance are partly motivated by prior literature on membership changes. March (1991) theorizes that employee turnover and interaction of new team members with existing members create diversity in the knowledge base, which facilitates *exploration* of new ideas. This has been validated by experimental studies that find improvement in team creativity following exogenous membership changes. Gruenfeld et al. (2000) make one member of an essay-writing group rotate through other groups and find that his return to the original group stimulates significantly more ideas among members who did not rotate. Similarly, Choi and Thompson (2005) compare two types of groups—open (i.e., experiencing membership changes) and closed (i.e., no membership changes)—and find that open groups generate a larger number of ideas as well as more diverse ideas. Our work differs from these experimental studies on three key dimensions. First, our context comprises fluid teams, not dichotomous open or closed groups. Second, our outcome is operational performance, as compared to a measure of team's ability to generate ideas. Third, in addition to prior partner exposure, we measure the impact of team familiarity, which was not considered in this experimental literature.

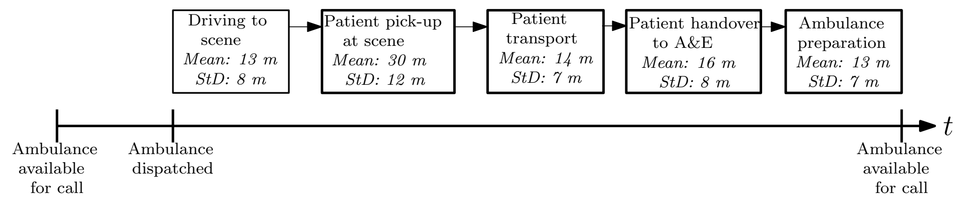
2.3. Process characteristics and operational performance

A growing body of literature documents how underlying characteristics of the process and associated knowledge moderate the effect of team characteristics on performance. Huckman and Staats (2011) show that greater familiarity enables teams to better cope with changes in task description. Arrow and McGrath (1993) find that student teams that experience membership change perform better on tasks requiring more active reflection by team members (e.g. essay writing). Similarly, Argote et al. (1995) show experimental evidence that the negative effects of membership change on team performance are less pronounced for complex tasks. On the flip side, Espinosa et al. (2007) find that beneficial effects of team familiarity decline for more complex tasks. Lapré and Van Wassenhove (2001) suggest that teams with a more diverse knowledge base are more effective in understanding causal mechanisms, which are necessary for transferring non-codified knowledge. Hansen (1999) finds that knowledge transfer between organizational units who have infrequent contact (also called weak ties, see Granovetter (1973)) is effective for codified knowledge but less so for complex or tacit knowledge. Our results contribute to this literature by suggesting that the effects of partner exposure may also be contingent on the characteristics of the underlying process and the type of knowledge required to execute it.

2.4. Workload and operational performance

Finally, a stream of research has demonstrated how workload can impact processing rates in various service systems (see Delasay et al. (2018), for an overview). This literature has identified ways

Figure 2 Ambulance transport process diagram



Ambulance utilized		✓	✓	✓	✓	✓
Ambulance crew with patient			✓	✓	✓	
Time duration largely under crew control			✓		✓	✓

in which workers can react at times of high workload, in the absence of formal process changes, in order to minimize disruptions—e.g., in the form of long waits—due to the high utilization. Batt and Terwiesch (2016) consider a multistage service operation and identify early-task-initiation (proactively initiating tasks to shorten delays) as a response mechanism to high workload in an emergency department. Kim et al. (2014) show that ICU admission decisions become more conservative. Freeman et al. (2016) find that midwives manage their workload through the rationing of services and by adjusting specialist referral rates. Berry-Jaeker and Tucker (2016) show that speeding up (e.g. through early discharge) can only relieve workload up to a saturation point, beyond which it no longer mitigates the workload. Kuntz et al. (2014) find evidence of health outcomes deteriorating beyond a tipping point in utilization. We contribute to this literature by showing that workers with high degree of prior partner exposure are able to shorten task completion times to a greater extent than their counterparts with less prior partner exposure, during periods of high workload.

3. Empirical setting: London Ambulance Service

In the first part of this section, we provide a brief overview of the operating structure of LAS and its crew scheduling policies, based on extensive interviews with its management and staff (§3.1). In the second part of this section, we provide a detailed description of the processes involved in ambulance transport based on field observations on ambulance runs and at the dispatch center (§3.2) as well as interviews with ambulance crews.

3.1. Operating structure and policies

3.1.1. Dispatching. The LAS operates over 100 ambulance stations spread across the city of London. A central control center at the LAS headquarters receives and triages all emergency calls and transfers them to one of the three dispatch desks (West, East, and South) depending on the location of the incident. Each dispatch desk comprises six dispatch sectors, each of which has a designated dispatcher, responsible for assigning ambulances to incidents as the need arises.

Table 1 **End-of-year statistics (for final sample of new recruits)**

Variable	Mean	St. Dev.
# of ambulance transports	155	119
# of partners	16	11
% of transports with the most frequent partner	29%	26%
# of A&E departments	11	5
% of transports to most frequent A&E department	35%	15%
# of ambulance stations	4	2
% of transports at most frequent ambulance station	39%	27%
# patient transports per shift	3	1.5
# of unique sets of partners within a shift	1	0.12

3.1.2. Shift scheduling. On a daily basis, paramedics are scheduled to shifts of various lengths (8, 9, 10, or 12 hours in duration) and with varying start times throughout the day and night (LAS 2017), to match the variable demand for ambulance transport. Paramedics with more than two years of experience are permanently assigned to one of the ambulance stations and typically have a stable partner and shift pattern. In contrast, during the first two years of tenure at LAS, new recruits are scheduled on a *relief roster*, which is used for: (i) staffing of normal shifts when stable partners of senior paramedics go on (scheduled or un-scheduled) leave, (ii) scheduling extra capacity for special events, and (iii) filling unpopular shifts. This scheduling is done by a central resources team at LAS, whose priority is to satisfy administrative rules such as allowing for eight hours of rest between consecutive shifts, giving adequate notice before shift changes, and trying to schedule new recruits close to their home base. Thus, new recruits on the relief roster are frequently assigned different partners from different stations for a short period (e.g., one shift) on the basis of administrative convenience rather than previous performance or partners[3].

Table 1 includes summary statistics describing the experience of new recruits for their first year on the relief roster. We observe that new recruits conducted, on average, 115 transports during 2011. The large standard deviation (119) is mostly due to the fact that new recruits started their job at LAS at varying time-points throughout the year. The average new recruit worked with 16 partners, was dispatched from 4 distinct ambulance bases in London, and visited 11 different A&E departments. In an average shift, the new recruits worked with only one partner and transported 3 patients from a scene to an A&E. E-companion A provides a more detailed analysis of the scheduling of the relief roster. In summary, we find no evidence that new recruits are more likely to be assigned a stable senior partner or are more likely to spend longer time with him/her as their experience grows. Similarly, their first month performance is not associated with subsequent partner changes.

[3] In fact, our correspondence with LAS has revealed that the variability in partner assignment (as illustrated in Figure 1) "is not planned, it just depends on who else is off work, which cannot be predicted on all occasions" (LAS 2017). Rather, this results in a system in which "as a relief you will have many partners as you are filling in for those absent from work" (LAS 2017).

Table 2 Illustration of the variety of scene scenarios encountered on a single day, during one of the field visits conducted by the authors

Patient	Description	Clinical challenges	Non-clinical challenges
1: Male (90)	Lives with daughter; severe diarrhoea	Patient senile; had a serious diarrhoea episode; cause unclear.	Calming hysterical daughter; cleaning; and carrying patient down stairs.
2: Male (42)	Drug addict; haemorrhage	No clear diagnosis; medical history unclear.	Getting the patient (stuck in a motel room) to ambulance; and rationing 'gas and air'.
3: Male (50)	French tourist; dizzy, shortness of breath	No clear diagnosis; unclear need for tests; some simple tests conducted.	Communication; getting a clear description of the symptoms.
4: Female (80)	Senile; lit hair on fire	Understanding which medicine the woman had taken.	Explaining situation to the senile woman.
5: Female (50)	Speaks no English; rapid heartbeat	No clear diagnosis; multiple tests conducted, in apartment and ambulance.	Entire family observing; only one English speaker.

3.2. Ambulance transport processes

Figure 2 depicts the process flow for a typical ambulance transport from the moment an ambulance is dispatched for an emergency call until its crew becomes available again for the next dispatch after handing over the patient to the A&E. Shortening the duration of the processes in Figure 2 is an important operational objective for LAS because it reduces response times and increases ambulance availability thereby improving patient outcomes.

3.2.1. Dispatch. Once an emergency call has been triaged by the call center, the incident location, along with its severity score, appears on the computer terminal of the dispatcher responsible for that dispatch sector. The dispatcher also observes the location and status of the emergency vehicles closest to the scene and makes the dispatch decision based on this information. When called upon to be dispatched, an ambulance crew drives to the scene as quickly as possible.

3.2.2. Patient pick-up. A simplified description of the work performed by an ambulance crew at the scene is that it must locate and stabilize the patient, conduct a rudimentary diagnosis of his condition, and bring the patient into the ambulance for transport to an A&E. However, situations at the scene differ substantially along clinical and non-clinical dimensions making it impossible to fully specify the process or knowledge required to guarantee good operational (scene time) or clinical (patient outcome) performance (LAS 2015). Table 2 demonstrates the variety of challenges met by an ambulance crew during a single shift, on clinical as well as non-clinical dimensions.

On the clinical dimension, the paramedics must make diagnosis and treatment decisions regarding pain management and drug administration. They must immediately ensure that a patient's airway is clear and breathing is normal, and conduct a circulatory and disability assessment, while simultaneously taking into account the legal and ethical considerations of their actions (Fisher et al. 2006). On some occasions the clinical diagnosis is straightforward, given the symptoms (e.g., Patient 1 in Table 2 had diarrhoea whereas Patient 4 had lit her hair on fire). However, on other occasions, the clinical task is difficult if symptoms cannot be directly linked to a particular condition (Patients 3 and 5). In such cases, the ambulance crew members must rely on their experience and knowledge to decide whether to conduct a battery of tests at the scene (Patient 5) or to rush to the A&E after only a couple of simple tests (Patient 3).

On the non-clinical dimension, the physical and social surroundings at the scene can create challenges for paramedics. Carrying a 90 year old down a narrow staircase in a high-rise building or trying to move a wheelchair-bound drug addict through a narrow motel room door that does not accommodate a wheelchair (Patients 1 and 2, respectively) are two specific examples that capture the nature of these challenges. Interacting with family members of patients, bystanders, or patients themselves may also require varied skills and tact depending on their emotional state (Patient 1). Similarly, the non-clinical dimension can interact with the clinical dimension. For instance, the assessment of symptoms can be difficult because of language barriers (e.g., Patients 3 and 5). In summary, the variety of medical and non-medical considerations that the paramedics must account for and deal with as part of their job make the patient pick-up process at the scene a divergent one (Shostack 1987) thereby precluding the creation of explicit SOPs[4].

3.2.3. Patient transport. Once the ambulance crew has administered the appropriate level of care at the scene and safely brought the patient into the ambulance, the patient is taken to an A&E as quickly as possible. The ambulance crew chooses the geographically closest A&E based on information available on a computer screen and thereafter follows the shortest driving route to it.

3.2.4. Patient handover. In the UK, barring extremely serious cases[5], ambulance patients arrive to the A&E through a special entrance but are not prioritized over other A&E patient arrivals as part of a deliberate policy to encourage self-transportation and reduce ambulance utilization. Upon their arrival at the A&E, the ambulance crew places the patient at the end of the queue in front of the triage nurse's station. Thereafter, the crew assigns the responsibility of the patient to the A&E staff in two steps. First, when the triage nurse becomes available, the crew communicates the main clinical information about the patient using a standardized patient report form. The triage nurse, aided by a standard checklist and results of diagnostic tests, if any, assigns the patient to one of the three A&E units: minor incidents, major incidents, or resuscitation. Second, upon assignment, the crew physically moves the patient to the corresponding unit and places the patient safely in an empty bed as suggested by the head nurse of that unit. Finally, the crew obtains the signature of the head nurse to confirm transfer of patient responsibility.

[4] When asked about the variety of non-clinical issues, a crew member replied that the best characterization of their job at the scene was, in fact, 'problem solving'.

[5] For extremely serious cases, the crew gives advance notice to the resuscitation unit on its way to the A&E using a "blue call" and bypasses the triage nurse upon arrival. We control for such cases in our analysis.

3.2.5. Ambulance preparation. After transferring the patient to the A&E, the crew cleans the ambulance, picks up necessary materials from the A&E store, and restocks the ambulance to get it ready for the next call. Occasionally, especially following a strenuous case, the crew members also use this time to recuperate and prepare themselves for the next dispatch.

For the remainder of the paper, we focus on the patient pick-up process at the scene and the patient handover process at the A&E because these two processes affect ambulance utilization, involve the patient, and are substantially under the control of the crew. They also constitute a large portion of the prehospital delay (see Figure 2 and histograms in e-companion C for the duration distribution for each step of a patient transport).

4. Partner exposure and operational performance

In this section, we discuss how partner exposure might affect the ambulance crew's performance during the patient pick-up process at the scene (§4.1) and the patient handover at the A&E (§4.2). We also discuss how the crew workload might amplify these effects (§4.3). To this end, we build on the theoretical arguments from the prior literature (§2) and operational details of the empirical setting from our field observations and interviews (§3).

4.1. Patient pick-up at scene

As explained in §3.2.2, the patient pick-up process at the scene comprises both clinical and non-clinical components. Although some guidelines are provided to the crew for the clinical component, there is substantial leeway in interpreting and executing them during routine operations (Fisher et al. 2006). Furthermore, no SOPs exist for the non-clinical component demonstrated in Table 2. Therefore, good operational performance often hinges on the expertise, judgment, and tacit knowledge of the ambulance crew, which can be affected by prior partner exposure in several ways.

First, increased partner exposure can enable new recruits to identify and locate existing, useful knowledge from their partners. Given the divergent nature of the patient pick-up process at the scene, senior crew members are likely to have developed their own methods and techniques, especially for the non-clinical component of the job. Consequently, working with a diverse set of partners can create more opportunities for the new recruits to observe and internalize a variety of methods (also called non-redundant useful knowledge; Granovetter 1973) of executing a task.

Second, partner exposure can increase the amount and the novelty of new knowledge generated. Since new recruits are continually exposed to short collaborations with different partners, crews that have a new recruit on board must implicitly or explicitly agree on certain operational practices as a team. This induces active reflection and rethinking of the practices that team members have learned or used before, thus helping them to generate new knowledge and techniques (Arrow and McGrath 1993, Nonaka 1994, Delaney et al. 1998). For instance, before carrying an old lady strapped to an ambulance chair down a narrow staircase the crew must discuss which method best ensures her safety and decide on the appropriate method, e.g., for both paramedics to lean against the staircase wall for stabilization while carrying the patient down the stairs. Furthermore, generated ideas are often more creative and diverse if team members have experience of working in other teams (Gruenfeld et al. 2000, Choi and Thompson 2005). The learning gains from partner exposure are likely to be substantial for the first few transports (and first few partners) while there is still useful knowledge for the new recruit to be exposed to, but then demonstrate diminishing returns as the new recruit has acquired more and more knowledge (McFadyen and Cannella 2004). Overall, a new recruit who has observed a variety of methods can contribute more ideas, which can be creatively combined with those of his partner to further improve their effectiveness.

Third, because the process is divergent, i.e., it does not have rigidly defined SOPs, crew members possess executional latitude in applying the new knowledge and techniques to perform the current task at hand (Shostack 1987). Hence, the ideas contributed by the new recruits are also likely to be actually implemented thereby resulting in improved operational performance.

Based on the above arguments, the effect of partner exposure on the crew's performance in the patient pick-up process at the scene can be formalized in the following hypothesis:

***H1**: Greater prior partner exposure reduces average scene pick-up time.*

4.2. Patient handover at hospital

The patient handover process at the A&E is more structured than the pick-up process at the scene, with well defined SOPs (see §3.2.4). Furthermore, the environment at A&Es across London is much more uniform and controlled than that at the scene. Consider, for example, a patient in a car crash. At the scene, even approaching the patient might be difficult; he might be unsafe to move; and the environment might induce clinical and non-clinical complications. In contrast, at the A&E the patient is already on a gurney, access is straightforward, and the environment is specifically designed to deal with complications. As a result of these differences in process characteristics, we expect the impact of prior partner exposure on performance during patient handover to be different from that during patient pick-up.

First, due to the standardized nature of the patient handover process, workers are likely to employ similar techniques. Hence, despite prior exposure to multiple partners, a new recruit has fewer opportunities to observe and acquire non-redundant knowledge during patient handover than during patient pick-up. Second, even if a new recruit has acquired useful knowledge for the task at hand, it is unlikely to be utilized because crew members are more likely to revert to the rigidly defined SOPs when in doubt about the next steps (Amabile 1997) rather than actively reflect upon the task (Arrow and McGrath 1993). Third, SOPs are typically designed to guarantee good performance on average. Hence, crew members are unlikely to overrule the SOP unless they are quite sure that doing so is likely to positively impact performance. Developing such insights is possible only if new recruits have sufficient experience in both the clinical and the operational components of the patient handover process. For instance, consider the use of the patient report form during the patient handover process. A crew member minimizes the probability of accidentally leaving out critical clinical information by explicitly communicating all the information on the form to the triage nurses. However, a paramedic with substantial experience can shorten the process considerably by overriding the SOP and highlighting only the most important clinical information needed to decide the next course of action.

Summarizing the above discussion we obtain the following hypothesis:

***H2**: Greater prior partner exposure reduces average handover times, for new recruits with sufficiently high individual experience.*

4.3. The impact of workload

The existing literature (see §2) has established how service rates are often endogenous to system utilization since workers can adjust their practices in reaction to their environment. Different mechanisms have been suggested for how service rates are adjusted, ranging from speeding up (Delasay et al. 2016), to altering operating procedures (Freeman et al. 2016, Batt and Terwiesch 2016, Berry-Jaeker and Tucker 2016, Tan and Netessine 2014). Usually, these service rate changes are not the result of a protocol but an effort on the worker's part to adjust to high workloads.

In order to make this adjustment, workers must have the required skill or knowledge to adjust how they finish the task at hand. One way to acquire that skill set is by getting the opportunity to observe the methods and problem-solving techniques of multiple partners. Hence, based on our earlier reasoning, we expect workers with high prior partner exposure to be better equipped to make adjustments to their practice, in reaction to high workload.

As with many service systems, the paramedics in the LAS system experience workload through how quickly they are dispatched to a new incident after their ambulance goes green following a previous dispatch, i.e. through their individual workload. We therefore expect paramedics to adjust their service rates (to the extent that they can) at times of high workload.

We have argued how the acquisition and application of such useful knowledge depends on the process type. Combining these arguments, we arrive at the two hypotheses below, complementing **H1** and **H2**, respectively.

***H3**: Greater prior partner exposure leads to greater reduction of average scene time during periods of high workload.*

***H4**: Greater prior partner exposure leads to greater reduction of average handover times during periods of high workload, for new recruits with sufficiently high individual experience.*

5. Data and variables

Our main dataset comprises operational and clinical information on 5,773 ambulance transports staffed by one of the 81 new recruits (recruited in 2011) along with one or more of 702 senior paramedics, during the entire calendar year 2011[6]. The operational information includes arrival and departure times at the scene and A&E that are recorded electronically by the ambulance crew. The clinical information—including the *Advanced Medical Priority Dispatch System* (AMPDS) primary condition classification, used for call triaging by the emergency call handler—is collected manually through A&E forms and later collated and digitized by LAS. We supplement this operational dataset with a de-identified crew dataset that contains information on the job tenure of the senior crew members. Table 3 provides summary statistics and correlation values for all main variables.

5.1. Outcome variables

We measure the performance of the ambulance crew for the patient pick-up and patient handover processes by measuring the time spent at the scene and at the A&E, respectively. $Scene\_Time_{rt}$ for the t^{th} ambulance transport of new recruit r is defined as the time interval between the arrival of the ambulance at the scene and its departure towards an A&E. Similarly, $Handover\_Time_{rt}$ for the t^{th} transport of new recruit r is defined as the time from arrival of the ambulance at the A&E to completion of both the clinical and physical handover of the patient to the ambulance staff .

5.2. Main predictor variables

Prior partner exposure. We quantify the extent to which a new recruit has been exposed to useful knowledge through interacting with multiple partners using the familiar Hirschman-Herfindahl index (HHI). This measure captures a new recruit's dispersion of experience across all prior partners and is defined as follows:

$$Partner\_HHI_{rt} = \sum_{p \in \mathcal{P}_{rt}} \left(\frac{Joint\_Exp_t^{rp}}{Exp_{rt}} \right)^2,$$

where $Joint\_Exp_t^{rp}$ denotes the cumulative number of transports undertaken by the new recruit r with partner p prior to his t^{th} ambulance transport, the set $\mathcal{P}_{rt}$ denotes all partners that the new recruit r has worked with prior to his t^{th} transport, and Exp_{rt} denotes the total number of ambulance transports undertaken by the new recruit prior to his t^{th} transport. For a new recruit with minimal partner exposure, i.e., if she has worked with a single partner for all prior transports,

[6] Before conducting our analysis we refined and cleaned the data to focus on standard ambulance transports that conveyed patients to an A&E. We excluded patient transports on other vehicles such as motorcycles, helicopters, etc. and to other destinations such as long-term care facilities and specialty departments. We excluded observations where key variables were missing or had extreme outlier values. Finally, we also excluded transports involving one of the six paramedics with substantial prior experience, who were laterally recruited by LAS during 2011. For more detail, see e-companion B

Table 3 Summary statistics and correlation table

	Summary statistics		Correlation														
Dependent variables	Mean	StD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. *Scene_Time*	30.5	12.7	1.00														
2. *Handover_Time*	16.5	7.9	0.15	1.00													
Prior Partner Exposure & Team Familiarity																	
3. *Partner_HHI*	0.30	0.21	0.02	-0.03	1.00												
4. *Team_Familiarity*	26.9	42.4	-0.01	-0.08	0.10	1.00											
Controls																	
5. *Exp*	108.4	88.3	-0.01	-0.03	-0.35	0.36	1.00										
6. *Task_Exp*	19.3	27.4	0.09	0.06	-0.19	0.20	0.60	1.00									
7. *A&E_Exp*	21.1	27.4	-0.04	-0.01	-0.26	0.16	0.58	0.34	1.00								
8. *Crew_Workload*	0.60	0.34	-0.03	0.01	0.06	0.07	-0.08	-0.03	-0.09	1.00							
9. *Partner_Tenure*	2.79	3.15	-0.09	0.00	-0.02	-0.05	-0.09	-0.09	0.07	0.05	1.00						
10. *Number_Of_Partners*	1.2	0.4	-0.03	0.00	0.11	0.06	-0.44	-0.29	-0.25	0.14	0.20	1.00					
11. *Blue_Call*	0.03	0.16	0.04	-0.10	0.01	-0.01	-0.05	-0.04	-0.02	0.03	0.03	0.07	1.00				
12. *Recent_Base_Dispatches*	11.4	6.5	0.02	0.04	0.09	0.01	-0.05	0.01	-0.05	0.15	-0.05	-0.13	-0.02	1.00			
13. *Average_Base_Dispatches*	81.2	40.9	0.02	0.01	0.09	0.09	0.05	0.06	0.04	0.04	-0.03	-0.14	-0.02	0.58	1.00		
14. *Recent_A&E_Arrivals*	7.4	3.8	-0.01	0.16	-0.09	-0.09	-0.03	-0.01	0.17	0.08	0.06	-0.04	0.01	0.16	0.08	1.00	
15. *Average_A&E_Arrivals*	7.0	2.3	-0.02	0.14	-0.15	-0.15	0.00	0.01	0.29	-0.02	0.09	-0.11	0.02	0.13	0.09	0.66	1.00

All correlation entries of absolute values over 0.03 are statistically significant at the 5% level.

$Partner\_HHI_{rt}$ takes the value of 1, whereas for a new recruit with maximal partner exposure, i.e., if her prior experience is distributed equally among all her partners, $Partner\_HHI_{rt}$ takes the value of $\frac{1}{|\mathcal{P}_{rt}|}$. Generally, a smaller value of $Partner\_HHI_{rt}$ denotes greater prior partner exposure.

An HHI measure is ideal for our purposes as it reflects both the number of prior partners and the depth of each new recruit's exposure to these partners (Narayanan et al. 2009). For instance, a new recruit who has worked with two senior partners on 50 ambulance transports each ($Partner\_HHI$ = 0.5) is likely to have broader base of knowledge as compared to one who has worked on 1 and 99 transports with the two partners, respectively ($Partner\_HHI$= 0.98). Additionally, the marginal impact on $Partner\_HHI$ is diminishing in the number of ambulance transports conducted with the same partner, reflecting the fact that a new recruit is less likely to be exposed to new knowledge the more often they have worked with the same partner. Similarly, the marginal impact on the value of $Partner\_HHI$ is diminishing in the number of new partners, since a new recruit is more likely to acquire new and useful knowledge from the first few senior paramedics they interact with than from subsequent ones (McFadyen and Cannella 2004).

To examine how individual experience moderates the impact of partner exposure on the handover time, we define an indicator variable for sufficient individual experience as follows:

$$Suff\_Exp_{rt} = \begin{cases} 1 & if \quad t > Exp\_Threshold \\ 0 & otherwise. \end{cases}$$

and interact it with $Partner\_HHI_{rt}$. For our main analysis we define $Suff\_Exp_{rt}$ using an experience threshold corresponding to the median number of ambulance transports undertaken by new recruits during their first four months at LAS ($Exp\_Threshold = 157$). Prior work has found that for over 90% of paramedics the medium time on the job to reach 90% productivity is four months or less (Patterson et al. 2010)[7].

5.3. Control variables

Next, we describe four groups of control variables that are included in our empirical analysis, to control for various effects which have previously been found to impact team performance.

5.3.1. Cumulative experience. We include the following variables to control for various dimensions of the cumulative experience of the new recruit. Those have been shown to impact operational performance in the prior literature.

Individual experience. As defined above, Exp_{rt} denotes the cumulative individual experience of new recruit r prior to ambulance transport t. This variable controls for any individual learning effect of the new recruit (Reagans et al. 2005, Ramdas et al. 2018, Staats and Gino 2012).

Team familiarity. Consistent with the team productivity literature (Reagans et al. 2005, Huckman et al. 2009, Staats 2012), we measure team familiarity using the average number of prior ambulance transports undertaken jointly over all pairs of crew members. More formally, we define $Team\_Familiarity_{rt}$ for the t^{th} ambulance transport of new recruit r as follows:

$$Team\_Familiarity_{rt} = \frac{\sum_{p \in \mathcal{T}_{rt}} \sum_{q \in \mathcal{T}_{rt}} Joint\_Exp_t^{pq}}{\frac{N_{rt}(N_{rt}-1)}{2}},$$

where $\mathcal{T}_{rt}$ denotes the set of individuals on the crew including the focal new recruit, $N_{rt} = |\mathcal{T}_{rt}|$ denotes the the size of the crew, and $Joint\_Exp_t^{pq}$, defined as before, captures the prior joint experience of any pair $p, q \in \mathcal{T}_{rt}$, $p \neq q$. For a typical ambulance crew with one new recruit and one senior partner, this measure becomes the number of joint transports the two have undertaken.

Task experience. Let C_{rt} denote the primary clinical condition of the patient in the t^{th} ambulance transport of new recruit r. The condition C_{rt} is defined as an element of the set $\mathcal{C}$ of AMPDS codes for different clinical conditions. $Task\_Exp_{rt}$ denotes new recruits r's cumulative experience of transporting patients with primary condition C_{rt} to the A&E, prior to his t^{th} transport. This variable controls for task specific knowledge gained on the job, which has been shown to positively impact performance (Clark et al. 2013, Staats and Gino 2012).

A&E experience. Prior research has demonstrated that the performance benefits of cumulative experience are not easily transferable across organizations (Clark et al. 2013, Huckman and Pisano 2006). Hence, while analyzing the operational performance of the patient handover process, we also control for the cumulative experience of the new recruit r at the focal A&E prior to the current transport t, denoted by $A\&E\_Exp_{rt}$.

[7] In e-companion D, we check the robustness of our results by varying $Exp\_Threshold$ around the median.

5.3.2. Ambulance transport controls. We control for three characteristics of the ambulance transport and partners of the new recruit which can impact performance.

Senior partner tenure. Greater individual experience of the partners of the new recruit is also likely to have beneficial impact on the operational performance of the crew. However, many partners have a tenure at LAS spanning several years and ambulance transport data is not available to us over that period. Therefore, controlling explicitly for their ambulance transport experience is infeasible given our data. Hence, we use the average tenure (in years) of the partners of new recruit r on ambulance transport t as a proxy for their cumulative experience:

$$Partner\_Tenure_{rt} = \sum_{n=1}^{N_{rt}} \frac{Tenure_{rt}^{n}}{N_{rt}}.$$

Team size. $Number\_Of\_Partners_{rt}$ denotes the total number of senior crew members on the crew along with the new recruit r for his t^{th} ambulance transport. The typical crew size is two paramedics (one new recruit and one senior partner in our data), but occasionally one or two more seniors are present.

Blue call. For extremely critical patients, the ambulance crew can alert the A&E staff in advance to expedite the patient handover process on arrival (see §3.2.4). We use an indicator variable $Blue\_Call$ to control for such cases.

5.3.3. A&E workload. The handover times at the A&E can be affected by the workload of the A&E staff at the time of arrival of the focal ambulance transport. Although we do not have access to the actual workload data for the 37 A&Es appearing in our data, we include two variables as proxies for the predictable and unpredictable workload, respectively, of the receiving A&E.

Average workload. $Average\_A\&E\_Arrivals_{rt}$ denotes the average number of ambulance arrivals at the receiving hospital's A&E during the time of day (in 2 hour periods) of the arrival of the ambulance, for the year of 2011.

Recent workload. $Recent\_A\&E\_Arrivals_{rt}$ denotes the number of arrivals at the receiving hospital's A&E during the last two hours and eight minutes, which corresponds to the median length of stay of A&E patients (Health & Social Care Information Centre 2014).

5.3.4. Base workload. we control for base workload by calculating the average and recent ambulance dispatches from the home base of the paramedic crew at the time of each transport.

Average workload. $Average\_Base\_Dispatches_{rt}$ denotes the average number of ambulance dispatches from the home base of the paramedic crew during the time of day (in 2 hour periods) of the arrival of the ambulance, for the year of 2011.

Recent workload. $Recent\_Base\_Dispatches_{rt}$ denotes the actual number of dispatches from the home base of the paramedic crew during the last two hours.

5.3.5. Individual workload. Furthermore, we control for the shift utilization of the paramedic crew. The LAS data does not include explicit indicators for when individual shifts start and end. In addition, according to LAS managers the shift durations can vary between 8 hours and 12 hours. We extract the shift structure by assigning a new shift following very long idle times[8], and calculate the shift utilization accordingly.

Crew workload. Similar to prior literature (Kc and Terwiesch 2009), we include a measure of recent workload. The $Crew\_Workload_{rt}$ variable measures the utilization of the paramedic crew on the current shift, prior to the current transport. To calculate this utilization measure, we consider the time from each dispatch until the crew 'goes green' (see Figure 2) to be active time and the period from going green until they receive the next dispatch to be idle time. As part of our robustness checks in §8 we explore specifications allowing for non-linear effects of crew workload.

High workload. To test our hypotheses regarding the moderating effect of workload on the positive impact of partner exposure, we define the binary variable $High\_Workload_{rt}$ to take the value of 1 when $Crew\_Workload_{rt}$ exceeds 0.88 (75th percentile of all transports) and 0 otherwise. We conduct extensive sensitivity analysis for this threshold and report those results in e-companion E.

5.3.6. Other controls. Finally, we include a large set of control variables to account for unobserved heterogeneity across individual recruits, hospital A&Es, tasks, and time periods.

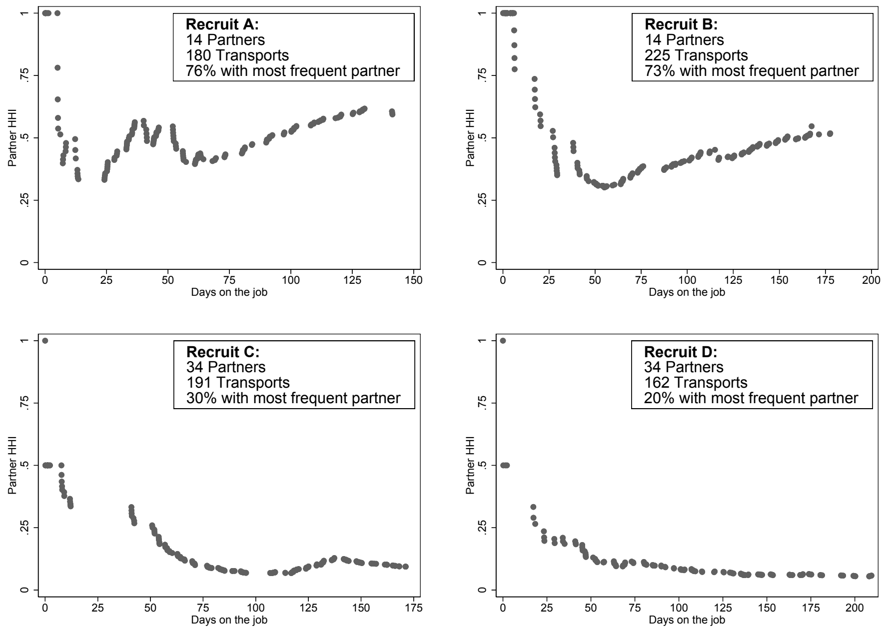
Inherent individual capability. New recruits may differ in their innate ability and aptitude to handle ambulance transports. There can be differences in idiosyncratic time invariant traits (such as their intelligence and dexterity) as well as in the average effect of time-varying factors (such as their motivation to perform well). These can create systematic differences in the performance of the paramedics. Hence, we include a fixed effect for each new recruit.

A&E factors. Similarly, some hospital A&Es might systematically be more or less efficient in completing the tasks associated with the patient handover process, resulting in lower or higher handover times even if other factors were kept constant. To control for this variation, we include a fixed effect for each A&E. These capture time-invariant differences across A&Es along dimensions such as staffing levels, information systems and patient mix.

Task type. The scene and handover times can differ systematically based on the clinical condition of the patient. To control for this source of variation, we include a fixed effect for the AMPDS code assigned to each patient based on their clinical condition.

[8] We assume that if there is five hours or more of idle time between consecutive transports, a new shift was started. This results in a very reasonable shift structure in terms of number of shifts per month, the length of an average shift, and vehicle usage patterns (paramedics almost never change vehicles within shifts but frequently start a new shift in a new vehicle).

Figure 3 **Partner exposure ($Partner\_HHI$) of the 4 new recruits from Figure 1.**



Task severity. In addition to the clinical codes described above, the LAS also assigns a severity score for the clinical status of the patient in each ambulance transport. The data includes eleven distinct ordinal scores. We include fixed effects for each of these.

Seasonality and weather. The working conditions of the ambulance crew, and consequently the scene and handover times, can be affected by external factors. We include controls for the weather conditions during the day of the transport (average wind, rainfall, and temperature). Furthermore, we include indicator variables for the time of day (morning, afternoon, evening, night), the day of the week, and the month of the year to control for other temporal variations.

6. Econometric models and main results

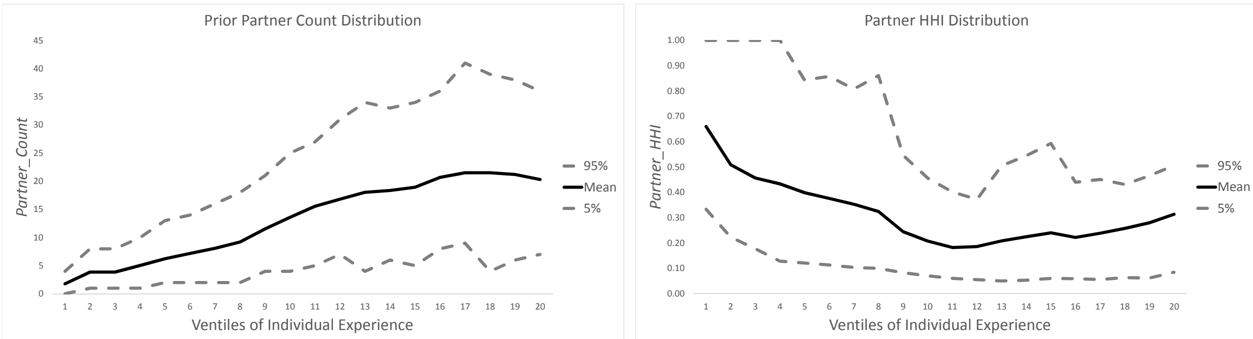
We discuss our identification strategy in §6.1, our empirical models and results for the impact of partner exposure on performance in the patient pick-up process in §6.2, and those for the patient handover process in §6.3.

6.1. Identification strategy

To identify the impact of prior partner exposure and team familiarity on team performance we rely on the fact that the assignment of partners to new recruits is exogenous to performance and that this generates adequate variation in both prior partner exposure and team familiarity for new recruits at all levels of individual experience.

We have confirmed that the manager overseeing the relief roster does not have access to prior performance data. Figure 1 illustrates how 4 new recruits have very different experience profiles in

Figure 4 The distribution of prior partner count and partner exposure for each ventile of individual experience.



terms of how many partners they work with during their first year and how often. This translates directly into a variety of sample paths for our partner exposure variable, as illustrated in Figure 3.

Figure 4 provides a more systematic view of the variability used to identify the effect of partner exposure, demonstrating the variation in partner count and partner exposure for our entire sample of new recruits as they gain individual experience in the first year. We observe that for any level of individual experience our data includes new recruits who have had considerable prior partner exposure ($Partner\_HHI$ close to 0) and new recruits who have had less prior partner exposure. E-companion A further demonstrates that we find no evidence in the data that new recruits are more likely to be assigned a stable senior partner or are more likely to spend longer time with him/her as their experience grows during their first year on the job.

6.2. Partner exposure and scene time (H1 & H3)

We use the following panel specification to identify the impact of $Partner\_HHI$ on $Scene\_Time$:

$$\begin{aligned} Scene\_Time_{rt} = & \alpha_0 + \alpha_1\ Partner\_HHI_{rt} + \alpha_2\ Partner\_HHI_{rt} * High\_Workload_{rt} \\ & + \alpha_3\ Team\_Familiarity_{rt} + \alpha_4\ Exp_{rt} + \alpha_5\ Exp^2_{rt} + \alpha_6\ Task\_Exp_{rt} \\ & + \alpha_7\ Crew\_Workload_{rt} + \alpha_8\ Partner\_Tenure_{rt} + \alpha_9\ Number\_of\_Partners_{rt} \\ & + \alpha_{10}\ Blue\_Call_{rt} + \alpha_{11}\ Recent\_Base\_Dispatches_{rt} + \alpha_{12}\ Average\_Base\_Dispatches_{rt} \\ & + \alpha_{\mathbf{13}}\ Controls_{rt} + \epsilon^S_{rt}. \end{aligned} \tag{1}$$

The main explanatory variable of interest is our measure for partner exposure, $Partner\_HHI_{rt}$. We first fix $\alpha_2 = 0$ and estimate (1). A positive and significant value of α_1 would indicate that greater prior partner exposure of new recruits reduces the scene time, supporting **H1**. We then estimate the full equation, where a positive and significant value of α_2 would indicate that the effect is stronger at times of high workload, providing support for **H3**. In addition, we include all the controls listed in §5.3, that might affect scene performance, in (1).

Columns (A) and (B) in Table 4 report the coefficient estimates and heteroscedasticity-consistent standard errors of model (1). We cluster the standard errors by the paramedic crew, to account for autocorrelation across ambulance transports conducted by the same crew[9]. We observe a strong association of both team familiarity and partner exposure with how long the crew spends at the scene. The positive coefficient of $Partner\_HHI$ in our base model (column (A)) indicates that teams including new recruits with a prior experience focused on few partners spend longer at the scene than their counterparts with more partner exposure, which is consistent with **H1**. A strict interpretation of the magnitude of the coefficient implies that crews involving new recruits with a fully focused partner experience ($Partner\_HHI = 1$) spend on average 5.3 minutes (p =0.009) longer at the scene as compared to their counterparts involving new recruits with a fully diverse partner experience ($Partner\_HHI = 0$). Alternatively, increasing the partner exposure of new recruits by one standard deviation would decrease scene times by over one minute[10].

The model in column (B) includes the interaction between high workload during the shift and prior partner exposure. We find that the marginal impact of prior partner exposure during times of high workload ($\alpha_2 = 3.6$ minutes, $p = 0.007$) is statistically significant. Additionally, the coefficient (and significance) for the effect of prior partner exposure is lower ($\alpha_1 = 4.5$ minutes, $p = 0.031$) during periods of low utilization than during periods of high utilization ($\alpha_1 + \alpha_2 = 8.1$ minutes, $p < 0.001$). These results indicate that teams involving new recruits with prior exposure to a diverse set of partners are able to perform faster during periods of high workload than teams whose new recruits have less prior partner exposure. We note that although the results from this main analysis provide some support for **H3**, our sensitivity analyses reveal that this result is sensitive to how we control for crew workload. §8 includes robustness checks, allowing for non-linear effects of $Crew\_Workload$, in which the interaction effect $Partner\_HHI$ * $High\_Workload$ is no longer significant (although the direct effect of $Partner\_HHI$ remains significant in all models).

The effect of team familiarity is negative and significant, indicating that higher team familiarity of paramedic teams results in shorter scene times. Specifically, with each additional joint ambulance transport the scene time is shortened by about 0.84 seconds ($p = 0.023$). According to our data a new recruit can accumulate a $Team\_Familiarity$ of up to 248 jobs with the same partner in the first year. This would correspond to a 3.5 minute (11%) reduction of average scene times for that

[9] Table 30 in the e-companion includes a robustness check in which we use two-way clustering of standard errors (Cameron et al. 2011) by paramedic crew and day-of-year, showing similar results.

[10] It is worth noting that including a $Partner\_HHI * Suff\_Exp$ interaction (which we use in our analysis of handover times) does not impact our results and the coefficient of that interaction is insignificant, see e-companion F.

paramedic pair, throughout the course of the year[11]. Similarly, an increase in team familiarity by one standard deviation corresponds to over half a minute (2%) shorter scene times, on average[12].

Summarizing the impact of various aspects of prior experience on operational performance, we observe that while our estimates for the impact of individual experience and task-specific experience are negative (with slightly diminishing returns for individual experience[13]), suggesting that experience gains improve performance, we cannot reject the null hypotheses that both of those effects are zero (joint significance test has p-value of 0.63). In contrast, the team-related variables, prior partner exposure and team familiarity, each have a statistically significant impact on performance. One possible explanation, provided by LAS paramedics in our discussions with them, is that the non-medical problem solving and coordination challenges faced by new recruits at a scene have a more significant impact on performance than disease-specific challenges.

In terms of workload controls we observe that team workload ($Crew\_Workload$) is significant but system workload ($Recent\_Base\_Dispatches$ and $Average\_Base\_Dispatches$) is not. Specifically, the coefficient of $Crew\_Workload$ is negative indicating that if the crew has experienced high prior utilization during the shift they spend less time at the scene. In other words, it seems that, on average, the first order effect of high workload is that teams tend to speed up.

6.3. Partner exposure and handover time (H2 & H4)

Next, we estimate the impact of partner exposure on the performance of the patient handover process at the A&E using the following panel specification:

$$\begin{aligned}
Handover_Time_{rt} = {} & \beta_0 + \beta_1\ Partner_HHI_{rt} + \beta_2\ Partner_HHI_{rt} * Suff_Exp_{rt} \\
& + \beta_3\ Partner_HHI_{rt} * Suff_Exp_{rt} * High_Workload_{rt} \\
& + \beta_4\ Team_Familiarity_{rt} + \beta_5\ Exp_{rt} + \beta_6\ Exp^2_{rt} + \beta_7\ Task_Exp_{rt} + \beta_8\ A\&E_Exp_{rt} \\
& + \beta_9\ Crew_Workload_{rt} + \beta_{10}\ Partner_Tenure_{rt} + \beta_{11}\ Number_of_Partners_{rt} \\
& + \beta_{12}\ Blue_Call_{rt} + \beta_{13}\ Recent_A\&E_Arrivals_{rt} + \beta_{14}\ Average_A\&E_Arrivals_{rt} \\
& + \boldsymbol{\beta_{15}}\ Controls_{rt} + \epsilon^H_{rt},
\end{aligned} \tag{2}$$

[11] Our sample includes teams in which a single new recruit works with one or more senior paramedics. Therefore the measure for team familiarity is likely to be underestimated as the senior paramedics may have worked with each other in the past, but those data are not available to us. Our robustness section (§8) includes results for the same models run on the subsection of data which includes only teams of one new recruit and one senior partner.

[12] In addition, we examine the variance inflation factors (VIFs) of our estimates. The VIFs for our main variables of interest, $Partner\_HHI$ and $Team\_Familiarity$ are below 6 and 3, respectively, and the average VIF of the variables in columns A and D of Table 4 are 2.3 and 3.4, respectively. Furthermore, other than the Exp and Exp^2 variables (which are highly correlated by definition) none of the VIFs are higher than 10 (aside from the control variable $Average\_A\&E\_Arrivals$, which has a VIF of 10.81).

[13] We have conducted robustness checks allowing for diminishing returns of $Team\_Familiarity$ and $Task\_Exp$ as well. This has no effect on our results (regression tables omitted).

Table 4 **OLS coefficient estimates for pick-up time at scene regressions**

	(A) Scene Time	(B) Scene Time	(C) Handover Time	(D) Handover Time	(E) Handover Time
Partner_HHI	5.348**	4.475*	1.717	1.200	1.206
	(2.048)	(2.069)	(1.208)	(1.191)	(1.191)
Partner_HHI * High_Workload		3.613**			
		(1.338)			
Partner_HHI*Suff_Exp				2.643*	1.159
				(1.325)	(1.476)
Partner_HHI*Suff_Exp*High_Workload					5.201**
					(1.932)
Team_Familiarity	-0.014*	-0.014*	-0.007	-0.008+	-0.008+
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Experience controls					
Exp	-0.018	-0.016	-0.009	-0.014	-0.014
	(0.017)	(0.017)	(0.012)	(0.012)	(0.012)
Exp Sq.	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.019	-0.022	0.002	0.002	-0.001
	(0.030)	(0.030)	(0.019)	(0.018)	(0.018)
A&E_Exp			-0.010+	-0.011+	-0.011+
			(0.006)	(0.006)	(0.005)
textitOther time-varying controls					
Crew_Workload	-1.054+	-1.895**	-0.098	-0.091	-0.355
	(0.543)	(0.595)	(0.271)	(0.270)	(0.291)
Recent_Base_Dispatches	-0.001	0.002			
	(0.035)	(0.035)			
Average_Base_Dispatches	0.001	0.001			
	(0.006)	(0.006)			
Recent_A&E_Arrivals			0.224***	0.221***	0.222***
			(0.041)	(0.040)	(0.040)
Average_A&E_Arrivals			0.348**	0.356**	0.348**
			(0.132)	(0.133)	(0.130)
Partner_Tenure	-0.015	-0.015	0.001	0.002	0.001
	(0.074)	(0.074)	(0.050)	(0.050)	(0.050)
Number_of_Partners	-1.429	-1.586+	0.577	0.578	0.581
	(0.901)	(0.900)	(0.648)	(0.642)	(0.644)
Blue_Call	4.385***	4.385***	-4.884***	-4.875***	-4.840***
	(1.199)	(1.197)	(0.732)	(0.732)	(0.724)
Observations	5483	5483	5568	5568	5568
Adjusted R^2	0.096	0.097	0.114	0.114	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

which includes the same variables as (1) with four exceptions. First, we include an interaction between the $Partner\_HHI$ variable and $Suff\_Exp$. A positive and significant β_2, while fixing $\beta_3 = 0$, would support **H2**. To test **H4** we include a triple interaction (i.e., we also estimate β_3) to evaluate the moderating effect of high workload on the impact of $Partner\_HHI$ for sufficiently experienced new recruits. Second, we include the cumulative prior experience of new recruits at the specific A&E, to account for any hospital specific learning effects. Third, we control for A&E workload instead of base workload as the workload in an A&E is likely to directly affect the handover of patients. Fourth, we include additional A&E fixed effects to account for any time-invariant characteristics which might impact handover times. For the handover we calculate two-way standard errors clustered by A&E and the paramedic crew (Cameron et al. 2011), which allows for the correlation of errors as long as either the crew or the A&E department is the same[14].

Columns (C), (D), and (E) in Table 4 report results for model (2). First, we observe from column (C) that while the average effect of $Partner\_HHI$ is positive—indicating shorter handover times for teams whose new recruit have higher parter exposure—the effect is statistically insignificant. However, as we expect from §4, column (D) shows that the coefficient of the interaction $Partner\_HHI * Suff\_Exp$ is positive and statistically significant, indicating a stronger effect of prior partner exposure for new recruits who have accumulated sufficient individual experience. Furthermore, the aggregate effect of prior partner exposure during period of high workload ($\beta_1 + \beta_2$) is also significant ($p < 0.025$). This implies that increase in partner exposure reduces handover times significantly when cumulative experience of the new recruit is greater than the median number of transports conducted in the first four months on the job, providing support for **H2**.

The interpretation of the sum of the $\beta_1 + \beta_2$ coefficients is that having a fully diverse partner experience ($Partner\_HHI = 0$), as opposed to a fully focused partner experience ($Partner\_HHI = 1$), reduces the handover time of teams involving new recruits by 3.8 minutes on average when cumulative experience of the new recruit is greater than the median number of transports conducted by a new recruit in their first four months (i.e. 157 transports). Alternatively, increasing the partner exposure of new recruits such that $Partner\_HHI$ is reduced by one standard deviation would shorten handover times by 0.8 minutes (4.8%) once the new recruits have accumulated sufficient experience. Our results are robust to changes in this threshold (E-companion D)[15]. We note that while our results (as well as prior work (Patterson et al. 2010)) suggest that for the LAS, the relevant $Exp\_Threshold$ is roughly equivalent to the median number of ambulance transports conducted on the first four months on the job, such a threshold is likely to be context specific.

Column (E) lists the estimates for the handover time regression with the interaction of prior partner exposure with both sufficient experience and high workload. We observe that the triple interaction of $Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$ has a positive and significant coefficient ($\beta_3 = 5.2$, $p = 0.007$). In addition, the aggregate impact of prior partner exposure, $\beta_1 + \beta_2 + \beta_3$, is statistically significant at $p < 0.001$, providing support for **H4**. Interestingly, once the high workload interaction is included in the regression, the coefficient of $Partner\_HHI$ * $Suff\_Exp$

[14] Table 30 in the e-companion includes a robustness check in which standard errors are two-way clustered (Cameron et al. 2011) by paramedic crew and day-of-year.

[15] Specifically, the coefficients of the two main interactions ($Partner\_HHI$ * $Suff\_Exp$ and $Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$) remain consistent in size and significance for values of $Exp\_Threshold$ ranging from 156-171.

becomes insignificant (while still positive). This indicates that the benefits of partner exposure for the handover process are focused on periods of high workload[16].

As before, the coefficients of team familiarity are negative, indicating that the higher the team familiarity of a paramedic crew conducting an A&E handover, the more efficient they are. The coefficient size indicates that the average reduction in handover time associated with each joint transport undertaken by the same team is about half a second ($p = 0.087$). In practical terms, if a new recruit accumulates 248 joint transports with the same partner (the maximum we observe in the first year for new recruits at LAS), that would result in a 2 (12%) minute shortening of handover times on average. Similarly, an increase of one standard deviation in team familiarity would correspond to 2% shorter handover times. Since we are using the entire sample, which includes teams of new recruits working with more than one senior paramedic, we may be underestimating the extent of team familiarity. By running the analysis on the subset of data in which a new recruit works with a single senior paramedic we capture team familiarity exactly and its significance in all regressions becomes significant at the 5% level (see §8) with comparable coefficient sizes.

Similar to the scene regression results, the coefficient of the individual experience is negative ($\beta_5 = -0.014,\ p = 0.248$) but not significant and the squared term is positive but very small. However, we do observe that the prior experience of the new recruit at the particular hospital ($A\&E\_Experience$) has a lower p-value ($p = 0.054$). Specifically, each prior handover to a specific A&E results in a 0.67 second reduction in subsequent handover times at that same A&E. In our data the maximum number of handovers a new recruit conducts at the same hospital in their first year is 193, which would correspond to a shortening of handover times at that hospital of over 2 minutes on average, throughout the first year on the job. These results demonstrate that in the 'joint production process' between the triage nurses and the ambulance crew, it is more beneficial for the new recruit to have had some prior experience at the hospital than having had prior experience with the medical condition of the patient. As with the scene, the coefficients of task experience are highly non-significant (the estimated coefficients turn out to be positive but the standard errors are relatively large).

7. Implications for team formation strategies

Our results from the previous section confirm our hypotheses regarding the benefits of prior partner exposure and also reconfirm the benefits of team familiarity reported earlier in the literature. From a managerial perspective, these results raise a question about team formation strategies: Should

[16] We also note that including an interaction of $Partner\_HHI$ with $High\_Workload$ does not result in a significant coefficient (regression table omitted), indicating that even at times of high workload it is indeed necessary for new recruits to have gained a sufficient level of individual experience for the benefit from partner exposure to accrue.

Table 5 Summary statistics for counterfactual analysis

	Data		Counterfactual values			
			Partner Exposure Strategy		*Partner Focus Strategy*	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
$Partner\_HHI$	0.297	0.210	0.033	0.530	1	0
$Team\_Familiarity$	27.0	42.5	1.0	1.5	109.4	88.1

Table 6 Performance predictions for Partner Focus and Partner Exposure team formation strategies, with and without the knowledge of partner exposure

	Prediction in knowledge of Partner Exposure		*Prediction in absence of Partner Exposure*	
	Scene time	Handover time	Scene time	Handover time
Partner focus strategy	33.2 (33.1, 33.4)	17.2 (17.1, 17.3)	29.7 (29.6, 29.9)	16.0 (15.9, 16.1)
Partner exposure strategy	29.5 (29.4, 29.7)	16.2 (16.2, 16.3)	30.9 (30.8, 31.0)	16.6 (16.6, 16.7)
Performance difference	3.71 (3.66, 3.77)	0.94 (0.91, 0.98)	-1.15 (-1.18, -1.13)	-0.62 (-0.63, -0.60)

95% confidence intervals in parentheses. The difference in performance for the two hypothetical team formation strategies (or the current performance) is statistically significant with $P < 10^{-4}$.

managers aim to keep teams intact—to induce high team familiarity (Huckman and Staats 2013)—or change partner assignments more frequently—to induce high partner exposure? In this section, we address this question through counterfactual analysis based on our model predictions.

We consider two contrasting hypothetical team formation strategies for new recruits at the LAS. The first, a *partner focus strategy*, assumes that new recruits are assigned a stable partner from the start thus yielding $Partner\_HHI = 1$ for all ambulance transports. The second, a *partner exposure strategy*, assumes that new recruits take turns working with every senior paramedic at their ambulance base, yielding the lowest practically feasible (given the number of senior partners at the base) value of $Partner\_HHI$ for each transport. We generate counterfactual values (see comparison in Table 5) for partner exposure and team familiarity based on these definitions.

We then use this counterfactual data and the coefficient estimates of columns (B) and (E) in Table 4 to predict the hypothetical performance for each ambulance transport for the two strategies. The left-hand side of Table 6 includes the predicted values of scene time and handover time for each of the two partner assignment strategies[17]. The partner exposure strategy outperforms the partner focus strategy at the scene by about 11% (29.5 minutes vs. 33.2 minutes) and by about 5.5% (16.2 minutes vs. 17.2 minutes) for handover. Consequently, these results suggest that emphasizing exposure to multiple partners is preferable to emphasizing stable teams in the context of new recruits at the LAS, and particularly for the divergent process of patient pick-up at the scene.

Finally, to highlight the importance of incorporating partner exposure into performance predictions, we note that not including partner exposure in the analysis would result in the wrong managerial recommendation. We compare the predicted performance of the two team formation

[17] The current performance is 30.5 min and 16.5 min on average for Scene and Handover, respectively.

strategies, with and without including the impact of partner exposure. We first re-estimate the regression coefficients of (1) and (2), ignoring the effect of partner exposure (i.e. imposing $\alpha_1 = \alpha_2 = \beta_1 = \beta_2 = \beta_3 = 0$). We then use the new coefficient estimates to predict the scene and handover times for the two team formation strategies described above. As expected, the partner focus strategy is erroneously (due to the incomplete model, ignoring partner exposure) predicted to outperform the partner exposure strategy for both patient pick-up and handover processes. These findings emphasize that managers responsible for designing team formation strategies must simultaneously account for the benefits of partner exposure and team familiarity.

8. Robustness analysis

In this section, we investigate the robustness of our results to changes in the econometric specification, definitions of key variables, and data inclusion/exclusion criteria. Since each robustness check involves 4 separate regressions we relegate all the regression tables (Tables 11 to 30) from this section to an e-companion.

8.1. Robustness to dependent variable definition

We conduct two sets of analyses to evaluate the robustness of our results to the definition of our dependent variables. First, we demonstrate that the effects we find for $Scene\_Time$ and $Handover\_Time$ actually translate to an overall improved performance by repeating our analysis with $Total\_Cycle\_Time$—defined as the time from ambulance dispatch until the ambulance and crew become available for the next job (see Figure 2)—as the dependent variable. The results are included in Table 11 and show a significant impact of prior partner exposure on cycle time during periods of low workload and a marginally larger effect at times of high workload. Second, we repeat our analysis with a log-transformation of the dependent variables. We find that our results for prior partner exposure remain the same, with the exception that the p-value of the direct effect of $Partner\_HHI$ on scene times is slightly higher than in our main analysis ($p < 0.10$ as compared to $p < 0.01$). In contrast, the coefficients for all our main variables during handover have increased significance (see Table 12).

8.2. Robustness to independent variable definition

We conduct two sets of additional analysis, changing the main independent variable. First, as described in §5 we define our partner exposure based on individual partners, i.e. the HHI measure captures the concentration of prior experience on individuals. About 18% of our sample comprises ambulance transports with more than one partner. We therefore generate an alternative to the $Partner\_HHI$ variable based on unique team compositions, instead of unique individuals, and denote it by $Team\_HHI$. We repeat our analysis and find that all our results continue to hold (see Table 13). Second, to contrast our notion of prior partner exposure to that of partner variety (i.e. the number of partners encountered, see Kim et al. (2019)) we repeat our analysis replacing $Partner\_HHI$ with $Partner\_Count$. Although the coefficient of $Partner\_Count$ is negative in all regressions (Table 14) the coefficients are only marginally significant.

8.3. Robustness to additional controls

We conduct eight sets of robustness checks to test the sensitivity of our results to control variable definitions. First, while we do not have enough data to get a good measurement of the prior partner exposure of senior paramedics, we can approximate this by their exposure to other paramedics during the year of 2011 (Table 15). Second, we allow for diminishing returns of the individual learning curve we re-run the analysis with piece-wise linear experience controls (Table 16). Third, we include non-linear controls for crew workload (Tables 17 and 18). Fourth, we include controls for the impact of interpersonal and intrapersonal task diversity on team performance (Bunderson and Sutcliffe 2002, Huckman and Staats 2011, Narayanan et al. 2013) (Table 19). Fifth, we repeat our analysis using dummies for each value of the number of senior partners (Table 20). Sixth, we repeat our analysis using a broader definition of task based on 32 main groups of AMPDS classification (Table 21). Seventh, we include the $Partner\_HHI * Suff\_Exp$ interactions in our scene regression (Table 22). Eigth, we repeat our analysis normalizing the $Average\_Base\_Dispatches_{rt}$, $Recent\_Base\_Dispatches_{rt}$, $Average\_A\&E\_Arrivals_{rt}$, and $Recent\_A\&E\_Arrivals_{rt}$ variables by the yearly total volume (as a proxy for unit size) observed by the individual bases and hospitals, respectively. The details of each set of analyses can be found in the e-companion. In summary, our results remain qualitatively the same for each check.

8.4. Robustness to data inclusion/exclusion

We conduct 4 sets of analyses excluding observations in which crew performance might conceivably be affected by unobservable factors. First, we exclude ambulance transports involving a blue call (as they are more critical and the handover process is expedited). Second, we exclude the first 10 transports of each new recruit (since partner exposure is limited, by definition, for the first few transports). Third, we repeat the analysis focusing on crews with only one senior paramedic. Fourth, to rule out start-of-shift or end-of-shift effects, we repeat our analysis excluding the first or last ambulance transport of each shift. Our results (reported in Tables 24 - 28 in the e-companion) are not affected by excluding any of those observations.

9. Conclusion

The impact of team member interactions on team performance in operational systems has long been of interest to management scholars (Mas and Moretti 2009, Tan and Netessine 2018, Schultz et al. 1998, Valentine and Edmondson 2015). A dominant paradigm in team formation, emerging out of the recent operations management literature, is that of a beneficial effect of team familiarity on team productivity (Reagans et al. 2005, Huckman et al. 2009, Huckman and Staats 2011, Staats 2012). On the other hand, research in psychology and sociology has documented the benefits of occasional contacts and new team members on knowledge acquisition and creativity (Granovetter 1973, Gruenfeld et al. 2000, Choi and Thompson 2005). Our paper unifies these perspectives and provides empirical evidence for the simultaneous effect of both these aspects of worker experience (team familiarity and prior partner exposure) on the performance of teams using field data.

These findings have important managerial implications at two levels. First, in the specific empirical setting of the LAS, our results show that a team formation strategy that encourages partner exposure of new recruits can outperform one that encourages team familiarity. The magnitude of improvement (almost 5 minutes or 9.2%) is likely to have a significant impact on patient outcomes for approximately 20% of the transports in our data that are classified as "*Category A – Immediately life-threatening*" (Sacco et al. 2005, Bradley et al. 2006). Second, for more general service settings, our results highlight the need for managers to balance the beneficial effects of team familiarity and partner exposure by analyzing the work history of their employees (e.g. who has worked with whom in the past and on what tasks) and their performance. Such data is routinely captured by enterprise IT systems (Huckman and Staats 2013) and could be used to inform improved team formation strategies. Our work also highlights that the appropriate balance between team familiarity and partner exposure depends on the type of task at hand. Furthermore, the existence of fluid teams often indicates a turbulent setting where stable partnerships can be managerially difficult to ensure. In such settings, understanding the benefits of partner exposure is particularly valuable.

Our work opens up several avenues for further investigation of the effects of partner exposure and its implications for team formation strategies. Although our results are indicative of how the standardization (or lack thereof) of a process interacts with team formation, we are unable to draw definitive conclusions because we examine only two processes. Therefore, external validation of these results in other empirical settings would help to strengthen the knowledge base for practicing managers. Second, we focus our analysis on new recruits to exploit exogenous variation in the main independent variable of interest. Future studies should investigate whether the beneficial effects of partner exposure extend to workers with longer tenure. Third, while shortening scene and handover delays is considered a key objective at LAS—many settings are characterized by a general trade-off between speed and quality. Future work should develop knowledge to distinguish which properties of prior experience improve outcomes on each (or possibly both) of those fronts. Finally, given the multiple ways through which team composition affects operations performance simultaneously, future research could focus on embedding these effects into modern crew scheduling models, which have hitherto often focused on operational feasibility.

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E-companion for "Learning from Many: Partner Exposure and Team Familiarity in Fluid Teams"

Appendix A: Partner assignment of new recruits on the relief roster

§3.1.2 describes the partner scheduling of new recruits on the relief roster. According to various operations managers at LAS the assignment of new recruits on the relief roster to shifts and partners is driven by operational convenience without consideration of their previous experience, tenure, or performance. To better understand this assignment—and further ensure there are no obvious patterns to the scheduling of new recruits to partners—we perform a number of checks using the data.

First, one might suspect that new recruits may be randomly assigned to partners at first but become more likely to be assigned a stable partner as their experience grows. For example, it could be the case that a stable partner assignment occurs if the new recruit and a particular partner work well together and ask to be teamed up, which would be an omitted variable that would impact performance. Using the data, we examine if it is the case that stable partners emerge over time as follows. For each new recruit, define each period of his or her consecutive transports with the same team as a *stint*, and the number of transports in a stint as its duration[18]. Note that a new recruit's experience at any point in time is the sum durations of all his or her prior stints. If new recruits are more likely to pair off with stable partners over time, then stint duration should be positively correlated with experience. However, in our data, this correlation is close to zero and is insignificant (-0.0026, p-value 0.9155).

Second, the above analysis does not rule out the possibility that a new recruit mostly works with the same partner but occasionally does shifts with other partners. In such cases there would be little correlation between the total number of partners during the year and the total number of stints during the year for a new recruit. In contrast, we find that in our data there is a high correlation between the number of distinct partners and the number of stints (0.6343, p-value 0.0000) for the new recruits in 2011. Furthermore, the average ratio of the number of partners to the number of stints is 0.8, where this average is taken across all new recruits. This indicates that on average eighty percent of a new recruit's stints are with different partners.

Third, we examine whether the initial (first month) performance of new recruits is correlated with the extent of subsequent partner changes. We do this in three steps:

- We calculate the average performance of each new recruit on their first month on the job. We do this for both the scene time and handover time and denote the variables by $Average\_Initial\_Scene\_Time_r$ and $Average\_Initial\_Handover\_Time_r$ for each new recruit r.
- We then split the remaining observations into two groups. *Group A (New Partner)* contains ambulance transports t in which the new recruit works with a new partner (i.e., a different partner than in ambulance transport $t-1$). *Group B (Same Partner)* contains the rest of the observations.

[18] We note that none of the above results change by defining *stints* as consecutive transports undertaken by a new recruit with a single partner, regardless of whether other senior partners join the team for some transports

- We then compare the initial performance of the two groups to examine whether partner changes (after the first month) are associated with initial performance (during the first month). We find that there is no statistical difference between the mean $Average\_Initial\_Scene\_Time_r$ (p-value of t-test for non-zero difference is 0.6411) and $Average\_Initial\_Handover\_Time_r$ (p-value for t-test for non-zero difference is 0.3118) of the two groups. This indicates that the initial performance of a new recruit is not associated with the likelihood that a new recruit is assigned a new partner on subsequent transports.

Fourth, we examine whether there is any correlation between performance and the probability of working with more than one senior paramedic in the next ambulance transport. We do this in two steps:

- Again, we split observations into two groups. *Group C (Senior Added)* contains ambulance transports t after which the new recruit was assigned to work with an additional senior partner in $t+1$. *Group D (No Senior Added)* contains the rest of the observations.

- We then compare the scene and handover performance of the two groups. We find that there is statistically no difference between the average $Scene\_Time_t$ (p-value of t-test for non-zero difference is 0.6363) or $Handover\_Time_t$ (p-value for t-test for non-zero difference is 0.8931) of the two groups. This indicates that the paramedic performance on a given ambulance transport is not associated with the likelihood of working with an additional senior partner on a subsequent transport.

Fifth, we have repeated our analysis excluding all time-varying controls. The results, which are not affected by removing those controls, are reported in Table 29.

Table 7 Overview of dataset, data cleaning, and data inclusion/exclusion criteria.

Data overview	
# of dispatches involving new recruits	20,192
# of patient transports	11,635
# of patient transports to A&E	10,592
# of patient transports to A&E in Ambulance	10,588
Data cleaning	
# of observations after removing negative delay components	10,328
# of observations after removing outliers	9,910
Data inclusion/exclusion	
# of observations excluding horizontal hires	8,613
# of observations excluding the first activation of each new recruit	8,500
# of observations excluding transportations with multiple new recruits	5,785

Appendix B: Data cleaning and inclusion criteria

Table 7 includes an overview of our data cleaning and exclusion process. In summary, LAS dispatched over 2 million vehicles during 2011, 20,192 of those involved new recruits. First, a subset of the observations in our raw data (8,554 observations) describe ambulance dispatches which, for various reasons, are completed earlier (we will refer to these observations as *dispatches*, to distinguish from a full *activation*). Reasons for early completion vary, but include a dispatch being canceled before the ambulance arrives at the scene because another vehicle got there earlier, the paramedics deciding that the patient does not require A&E treatment (e.g., false alarms), or the paramedics being dispatched completely as a safety precaution (e.g., to accompany other emergency response services such as the fire or police departments, but not actually interacting with any patients). Based on our observational shifts (during which we observed both dispatches resulting in early completion and dispatches resulting in patient transport) and discussions with paramedics it is clear that these two different types of dispatches are quite distinct. (This can also be observed from the data, with the average completion time of patient transports (including all paramedics) being 74 minutes but the average completion time of early-completion dispatches being 4.1 minute.)

Second, 1,043 of the patient transports did not bring a patient to an A&E. Instead the patient may have been brought to a specialty unit (e.g., for stroke or burn victims) which may have different operating procedures for receiving patients and are therefore excluded from the analysis. Third, 4 of the resulting patient transports to A&E departments were not conducted by an ambulance and so the process steps at the scene (e.g., bringing the patient into the vehicle) and the handover (e.g., moving the patient without a gurney) could be different. We therefore ignore those observations. Fourth, we remove observations with clear data entry errors (260 observations) and clean the data of outliers (418 observations) using the classical box plot method—i.e. remove observations for which scene and handover times are more than 3 times the interquartile range higher than the 75th percentile (Tukey 1977, Schwertman et al. 2004)

Fifth, we exclude transports (1297 observations) involving the six paramedics with substantial prior experience, who were laterally recruited by LAS during 2011. Since they had prior experience elsewhere we cannot control for their individual experience, which is a key element of our identification strategy.

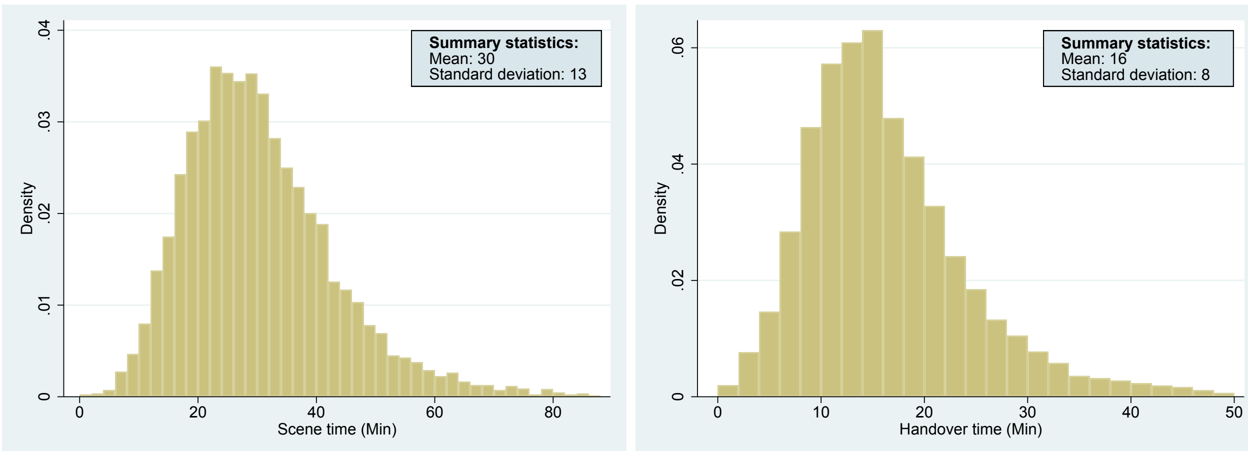
Finally, we focus our performance analysis on transports in which a single new recruit works with seniors. This is because treating new recruits as the focal unit of analysis makes the identification of the effect cleaner.

When we analyze the case with multiple new recruits, each of them has different prior partner exposure. In such cases it is unclear which new recruit has the most impact on the team's performance.

Appendix C: Distribution of outcome variables

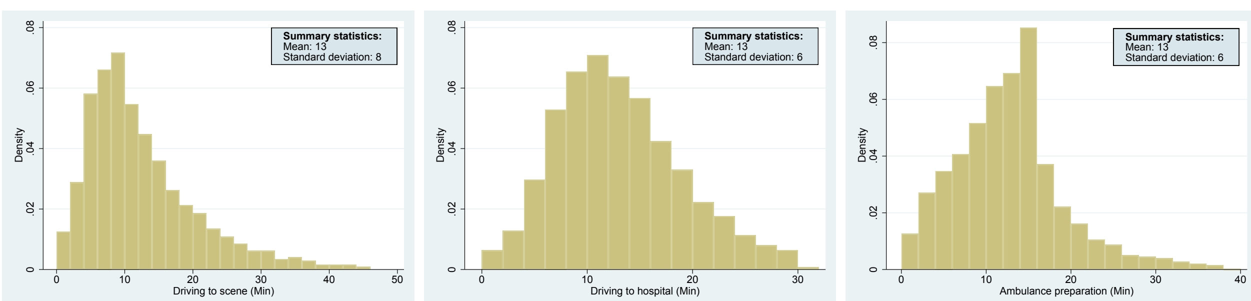
The main outcome variables in our analysis are scene time and handover time. The distribution of those is plotted below.

Figure 5 Descriptive statistics for the main outcome variables.



For comparison we also include the other three delay components from the time-line in Figure 2, below.

Figure 6 Descriptive statistics for the other delay components of an ambulance transport.



Appendix D: High individual experience threshold sensitivity analysis

Table 8 below summarizes the results of 62 robustness checks. Each line reports the coefficient estimates corresponding to the changing the threshold value of the indicator $Suff\_Exp$ for model (2). The first column lists the new threshold value, the second and third columns contain the coefficient estimate and standard errors for the β_2 coefficient of the $Partner\_HHI$ * $Suff\_Exp$ interaction (when $\beta_3 = 0$), respectively. The fourth and fifth column contain the coefficient estimates and standard errors for the β_3 coefficient of the $Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$ interaction in the full regression.

Table 8 **Result sensitivity to the high experience threshold of Table ??**

	Sensitivity analysis for model (D) in Table ??		Sensitivity analysis for model (E) in Table ??	
Threshold for High Exp.	Estimate of β_2	Robust std. err.	Estimate of β_3	Robust std. err.
145	0.872	(1.172)	4.411*	(1.890)
146	1.519	(1.216)	4.517*	(1.920)
147	1.928	(1.178)	4.659*	(1.950)
148	2.027$^+$	(1.214)	4.664*	(1.977)
149	2.361$^+$	(1.264)	4.714*	(1.878)
150	2.184$^+$	(1.230)	4.713*	(1.852)
151	1.810	(1.232)	4.744*	(1.876)
152	2.248$^+$	(1.271)	4.819*	(1.896)
153	2.238$^+$	(1.270)	5.205**	(1.919)
154	2.060	(1.326)	5.177**	(1.915)
155	2.105	(1.319)	5.217**	(1.917)
156	2.386$^+$	(1.356)	5.221**	(1.943)
157	2.643*	(1.325)	5.201**	(1.932)
158	2.755*	(1.316)	5.280**	(1.973)
159	3.066*	(1.344)	5.307**	(1.994)
160	3.137*	(1.330)	5.364**	(2.002)
161	3.265*	(1.373)	5.609**	(1.915)
162	3.181*	(1.527)	5.688**	(1.993)
163	3.072*	(1.465)	5.759**	(1.973)
164	3.434*	(1.455)	5.623**	(1.979)
165	3.228*	(1.434)	5.775**	(1.962)
166	2.998*	(1.466)	5.789**	(2.002)
167	2.683$^+$	(1.532)	6.109**	(1.990)
168	3.016*	(1.522)	6.182**	(2.046)
169	3.180*	(1.548)	6.243**	(2.104)
170	2.989*	(1.458)	5.485**	(1.931)
171	2.461$^+$	(1.347)	5.512**	(1.993)
172	2.296	(1.444)	5.392**	(2.034)
173	2.106	(1.393)	5.601**	(2.051)
174	2.071	(1.473)	5.983**	(2.067)
175	1.966	(1.537)	5.867**	(2.084)

Appendix E: High individual workload threshold sensitivity analysis

Tables 9 and 10 summarize the results of repeating the main analysis (scene and handover regressions, respectively) for alternate definitions of high workload. The tables demonstrate that the results are not sensitive to the precise threshold definition. For the scene, we observe that for a range of reasonable values defining high workload the direct effect of partner exposure is still statistically and economically significant. This is in line with the results in Table **??**. Similarly, we can replicate the handover results from Table **??** for a range of thresholds. In particular, the benefits of partner exposure for the handover operation seem to be concentrated to times of high workload.

Table 9 Sensitivity of scene results (Table ??) to threshold definition of $High\_Workload$.

Shift utilization threshold	Percentile of transports	$Partner\_HHI$ estimates		$Partner\_HHI$ * $High\_Workload$ estimates	
		α_1	Robust SE	α_2	Robust SE
0.78	0.41	4.689*	(2.048)	1.637	(1.235)
0.79	0.39	4.680*	(2.056)	1.756	(1.133)
0.80	0.38	4.593*	(2.066)	2.152*	(1.074)
0.81	0.36	4.423*	(2.059)	2.739*	(1.133)
0.82	0.35	4.621*	(2.052)	2.302^{+}	(1.192)
0.83	0.33	4.487*	(2.047)	2.733*	(1.232)
0.84	0.32	4.526*	(2.053)	2.710*	(1.212)
0.85	0.30	4.409*	(2.051)	3.128*	(1.249)
0.86	0.28	4.509*	(2.051)	2.991*	(1.223)
0.87	0.27	4.458*	(2.067)	3.309*	(1.311)
0.88	0.25	4.475*	(2.069)	3.613**	(1.338)
0.89	0.23	4.599*	(2.062)	3.316*	(1.300)
0.90	0.22	4.513*	(2.055)	3.875**	(1.304)
0.91	0.20	4.657*	(2.046)	4.099**	(1.313)
0.92	0.18	4.741*	(2.056)	3.626**	(1.315)

Table 10 Sensitivity of handover results (Table ??) to threshold definition of $High\_Workload$.

Shift utilization threshold	Percentile of transports	$Partner\_HHI$ estimates		$Partner\_HHI$ * $High\_Workload$ estimates		$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$ estimates	
		β_1	Robust SE	β_2	Robust SE	β_3	Robust SE
0.78	0.41	1.165	(1.191)	1.536	(1.696)	2.580	(1.910)
0.79	0.39	1.161	(1.191)	1.462	(1.712)	2.787	(1.949)
0.80	0.38	1.169	(1.192)	1.510	(1.736)	2.731	(2.020)
0.81	0.36	1.174	(1.192)	1.543	(1.767)	2.775	(2.264)
0.82	0.35	1.177	(1.189)	1.359	(1.704)	3.379	(2.182)
0.83	0.33	1.173	(1.189)	1.041	(1.698)	4.460*	(2.242)
0.84	0.32	1.181	(1.188)	1.060	(1.648)	4.590*	(2.172)
0.85	0.30	1.185	(1.189)	1.077	(1.564)	4.658*	(2.063)
0.86	0.28	1.203	(1.190)	1.009	(1.587)	5.017*	(2.026)
0.87	0.27	1.205	(1.191)	1.296	(1.482)	4.521*	(1.959)
0.88	0.25	1.206	(1.191)	1.159	(1.476)	5.201**	(1.932)
0.89	0.23	1.212	(1.188)	1.021	(1.488)	6.385**	(2.092)
0.90	0.22	1.229	(1.191)	0.933	(1.448)	7.139***	(2.099)
0.91	0.20	1.215	(1.195)	1.463	(1.304)	6.175**	(2.211)
0.92	0.18	1.173	(1.185)	1.607	(1.360)	7.183**	(2.786)

Appendix F: Regression tables for robustness results

F.1. Alternative Outcome Measure: $Total\_Cycle\_Time_t$

We repeat our analysis with $Total\_Cycle\_Time$—defined as the time from ambulance dispatch until the ambulance and crew become available for the next job (see Figure 2)—as the dependent variable. We find a significant impact of prior partner exposure on cycle time during periods of low workload and a marginally larger effect at times of high workload. Column (1) of Table 11 shows that the coefficient of the direct effect of $Partner\_HHI$ (ignoring the $Partner\_HHI * Suff\_Exp$ interaction) is 7.6 minutes (p=0.04), indicating that increasing the prior partner exposure of new recruits by one standard deviation shortens cycle times by 1.6 minutes. Column (2) of the table shows that the effect is marginally stronger during times of high workload, the aggregate effect of $Partner\_HHI + Partner\_HHI * High\_Workload$ being 11.9 minutes (p=0.004).

Table 11 OLS coefficient estimates for robustness checks with $Total\_Cycle\_Time$ as dependent variable.

Partner exposure & Team familiarity	(1) Cycle Time	(2) Cycle Time
$Partner\_HHI$	7.595*	6.299^{+}
	(3.753)	(3.746)
$Partner\_HHI * High\_Workload$		5.557*
		(2.256)
$Team\_Familiarity$	−0.032**	−0.031**
	(0.010)	(0.010)
Experience controls		
Exp	−0.016	−0.013
	(0.033)	(0.032)
Exp^2	0.000	0.000
	(0.000)	(0.000)
$Task\_Exp$	0.018	0.013
	(0.052)	(0.052)
$A\&E\_Experience$	−0.082***	−0.082***
	(0.018)	(0.018)
Other time-varying controls		
$Crew\_Workload$	−1.894^{+}	−3.179**
	(1.008)	(1.100)
$Recent\_Base\_Dispatches$	−0.009	−0.003
	(0.061)	(0.061)
$Average\_Base\_Dispatches$	−0.023*	−0.022*
	(0.011)	(0.011)
$Recent\_A\&E\_Arrivals$	0.268*	0.264*
	(0.120)	(0.119)
$Average\_A\&E\_Arrivals$	1.082**	1.064**
	(0.359)	(0.357)
$Number\_of\_Partners$	1.413	1.165
	(1.527)	(1.521)
$Partner\_Tenure$	0.146	0.145
	(0.114)	(0.113)
$Blue\_Call$	7.552***	7.560***
	(2.171)	(2.168)
Observations	5568	5568
Adjusted R^2	0.189	0.190

The models include fixed effects for new recruits, A&E, main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions. Standard errors are heteroscedasticity consistent and clustered by the paramedic crew. $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

F.2. Log specification of dependent variable

In some of the prior literature on learning and operational performance, researchers have used a log-transformation of the dependent variable (e.g., Huckman and Staats 2011, Narayanan et al. 2013). We re-estimate a log-linear version of the specifications (1) and (2) and find that our results for prior partner exposure remain the same, with the exception that the p-value of the direct effect of $Partner\_HHI$ on scene times is slightly higher than in our main analysis ($p < 0.10$ as compared to $p < 0.01$). In contrast, the coefficients for all our main variables during handover have increased significance (see Table 12).

Table 12 OLS coefficient estimates for robustness checks with log transformed dependent variables

Partner exposure & Team Familiarity	(1) Ln(Scene Time)	(2) Ln(Scene Time)	(3) Ln(Handover Time)	(4) Ln(Handover Time)
$Partner\_HHI$	0.111^{+}	0.082	0.040	0.040
	(0.066)	(0.066)	(0.070)	(0.077)
$Partner\_HHI$ * $High\_Workload$		0.121**		
		(0.046)		
$Partner\_HHI$ * $Suff\_Exp$			0.215**	0.111
			(0.083)	(0.101)
$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$				0.367***
				(0.096)
$Team\_Familiarity$	0.000^{+}	0.000^{+}	-0.001^{+}	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Experience controls				
Exp	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.001	−0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$A\&E\_Experience$			0.000	0.000
			(0.000)	(0.000)
Other time-varying controls				
$Crew\_Workload$	−0.042*	−0.070***	−0.017	−0.036*
	(0.017)	(0.019)	(0.017)	(0.017)
$Recent\_Base\_Dispatches$	0.000	0.000		
	(0.001)	(0.001)		
$Average\_Base\_Dispatches$	0.000	0.000		
	(0.000)	(0.000)		
$Recent\_A\&E\_Arrivals$			0.013***	0.013***
			(0.002)	(0.003)
$Average\_A\&E\_Arrivals$			0.026**	0.025**
			(0.009)	(0.008)
$Number\_of\_Partners$	−0.047	-0.052^{+}	0.042	0.042
	(0.031)	(0.031)	(0.040)	(0.048)
$Partner\_Tenure$	−0.002	−0.002	0.002	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
$Blue\_Call$	0.123**	0.123**	−0.536***	−0.534***
	(0.039)	(0.039)	(0.077)	(0.078)
Observations	5483	5483	5568	5568
Adjusted R^2	0.108	0.109	0.143	0.145

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

F.3. Alternate definitions of partner exposure variable

We generate an alternative to the $Partner\_HHI$ variable based on unique team compositions, instead of unique individuals, and denote it by $Team\_HHI$. We repeat our analysis and find that all our results continue to hold. In particular we observe a positive and significant impact of $Team\_HHI$ and ($Team\_HHI * High\_Workload$) on scene time and of ($Team\_HHI * Suff\_Exp$) and ($Team\_HHI * Suff\_Exp * High\_Workload$) on handover times. Other results are qualitatively similar except that the coefficient of $Team\_Familiarity$ becomes marginally insignificant in the handover regressions ($p = 0.104$ and $p = 0.125$—no change in significance for the scene regressions). Details are listed in Table 13.

Table 13 **OLS coefficient estimates for robustness checks with team-based prior partner exposure definition.**

Partner exposure & Team Familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
$Team\_HHI$	3.116*	2.206+	0.154	0.210
	(1.264)	(1.330)	(0.733)	(0.729)
$Team\_HHI * High\_Workload$		2.506**		
		(0.922)		
$Team\_HHI * Suff\_Exp$			2.931*	1.834
			(1.162)	(1.369)
$Team\_HHI * Suff\_Exp * High\_Workload$				3.892*
				(1.716)
$Team\_Familiarity$	−0.013*	−0.013*	−0.008	−0.008
	(0.006)	(0.006)	(0.005)	(0.005)
Experience controls				
Exp	−0.020	−0.019	−0.018	−0.018
	(0.017)	(0.017)	(0.012)	(0.012)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.019	−0.022	0.002	−0.001
	(0.030)	(0.030)	(0.018)	(0.018)
$A\&E\_Experience$			−0.011+	−0.011+
			(0.006)	(0.005)
Other time-varying controls				
$Crew\_Workload$	−1.054+	−1.779**	−0.091	−0.331
	(0.543)	(0.584)	(0.271)	(0.294)
$Recent\_Base\_Dispatches$	0.001	0.002		
	(0.035)	(0.035)		
$Average\_Base\_Dispatches$	0.001	0.001		
	(0.006)	(0.006)		
$Recent\_A\&E\_Arrivals$			0.220***	0.221***
			(0.040)	(0.040)
$Average\_A\&E\_Arrivals$			0.356**	0.351**
			(0.132)	(0.129)
$Number\_of\_Partners$	−1.770+	−1.940*	0.584	0.572
	(0.904)	(0.908)	(0.667)	(0.670)
$Partner\_Tenure$	−0.013	−0.011	0.001	0.001
	(0.075)	(0.074)	(0.050)	(0.050)
$Blue\_Call$	4.362***	4.344***	−4.864***	−4.839***
	(1.196)	(1.194)	(0.728)	(0.720)
Observations	5483	5483	5568	5568
Adjusted R^2	0.096	0.097	0.114	0.115

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^+$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

Table 14 OLS coefficient estimates for robustness check with $Partner\_Count$ as the main independent variable.

	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_Count	-0.105^{+}	-0.110^{+}	-0.082*	-0.083*
	(0.059)	(0.059)	(0.040)	(0.039)
Partner_Count*High_Workload		0.083*		0.033
		(0.032)		(0.022)
Partner_Count*Suff_Exp			0.029	0.029
			(0.018)	(0.018)
Partner_Count*Suff_Exp*High_Workload				0.021
				(0.025)
Team_Familiarity	-0.013*	-0.013^{+}	-0.008^{+}	-0.008^{+}
	(0.007)	(0.007)	(0.005)	(0.005)
Experience controls				
Exp	-0.021	-0.021	-0.009	-0.010
	(0.017)	(0.017)	(0.012)	(0.012)
Exp Sq.	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.017	-0.017	0.002	0.002
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			-0.010^{+}	-0.010^{+}
			(0.006)	(0.006)
Other time-varying controls				
Crew_Workload	-1.043^{+}	-1.892**	-0.097	-0.513^{+}
	(0.544)	(0.629)	(0.275)	(0.263)
Recent_Base_Dispatches	-0.004	-0.002		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.001	0.001		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.223***	0.223***
			(0.040)	(0.040)
Average_A&E_Arrivals			0.356**	0.351**
			(0.132)	(0.128)
Partner_Tenure	-0.021	-0.020	-0.002	-0.002
	(0.075)	(0.075)	(0.053)	(0.053)
Number_of_Partners	-1.347	-1.350	0.553	0.541
	(0.943)	(0.940)	(0.709)	(0.712)
Blue_Call	4.465***	4.476***	-4.876***	-4.863***
	(1.194)	(1.198)	(0.737)	(0.740)
Observations	5483	5483	5568	5568
Adjusted R^2	0.095	0.096	0.114	0.115

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew and day-of-year. $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

F.4. Including approximate partner exposure of senior paramedics.

While we do not have enough data to measure the prior partner exposure of senior paramedics, we can approximate this by their exposure to other paramedics during the year of 2011. We denote this variable by $Approx\_Senior\_Partner\_HHI$. The coefficient estimates (Table 15) of our main variables are practically the same as in our main analysis after including this variable. Similarly, the significance levels are the same, with the exception that the p-value of the marginal $Partner\_HHI * Suff\_Exp$ interaction changes from 0.046 to 0.051. (The p-value for the aggregate effect of $Partner\_HHI + Partner\_HHI * Suff\_Exp$ is 0.029.)

Table 15 OLS coefficient estimates for robustness checks including approximate Senior Paramedic *Partner_HHI*.

Partner exposure & Team Familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.395**	4.521*	1.173	1.177
	(2.049)	(2.070)	(1.206)	(1.206)
Partner_HHI*High_Workload		3.614**		
		(1.338)		
Partner_HHI*Suff_Exp			2.612+	1.129
			(1.339)	(1.489)
Partner_HHI*Suff_Exp*High_Workload				5.204**
				(1.935)
Approx_Senior_Partner_HHI	-0.678	-0.674	0.237	0.261
	(0.935)	(0.933)	(0.570)	(0.563)
Team_Familiarity	-0.014*	-0.013*	-0.008+	-0.008
	(0.006)	(0.006)	(0.005)	(0.005)
Experience controls				
Exp	-0.019	-0.017	-0.015	-0.014
	(0.017)	(0.017)	(0.012)	(0.012)
Exp^2	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.019	-0.023	0.002	-0.001
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			-0.011+	-0.010+
			(0.005)	(0.005)
Other time-varying controls				
Crew_Workload	-1.062+	-1.904**	-0.092	-0.355
	(0.543)	(0.595)	(0.271)	(0.292)
Recent_Base_Dispatches	-0.001	0.001		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.000	0.000		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.220***	0.222***
			(0.040)	(0.040)
Average_A&E_Arrivals			0.356**	0.349**
			(0.133)	(0.129)
Partner_Tenure	-0.010	-0.010	0.000	-0.001
	(0.075)	(0.075)	(0.049)	(0.049)
Number_of_Partners	-1.391	-1.544+	0.386	0.389
	(0.914)	(0.913)	(0.669)	(0.671)
Blue_Call	4.372***	4.371***	-4.853***	-4.819***
	(1.199)	(1.198)	(0.732)	(0.723)
Observations	5482	5482	5567	5567
Adjusted R^2	0.096	0.097	0.114	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

F.5. Piece-wise linear experience controls

To allow for diminishing returns of the individual learning curve we re-run the analysis with piece-wise linear experience controls. For this analysis we replace the Exp and Exp^2 variables with an interaction between Exp and dummies indicating the median number of ambulance transports undertaken by new recruits in their first 1, 2, 3,..., 6 (and more) months. All the main results remain the same (see Table 16).

Table 16 OLS coefficient estimates for robustness checks with piece-wise linear controls for individual experience.

Partner exposure & Team Familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	4.528*	3.722^{+}	0.991	0.992
	(2.080)	(2.116)	(1.123)	(1.117)
*Partner_HHI * High_Workload*		3.543**		
		(1.318)		
*Partner_HHI * Suff_Exp*			2.750*	1.223
			(1.333)	(1.500)
*Partner_HHI * Suff_Exp * High_Workload*				5.179**
				(1.942)
Team_Familiarity	−0.014*	−0.014*	−0.008^{+}	−0.008^{+}
	(0.006)	(0.006)	(0.004)	(0.005)
Experience controls				
*Exp * Under_1m_Exp*	−0.008	−0.004	−0.001	−0.001
	(0.036)	(0.036)	(0.021)	(0.020)
*Exp * Over_1m_Exp* (33 transports)	−0.029	−0.025	−0.014	−0.014
	(0.022)	(0.022)	(0.013)	(0.013)
*Exp * Over_2m_Exp* (64 transports)	−0.040*	−0.037*	−0.013	−0.013
	(0.018)	(0.018)	(0.011)	(0.011)
*Exp * Over_3m_Exp* (93 transports)	−0.010	−0.007	−0.018*	−0.018*
	(0.015)	(0.015)	(0.008)	(0.008)
*Exp * Over_4m_Exp* (122 transports)	−0.017	−0.016	−0.020*	−0.019*
	(0.013)	(0.013)	(0.008)	(0.008)
*Exp * Over_5m_Exp* (150 transports)	−0.012	−0.010	−0.021*	−0.020*
	(0.012)	(0.012)	(0.010)	(0.010)
*Exp * Over_6m_Exp* (184 transports)	−0.007	−0.006	−0.018*	−0.018*
	(0.011)	(0.011)	(0.008)	(0.008)
Task_Exp	−0.021	−0.024	0.003	0.000
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Experience			−0.011*	−0.011*
			(0.005)	(0.005)
Other time-varying controls				
Crew_Workload	−1.044^{+}	−1.865**	−0.070	−0.334
	(0.541)	(0.594)	(0.265)	(0.284)
Recent_Base_Dispatches	−0.003	0.000		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.000	0.000		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.219***	0.220***
			(0.040)	(0.040)
Average_A&E_Arrivals			0.354**	0.347**
			(0.136)	(0.133)
Number_of_Partners	−1.784*	−1.927*	0.521	0.523
	(0.905)	(0.905)	(0.630)	(0.632)
Partner_Tenure	−0.031	−0.031	0.002	0.001
	(0.074)	(0.073)	(0.049)	(0.049)
Blue_Call	4.316***	4.319***	−4.855***	−4.822***
	(1.197)	(1.195)	(0.732)	(0.723)
Observations	5483	5483	5568	5568
Adjusted R^2	0.098	0.099	0.114	0.115

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

Appendix G: Non-linear controls for crew workload

In our main analysis we include a direct control for crew workload (similar to Kc and Terwiesch 2009). To further allow for non-linear effect of those variable we conduct two alternate specifications based on recent OM literature: (i) modeling nonlinear workload effects through binary variables only (Kc and Terwiesch 2012, Chan et al. 2019), and (ii) controlling for workload using a piecewise linear specification (Berry-Jaeker and Tucker 2016). The results of these models are shown in Tables 17 (which controls for workload using the $High\_Workload$ indicator) and Table 18 (which allows for a piecewise linear effect of workload). We find that in these specifications the interaction between prior partner exposure and high workload is not significant for scene time, i.e., high workload does not enhance or diminish the effect of prior partner exposure for the more divergent process. However, the aggregate effect of prior partner exposure ($Partner\_HHI + Partner\_HHI * High\_Workload$) continues to remain significant even at the high workload condition (p-values of 0.043 and 0.065 in the two tables, respectively). All other results continue to remain statistically significant and similar in magnitude. Specifically, $Partner\_HHI$ has a significant impact on scene times (supporting **H1**), the $Partner\_HHI * Suff\_Exp$ interaction and the aggregate effect ($Partner\_HHI + Partner\_HHI * Suff\_Exp$) both have a significant impact on handover times (supporting **H2**), and this impact is increased during periods of high workload (supporting **H4**).

Table 17 Robustness with $High\_Workload$ indicator as control for crew workload.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.378**	5.419*	0.996	1.214
	(2.046)	(2.128)	(1.092)	(1.191)
Partner_HHI * High_Workload		−0.177		
		(2.165)		
Partner_HHI*Suff_Exp			2.650*	1.355
			(1.295)	(1.501)
Partner_HHI*Suff_Exp*High_Workload				4.540*
				(1.900)
Team_Familiarity	−0.014*	−0.014*	−0.008+	−0.008+
	(0.006)	(0.006)	(0.004)	(0.004)
Experience controls				
Exp	−0.017	−0.017	−0.017*	−0.014
	(0.017)	(0.017)	(0.007)	(0.012)
Exp Sq.	0.000	0.000		−0.000
	(0.000)	(0.000)		(0.000)
Task_Exp	−0.022	−0.022	0.001	−0.001
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			−0.011+	−0.011+
			(0.006)	(0.005)
Other time-varying controls				
High_Workload	0.842*	0.896	0.372	0.085
	(0.407)	(0.754)	(0.240)	(0.244)
Recent_Base_Dispatches	−0.016	−0.016		
	(0.034)	(0.034)		
Average_Base_Dispatches	0.002	0.002		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.217***	0.219***
			(0.040)	(0.040)
Average_A&E_Arrivals			0.335**	0.332*
			(0.130)	(0.129)
Partner_Tenure	−0.025	−0.025	−0.001	−0.001
	(0.075)	(0.075)	(0.050)	(0.050)
Number_of_Partners	−1.560+	−1.557+	0.470	0.561
	(0.905)	(0.906)	(0.660)	(0.646)
Blue_Call	4.376***	4.377***	−4.872***	−4.843***
	(1.206)	(1.207)	(0.731)	(0.723)
Observations	5483	5483	5568	5568
Adjusted R^2	0.096	0.096	0.115	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

Table 18 Robustness with piece-wise linear controls for crew workload.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.280**	5.431*	0.966	1.208
	(2.026)	(2.111)	(1.093)	(1.191)
Partner_HHI * High_Workload		−0.656		
		(2.185)		
Partner_HHI*Suff_Exp			2.609*	1.295
			(1.283)	(1.491)
Partner_HHI*Suff_Exp*High_Workload				4.580*
				(1.904)
Team_Familiarity	−0.014*	−0.014*	−0.008+	−0.008+
	(0.006)	(0.006)	(0.004)	(0.005)
Experience controls				
Exp	−0.014	−0.014	−0.017*	−0.013
	(0.017)	(0.017)	(0.007)	(0.012)
Exp Sq.	0.000	0.000		−0.000
	(0.000)	(0.000)		(0.000)
Task_Exp	−0.022	−0.022	0.001	−0.001
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			−0.011+	−0.011+
			(0.006)	(0.005)
Other time-varying controls				
Crew_Workload	−2.581***	−2.587***	−0.542*	−0.563*
	(0.660)	(0.661)	(0.276)	(0.275)
Crew_Workload * High_Workload	2.055***	2.269*	0.622*	0.328
	(0.524)	(0.882)	(0.274)	(0.247)
Recent_Base_Dispatches	0.002	0.002		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.001	0.001		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.220***	0.222***
			(0.040)	(0.040)
Average_A&E_Arrivals			0.348**	0.346**
			(0.129)	(0.128)
Partner_Tenure	−0.015	−0.015	0.001	0.001
	(0.073)	(0.073)	(0.050)	(0.050)
Number_of_Partners	−1.593+	−1.582+	0.453	0.551
	(0.893)	(0.894)	(0.666)	(0.650)
Blue_Call	4.390***	4.391***	−4.871***	−4.842***
	(1.201)	(1.201)	(0.733)	(0.725)
Observations	5483	5483	5568	5568
Adjusted R^2	0.099	0.099	0.115	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.1. Including intrapersonal and interpersonal task diversity

Prior work has demonstrated the impact of interpersonal and intrapersonal task diversity on team performance (Bunderson and Sutcliffe 2002, Huckman and Staats 2011, Narayanan et al. 2013). In line with this literature we capture the difference in task experience across the members of an ambulance crew (interpersonal task diversity) using the average pairwise Euclidean distance between their prior task experience levels as follows:

$$Task\_Diversity_{rt}^{Inter\_P} = \frac{\sum_{n=1}^{N_{rt}} \sum_{m=1}^{N_{rt}} \sqrt{\sum_{c \in \mathcal{C}} (Task\_Share_{rt}^{c,n} - Task\_Share_{rt}^{c,m})^2}}{\frac{N_{rt}(N_{rt}-1)}{2}},$$

where $Task\_Share_{rt}^{c,n}$ denotes the fraction of prior transports of crew member n that involved patients with primary condition c. The above measure takes the value of 0 if all members of a particular ambulance crew have spent an equal proportion of their prior ambulance transports on each patient condition and increases as these proportions become different from each other.

Similarly, we calculate the intrapersonal task diversity of an ambulance crew by first calculating Herfindahl's index over prior tasks of each individual crew member and then averaging over these different indices as follows:

$$Task\_Diversity_{rt}^{Intra\_P} = \sum_{n=1}^{N_{rt}} \frac{\left(1 - \sum_{c \in \mathcal{C}} (Task\_Share_{rt}^{c,n})^2\right)}{N_{rt}}. \tag{3}$$

Including these variables in our regressions does not change any of the results. Furthermore, the coefficient of neither variable is significant. We do not believe this is because these are not important predictors for performance in general. Rather, a plausible explanation is that since tasks (in terms of the condition of the patients) are completely randomly assigned to crews (not only exogenous but more or less uniformly distributed) in our setting, these variables have very little variation for a given level of experience, in contrast to the variation we have for $Partner\_HHI$ as illustrated in Figure 4. The coefficient estimates for this analysis are included in Table 19.

Table 19 OLS coefficient estimates for robustness checks including intrapersonal and interpersonal task diversity.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
$Partner\_HHI$	5.417**	4.512*	1.090	1.089
	(2.077)	(2.095)	(1.202)	(1.353)
$Partner\_HHI$ * $High\_Workload$		3.628**		
		(1.341)		
$Partner\_HHI$ * $Suff\_Exp$			2.780*	1.293
			(1.299)	(1.637)
$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$				5.249**
				(1.640)
$Team\_Familiarity$	−0.013*	−0.013*	-0.009^{+}	−0.009*
	(0.006)	(0.006)	(0.004)	(0.004)
Experience controls				
Exp	−0.015	−0.013	−0.018	−0.017
	(0.017)	(0.017)	(0.013)	(0.015)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.018	−0.022	0.001	−0.002
	(0.030)	(0.030)	(0.018)	(0.015)
$A\&E\_Experience$			-0.010^{+}	-0.010^{+}
			(0.006)	(0.005)
$Task\_Diversity^{Intra\_P}$	−1.120	−1.567	−0.034	−0.008
	(3.742)	(3.719)	(3.250)	(3.186)
$Task\_Diversity^{Inter\_P}$	1.458	1.330	−1.424	−1.528
	(2.609)	(2.610)	(1.726)	(3.186)
Other time-varying controls				
$Crew\_Workload$	-1.045^{+}	−1.888**	−0.094	−0.361
	(0.544)	(0.596)	(0.274)	(0.285)
$Recent\_Base\_Dispatches$	−0.001	0.002		
	(0.035)	(0.035)		
$Average\_Base\_Dispatches$	0.001	0.001		
	(0.006)	(0.006)		
$Recent\_A\&E\_Arrivals$			0.222***	0.223***
			(0.040)	(0.042)
$Average\_A\&E\_Arrivals$			0.356**	0.349**
			(0.133)	(0.117)
$Number\_of\_Partners$	−1.358	−1.497	0.551	0.551
	(0.921)	(0.920)	(0.692)	(0.755)
$Partner\_Tenure$	−0.012	−0.011	0.003	0.003
	(0.075)	(0.075)	(0.053)	(0.056)
$Blue\_Call$	4.381***	4.386***	−4.864***	−4.829***
	(0.921)	(1.198)	(0.731)	(0.741)
Observations	5483	5483	5568	5568
Adjusted R^2	0.096	0.097	0.114	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.2. Nonlinear controls for the number of senior partners

For simplicity our main models control for the number of senior partners on a crew in a linear way through the actual count. We repeat the analysis using dummies for each value of the number of senior partners and report coefficient estimates in Table 20. Our results remain the same as before in magnitude and statistical significance, with the exception of a slight increase in the p-values of $Team\_Familiarity$ for the handover regressions ($p = 0.115$ and $p = 0.073$).

Table 20 OLS coefficient estimates for robustness checks including non-linear controls for the number of senior partners.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
$Partner\_HHI$	5.379**	4.511*	1.116	1.122
	(2.049)	(2.070)	(1.190)	(1.342)
$Partner\_HHI$ * $High\_Workload$		3.599**		
		(1.336)		
$Partner\_HHI$ * $Suff\_Exp$			2.571*	1.095
			(1.312)	(1.651)
$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$				5.176**
				(1.608)
$Team\_Familiarity$	−0.014*	−0.014*	−0.007	-0.007^{+}
	(0.006)	(0.006)	(0.005)	(0.004)
Experience controls				
Exp	−0.018	−0.015	−0.017	−0.016
	(0.017)	(0.017)	(0.013)	(0.014)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.019	−0.023	0.003	0.000
	(0.030)	(0.030)	(0.018)	(0.015)
$A\&E\_Experience$			-0.010^{+}	-0.010^{+}
			(0.006)	(0.005)
Other time-varying controls				
$Crew\_Workload$	-1.061^{+}	−1.899**	−0.074	−0.336
	(0.543)	(0.595)	(0.272)	(0.277)
$Recent\_Base\_Dispatches$	0.000	0.003		
	(0.035)	(0.035)		
$Average\_Base\_Dispatches$	0.001	0.001		
	(0.006)	(0.006)		
$Recent\_A\&E\_Arrivals$			0.221***	0.222***
			(0.040)	(0.041)
$Average\_A\&E\_Arrivals$			0.359**	0.352**
			(0.133)	(0.118)
$Two\_Senior\_Partners$	−1.296	−1.443	−0.050	−0.043
	(0.971)	(0.969)	(0.688)	(0.810)
$Three\_Senior\_Partners$	−4.307	−4.628	6.795***	6.746***
	(3.391)	(3.408)	(1.273)	(1.304)
$Partner\_Tenure$	−0.016	−0.016	0.008	0.008
	(0.074)	(0.074)	(0.050)	(0.052)
$Blue\_Call$	4.386***	4.387***	−4.868***	−4.834***
	(1.199)	(1.197)	(0.733)	(0.737)
Observations	5483	5483	5568	5568
Adjusted R^2	0.096	0.097	0.115	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.3. Broader classification of the clinical condition

In the main analysis, $Task\_Exp_{rt}$ is defined on the basis of the most detailed AMPDS classification (332 in total) of a patient's condition. This implicitly assumes that there is minimal spillover of knowledge across subgroups that affects the operating performance. To acknowledge the possibility of such spillover, we repeat our analysis using a broader definition of task based on 32 main groups of AMPDS classification. Our results do not change for either patient pick-up at the scene or patient handover performance. Results are included in Table 21.

Table 21 OLS coefficient estimates for robustness checks with a broader classification of patients' clinical conditions.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.237*	4.389*	1.183	1.189
	(2.048)	(2.070)	(1.185)	(1.333)
*Partner_HHI * High_Workload*		3.519**		
		(1.330)		
*Partner_HHI * Suff_Exp*			2.641*	1.162
			(1.321)	(1.658)
*Partner_HHI * Suff_Exp * High_Workload*				5.179**
				(1.602)
Team_Familiarity	−0.014*	−0.013*	-0.008^{+}	−0.008*
	(0.006)	(0.006)	(0.005)	(0.004)
Experience controls				
Exp	−0.022	−0.020	−0.015	−0.014
	(0.017)	(0.017)	(0.012)	(0.014)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Broad_Task_Exp	0.019	0.018	0.004	0.003
	(0.012)	(0.012)	(0.005)	(0.004)
A&E_Experience			-0.011^{+}	−0.011*
			(0.006)	(0.005)
Other time-varying controls				
Crew_Workload	−1.075*	−1.894**	−0.094	−0.357
	(0.542)	(0.594)	(0.270)	(0.277)
Recent_Base_Dispatches	−0.001	0.002		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.001	0.001		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.221***	0.222***
			(0.040)	(0.041)
Average_A&E_Arrivals			0.354**	0.347**
			(0.133)	(0.117)
Number_of_Partners	-1.533^{+}	-1.683^{+}	0.564	0.566
	(0.899)	(0.899)	(0.648)	(0.734)
Partner_Tenure	−0.019	−0.019	0.001	0.001
	(0.074)	(0.074)	(0.050)	(0.051)
Blue_Call	4.358***	4.356***	−4.875***	−4.843***
	(1.195)	(1.193)	(0.734)	(0.741)
Observations	5483	5483	5568	5568
Adjusted R^2	0.097	0.098	0.114	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.4. Including interactions in scene regressions

Including $Suff\_Exp$ interactions in our scene regressions does not affect any of our results. Table 22 shows that including a ($Partner\_HHI$ * $Suff\_Exp$) interaction in our base model results in an insignificant coefficient of the interaction, whereas our main effect of $Partner\_HHI$ remains similar in size and significance. Similarly, adding a triple interaction ($Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$) to our high workload analysis does not result in a statistically significant effect whereas our main workload interaction ($Partner\_HHI$ * $High\_Workload$) remains statistically significant.

Table 22 OLS coefficient estimates for robustness checks including all interactions in the scene regression.

	DV: Scene time			
Partner exposure & Team familiarity	Main effect	Experience interaction	Workload interaction	All interactions
$Partner\_HHI$	5.348**	4.901*	4.051$^+$	4.077$^+$
	(2.048)	(2.173)	(2.199)	(2.196)
$Partner\_HHI$ * $Suff\_Exp$		2.206	2.108	1.871
		(2.676)	(2.659)	(2.758)
$Partner\_HHI$ * $High\_Workload$			3.598**	3.464*
			(1.334)	(1.390)
$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$				0.933
				(3.334)
$Team\_Familiarity$	−0.014*	−0.015*	−0.014*	−0.014*
	(0.006)	(0.006)	(0.006)	(0.006)
Experience controls				
Exp	−0.018	−0.023	−0.020	−0.020
	(0.017)	(0.019)	(0.019)	(0.019)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.019	−0.019	−0.023	0.000
	(0.030)	(0.030)	(0.030)	(0.000)
Other time-varying controls				
$Crew\_Workload$	−1.054$^+$	−1.047$^+$	−1.885**	−1.901**
	(0.543)	(0.543)	(0.593)	(0.597)
$Recent\_Base\_Dispatches$	−0.001	−0.001	0.002	0.001
	(0.035)	(0.035)	(0.035)	(0.035)
$Average\_Base\_Dispatches$	0.001	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)
$Number\_of\_Partners$	−1.429	−1.432	−1.588$^+$	−1.581$^+$
	(0.901)	(0.901)	(0.900)	(0.898)
$Partner\_Tenure$	−0.015	−0.013	−0.013	−0.013
	(0.074)	(0.074)	(0.074)	(0.074)
$Blue\_Call$	4.385***	4.391***	4.391***	4.396***
	(1.199)	(1.199)	(1.198)	(1.197)
Observations	5483	5483	5483	5483
Adjusted R^2	0.096	0.096	0.097	0.097

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^+$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.5. Normalizing base/A&E workload controls by yearly volume

Our main analysis controls for the workload of the dispatching ambulance base and receiving A&E for each ambulance transport, using $Average\_Base\_Dispatches_{rt}$, $Recent\_Base\_Dispatches_{rt}$, $Average\_A\&E\_Arrivals_{rt}$, and $Recent\_A\&E\_Arrivals_{rt}$. These variables capture the absolute number of average and recent base dispatches or A&E arrivals but are not adjusted for the size of the base or A&E. To further account for potential differences in volumes across bases and A&Es, we have repeated our analysis normalizing these variables by the yearly total volume (as a proxy for unit size) observed by the individual bases and hospitals, respectively. These results are reported in Table 23. Our results are not affected by these adjustments.

Table 23 OLS coefficient estimates for robustness checks with normalized base/A&E workload controls.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.652**	4.739*	1.154	1.160
	(1.921)	(1.946)	(1.191)	(1.190)
Partner_HHI * High_Workload		3.588**		
		(1.348)		
Partner_HHI * Suff_Exp			2.732*	1.263
			(1.314)	(1.469)
Partner_HHI * Suff_Exp * High_Workload				5.145**
				(1.936)
Team_Familiarity	-0.014*	-0.013*	-0.008+	-0.008+
	(0.006)	(0.006)	(0.005)	(0.005)
Experience controls				
Exp	-0.008	-0.006	-0.015	-0.014
	(0.011)	(0.011)	(0.012)	(0.012)
Exp^2			-0.000	-0.000
			(0.000)	(0.000)
Task_Exp	-0.019	-0.022	0.002	-0.001
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			-0.011*	-0.011*
			(0.005)	(0.005)
Other time-varying controls				
Crew_Workload	-1.103*	-1.931**	-0.048	-0.308
	(0.533)	(0.587)	(0.265)	(0.286)
Norm_Recent_Base_Dispatches	2.275	2.218		
	(2.218)	(2.243)		
Norm_Average_Base_Dispatches	0.006	0.010		
	(0.284)	(0.284)		
Norm_Recent_A&E_Dispatches			40.991***	41.103***
			(7.836)	(7.824)
Norm_Average_A&E_Dispatches			52.225+	50.564+
			(30.503)	(30.336)
Partner_Tenure	-0.021	-0.021	0.002	0.001
	(0.074)	(0.074)	(0.049)	(0.049)
Number_of_Partners	-1.311	-1.487+	0.579	0.582
	(0.872)	(0.873)	(0.637)	(0.639)
Blue_Call	4.407***	4.406***	-4.836***	-4.802***
	(1.200)	(1.198)	(0.740)	(0.731)
Observations	5483	5483	5568	5568
Adjusted R^2	0.097	0.098	0.114	0.115

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.6. Exclusion of blue calls

Since the patient condition in ambulance transports involving a blue call is usually critical, the process for handing over such patients at the A&E is expedited. Although we have included fixed effects to account for this in all our analyses we also re-estimate our models excluding blue calls. All our results remain unchanged for this subset of the data (see Table 24).

Table 24 OLS coefficient estimates for robustness checks excluding blue calls.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.926**	5.034*	1.444	1.450
	(1.970)	(1.996)	(1.233)	(1.464)
*Partner_HHI * High_Workload*		3.699**		
		(1.347)		
*Partner_HHI * Suff_Exp*			2.480^{+}	1.090
			(1.370)	(1.793)
*Partner_HHI * Suff_Exp * High_Workload*				4.826**
				(1.864)
Team_Familiarity	−0.014*	−0.014*	−0.007	−0.007*
	(0.006)	(0.006)	(0.004)	(0.003)
Experience controls				
Exp	−0.013	−0.010	−0.013	−0.012
	(0.018)	(0.017)	(0.012)	(0.013)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	−0.035	−0.038	0.000	−0.003
	(0.030)	(0.030)	(0.019)	(0.016)
A&E_Experience			−0.011*	−0.011*
			(0.005)	(0.005)
Other time-varying controls				
Crew_Workload	-0.985^{+}	−1.840**	−0.178	−0.425
	(0.543)	(0.592)	(0.254)	(0.276)
Recent_Base_Dispatches	−0.008	−0.006		
	(0.035)	(0.035)		
Average_Base_Dispatches	0.001	0.001		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.224***	0.225***
			(0.042)	(0.044)
Average_A&E_Arrivals			0.386**	0.379**
			(0.137)	(0.123)
Number_of_Partners	-1.573^{+}	-1.721^{+}	0.642	0.644
	(0.904)	(0.904)	(0.622)	(0.697)
Partner_Tenure	0.004	0.003	−0.002	−0.003
	(0.076)	(0.076)	(0.053)	(0.054)
Observations	5332	5332	5417	5417
Adjusted R^2	0.096	0.098	0.111	0.112

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.7. Excluding first 10 transports for each new recruit

By the definition of $Partner\_HHI$, most new recruits are assigned a $Partner\_HHI$ value of 1 following their first ambulance transport, as most likely they would have encountered only one senior partner. We therefore exclude the first two transports of each new recruit from our analysis. For robustness, we repeat our analysis excluding the first 10 transports of each new recruit, eliminating about 8% of our data. Despite the smaller sample size all our results continue to hold at the same significance levels as before (see Table 25).

Table 25 OLS coefficient estimates for robustness checks excluding the first 10 transports for each new recruit.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
$Partner\_HHI$	5.308*	4.338+	2.316	2.321
	(2.245)	(2.300)	(1.580)	(1.584)
$Partner\_HHI$ * $High\_Workload$		4.412***		
		(1.333)		
$Partner\_HHI$ * $Suff\_Exp$			3.015*	1.571
			(1.423)	(1.562)
$Partner\_HHI$ * $Suff\_Exp$ * $High\_Workload$				5.047**
				(1.927)
$Team\_Familiarity$	−0.014*	−0.013*	−0.011*	−0.011*
	(0.006)	(0.007)	(0.005)	(0.005)
Experience controls				
Exp	−0.020	−0.018	−0.020	−0.020
	(0.019)	(0.018)	(0.013)	(0.013)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Task\_Exp$	−0.013	−0.017	0.002	−0.001
	(0.030)	(0.030)	(0.018)	(0.018)
$A\&E\_Experience$			−0.009	−0.009
			(0.006)	(0.006)
Other time-varying controls				
$Crew\_Workload$	−0.944+	−1.908**	0.062	−0.211
	(0.555)	(0.606)	(0.298)	(0.326)
$Recent\_Base\_Dispatches$	0.011	0.015		
	(0.036)	(0.036)		
$Average\_Base\_Dispatches$	0.001	0.001		
	(0.006)	(0.006)		
$Recent\_A\&E\_Arrivals$			0.231***	0.232***
			(0.045)	(0.045)
$Average\_A\&E\_Arrivals$			0.336*	0.328*
			(0.139)	(0.136)
$Number\_of\_Partners$	−1.026	−1.194	0.638	0.640
	(0.913)	(0.909)	(0.679)	(0.679)
$Partner\_Tenure$	−0.050	−0.052	0.018	0.017
	(0.074)	(0.073)	(0.051)	(0.051)
$Blue\_Call$	4.073**	4.039**	−4.935***	−4.900***
	(1.293)	(1.301)	(0.767)	(0.755)
Observations	5123	5123	5197	5197
Adjusted R^2	0.098	0.100	0.116	0.117

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.8. Excluding transports with more than one senior

As we mention in the results section, our measure for team familiarity is likely to be underestimated for ambulance transports which include multiple senior partners, as they may have worked together prior to 2011. We repeat the analysis focusing on crews with only one senior. In this case, the effect of team familiarity is even stronger than in our main results. All other results remain unchanged (see Table 26).

Table 26 OLS coefficient estimates for robustness checks excluding transports with more than one senior partner.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Team_HHI	4.491*	3.931^{+}	1.923	1.900
	(2.068)	(2.076)	(1.291)	(1.450)
*Team_HHI * High_Workload*		3.151*		
		(1.448)		
*Team_HHI * Suff_Exp*			2.897*	1.873
			(1.162)	(1.473)
*Team_HHI * Suff_Exp * High_Workload*				3.699*
				(1.499)
Team_Familiarity	−0.017*	−0.017*	−0.011*	−0.011*
	(0.007)	(0.007)	(0.005)	(0.004)
Experience controls				
Exp	0.005	0.006	−0.017	−0.016
	(0.019)	(0.019)	(0.012)	(0.012)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	−0.028	−0.030	−0.005	−0.007
	(0.031)	(0.031)	(0.019)	(0.015)
A&E_Experience			−0.009	−0.009
			(0.006)	(0.006)
Other time-varying controls				
Crew_Workload	−1.336*	−2.081**	0.080	−0.186
	(0.587)	(0.645)	(0.333)	(0.330)
Recent_Base_Dispatches	0.032	0.034		
	(0.039)	(0.039)		
Average_Base_Dispatches	0.003	0.003		
	(0.007)	(0.007)		
Recent_A&E_Arrivals			0.233***	0.234***
			(0.041)	(0.045)
Average_A&E_Arrivals			0.508***	0.501***
			(0.096)	(0.083)
Number_of_Partners				
Partner_Tenure	−0.042	−0.043	0.001	0.001
	(0.083)	(0.083)	(0.063)	(0.069)
Blue_Call	3.881*	3.911*	−4.217***	−4.189***
	(1.539)	(1.542)	(0.702)	(0.801)
Observations	4555	4555	4634	4634
Adjusted R^2	0.101	0.102	0.127	0.128

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.9. Excluding first transport of every shift

To ensure that our results are not driven by start-of-shift or end-of-shift effects we have run two additional sets of analysis, excluding the first or last ambulance transport of every shift, respectively. The results are included in Tables 27 and 28. In summary, while we lose statistical power by eliminating (around 1000) observations, our results hold (in coefficient size and significance) in all cases, except the p-value of the direct effect of $Partner\_HHI$ on scene performance increases from 0.008 to 0.056 by eliminating the first transport of every shift while the significance level of all our main variables either stays constant or increases by eliminating the last transport of every shift.

Table 27 OLS coefficient estimates for robustness checks. Exclusion of first transport of every shift.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	4.429^{+}	3.351	0.916	0.948
	(2.319)	(2.375)	(1.412)	(1.395)
Partner_HHI * High_Workload		3.338^{*}		
		(1.435)		
Partner_HHI*Suff_Exp			3.093^{*}	1.078
			(1.571)	(1.716)
Partner_HHI*Suff_Exp*High_Workload				5.741^{**}
				(1.948)
Team_Familiarity	-0.012^{+}	-0.011^{+}	-0.006	-0.006
	(0.007)	(0.007)	(0.004)	(0.004)
Experience controls				
Exp	-0.018	-0.016	-0.017	-0.016
	(0.018)	(0.018)	(0.013)	(0.013)
Exp^2	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.033	-0.036	0.008	0.005
	(0.035)	(0.035)	(0.022)	(0.022)
A&E_Exp			-0.009	-0.009
			(0.007)	(0.007)
Other time-varying controls				
Crew_Workload	0.675	-0.647	0.021	-0.481
	(0.875)	(1.053)	(0.513)	(0.495)
Recent_Base_Dispatches	-0.017	-0.015		
	(0.038)	(0.038)		
Average_Base_Dispatches	0.004	0.004		
	(0.007)	(0.007)		
Recent_A&E_Dispatches			0.171^{***}	0.174^{***}
			(0.043)	(0.043)
Average_A&E_Dispatches			0.438^{*}	0.425^{**}
			(0.172)	(0.165)
Partner_Tenure	-0.065	-0.063	-0.020	-0.019
	(0.078)	(0.078)	(0.048)	(0.048)
Number_of_Partners	-2.041^{*}	-2.179^{*}	0.616	0.631
	(1.029)	(1.032)	(0.700)	(0.700)
Blue_Call	3.834^{**}	3.881^{**}	-4.445^{***}	-4.393^{***}
	(1.195)	(1.191)	(0.743)	(0.729)
Observations	4516	4516	4580	4580
Adjusted R^2	0.093	0.094	0.112	0.114

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

Table 28 OLS coefficient estimates for robustness check excluding last transport of every shift.

Partner exposure & Team familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.369*	4.504*	0.540	0.551
	(2.163)	(2.198)	(1.399)	(1.399)
Partner_HHI * High_Workload		3.012*		
		(1.512)		
Partner_HHI*Suff_Exp			3.921**	2.731+
			(1.346)	(1.524)
Partner_HHI*Suff_Exp*High_Workload				4.064*
				(1.980)
Team_Familiarity	-0.014*	-0.014*	-0.006	-0.006
	(0.006)	(0.006)	(0.004)	(0.004)
Experience controls				
Exp	-0.006	-0.004	-0.018	-0.018
	(0.018)	(0.018)	(0.014)	(0.014)
Exp^2	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.051	-0.053+	-0.009	-0.011
	(0.032)	(0.032)	(0.020)	(0.020)
A&E_Exp			-0.013*	-0.013*
			(0.006)	(0.006)
Other time-varying controls				
Crew_Workload	-1.018+	-1.717**	-0.147	-0.359
	(0.560)	(0.618)	(0.304)	(0.327)
Recent_Base_Dispatches	0.026	0.028		
	(0.038)	(0.038)		
Average_Base_Dispatches	-0.005	-0.005		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.241***	0.241***
			(0.047)	(0.047)
Average_A&E_Arrivals			0.194	0.194
			(0.140)	(0.139)
Partner_Tenure	-0.019	-0.020	-0.015	-0.015
	(0.084)	(0.084)	(0.052)	(0.052)
Number_of_Partners	-1.304	-1.414	0.144	0.152
	(1.017)	(1.013)	(0.782)	(0.785)
Blue_Call	3.505**	3.559**	-4.812***	-4.772***
	(1.244)	(1.241)	(0.750)	(0.741)
Observations	4442	4442	4508	4508
Adjusted R^2	0.099	0.100	0.113	0.114

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). +, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.10. Analysis Without Time-Varying Controls

Table 29 OLS coefficient estimates for robustness checks with no time-varying controls.

Partner exposure & Team Familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.981**	5.117*	0.611	0.633
	(1.990)	(2.006)	(1.257)	(1.257)
Partner_HHI*High_Workload		3.443*		
		(1.335)		
Partner_HHI*Suff_Exp			3.036*	1.511
			(1.380)	(1.514)
Partner_HHI*Suff_Exp*High_Workload				5.396**
				(1.883)
Team_Familiarity	-0.016**	-0.016**	-0.007	-0.007
	(0.006)	(0.006)	(0.004)	(0.004)
Experience controls				
Exp	-0.011	-0.008	-0.020	-0.020
	(0.017)	(0.016)	(0.013)	(0.013)
Exp^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Task_Exp	-0.019	-0.022	-0.003	-0.006
	(0.030)	(0.030)	(0.018)	(0.018)
A&E_Exp			-0.012*	-0.012*
			(0.005)	(0.005)
Observations	5483	5483	5568	5568
Adjusted R^2	0.093	0.095	0.097	0.098

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew (for scene time) and paramedic crew and A&E (for handover). $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

G.11. Two-way clustered standard errors by paramedic crew and day-of-year

Table 30 OLS coefficient estimates for robustness check with two-way clustering (paramedic crew and day-of-year) for both Scene and Handover.

Partner exposure & Team Familiarity	(1) Scene Time	(2) Scene Time	(3) Handover Time	(4) Handover Time
Partner_HHI	5.348*	4.475*	1.000	1.206
	(2.102)	(2.137)	(1.219)	(1.337)
Partner_HHI * High_Workload		3.613*		
		(1.437)		
Partner_HHI*Suff_Exp			2.679+	1.159
			(1.475)	(1.639)
Partner_HHI*Suff_Exp*High_Workload				5.201**
				(1.728)
Team_Familiarity	-0.014*	-0.014*	-0.008+	-0.008+
	(0.006)	(0.006)	(0.005)	(0.005)
Experience controls				
Exp	-0.018	-0.016	-0.018*	-0.014
	(0.017)	(0.017)	(0.008)	(0.013)
Exp^2	0.000	0.000		-0.000
	(0.000)	(0.000)		(0.000)
Task_Exp	-0.019	-0.022	0.002	-0.001
	(0.031)	(0.031)	(0.019)	(0.020)
A&E_Exp			-0.011	-0.011
			(0.007)	(0.007)
Other time-varying controls				
Crew_Workload	-1.054+	-1.895**	-0.089	-0.355
	(0.557)	(0.595)	(0.343)	(0.342)
Recent_Base_Dispatches	-0.001	0.002		
	(0.035)	(0.036)		
Average_Base_Dispatches	0.001	0.001		
	(0.006)	(0.006)		
Recent_A&E_Arrivals			0.221***	0.222***
			(0.036)	(0.036)
Average_A&E_Arrivals			0.355**	0.348**
			(0.133)	(0.133)
Partner_Tenure	-0.015	-0.015	0.002	0.001
	(0.074)	(0.074)	(0.044)	(0.044)
Number_of_Partners	-1.429	-1.586+	0.522	0.581
	(0.905)	(0.895)	(0.691)	(0.712)
Blue_Call	4.385***	4.385***	-4.877***	-4.840***
	(1.305)	(1.299)	(0.748)	(0.748)
Observations	5483	5483	5568	5568
Adjusted R^2	0.096	0.097	0.114	0.116

All models include fixed effects for new recruits, A&E (for handover), main conditions, severity scores, time of day, day of week, and month of year, as well as controls for weather conditions (for scene time). Standard errors are heteroscedasticity consistent and clustered by the paramedic crew and day-of-year. $^{+}$, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.