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Abstract
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The Effect of Shift Structure on Performance†

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The effect of shift structure on worker performance and productivity is of increasing interest to firms and regulatory bodies. Using approximately 743,000 emergency medical incidents attended by 2,381 paramedics in Mississippi, we evaluate the extent that paramedics' performance toward the end of shifts is impacted by shift length. We find evidence that performance deteriorates toward the end of long shifts, and argue that fatigue is the mediating factor. Our calculations imply that such deterioration may result in a 0.76 percent increase in 30-day mortality. These findings have implications for workforce organization, calling attention to regulation designed to limit extended work hours. (*JEL* J22, J24, J28, J45, M12)

Shift work is common in many industries and is universal in those operating around the clock. While widespread, the impact of shift structure and length on performance is not well understood. Most firms and organizations function in such a way that labor works in shifts of 12 hours or less on a daily basis, while others have shifts lasting 24 hours or more. Such long shifts reduce commuting and adaption time, and are associated with longer breaks and time off between consecutive shifts. On the other hand, the cumulative effect of night work and extended work hours can lead to fatigue-impaired employees.

Fatigue from long work hours, sleep deprivation, and circadian disruption has been recognized as a substantial cause of serious human errors (Veasey et al. 2002). In the context of health care, policies and procedures aimed at reducing the incidence of medical errors have either been voluntarily implemented by health care organizations or imposed by regulators. In medical education, for example, the Accreditation Council for Graduate Medical Education (ACGME) implemented duty hour restrictions in 2003 for all ACGME-accredited residency programs, following concerns about deaths associated with medical errors in US

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hospitals (Nasca, Day, and Amis 2010).[1] Similarly, in July 2011, after disclosing seven instances of air traffic controllers sleeping on the job, the Federal Aviation Administration (FAA) released new regulations governing air traffic control work schedules and acknowledging the widespread problem of controllers' fatigue.[2]

While quantifying the effect of fatigue resulting from long shifts has important implications for policy and safety regulation design regarding shift structure, there is a paucity of research that isolates fatigue as the mediating factor for deteriorations in real-time performance among health care workers who work extended hours.

In this study, we examine the relationship between shift structure and productivity in Emergency Medical Services (EMS), where there is considerable variation in shift structure. Specifically, we analyze paramedic performance in approximately 743,000 emergent medical and trauma incidents by tracking 2,381 paramedics in the state of Mississippi over five years. We first adopt a paramedic fixed-effects difference-in-differences approach and argue that fatigue is likely to be a key contributing factor in the deterioration of paramedic performance toward the end of longer shifts (e.g., a 24 hour shift). We later consider the relationship between time-in-shift (or time on duty) and provide a number of robustness checks that serve to complement the *within*-paramedic analysis. Performance measures track time markers for response, on-scene activity and transport as well as the number of interventions performed on-scene and minutes-per-procedure.

The practice of working both long and short shifts is prevalent in EMS, with over 93 percent of emergency medical technicians (EMTs) in our sample working both types of shifts. The most common reason for observing within-EMT variation in shift lengths is the practice of shift-splitting and back-to-back shifts (Kuehl 2002). We find that paramedics working longer shifts exhibit poorer performance toward the end of their shift compared to their own performance when working shorter shifts. In addition, estimating a *within*-shift relationship between time on duty at nighttime and performance produced consistent results. Our calculations imply that the poorer performance of paramedics toward the end of long shifts may result in a 0.76 percent increase in 30-day mortality and a 1.35 percent increase in 1-year mortality. We also explore how this deterioration in performance may affect outcomes for emergent conditions with specific, time-sensitive treatments.

The existing literature on the effects of extended work hours on healthcare providers' focuses on deterioration in cognitive ability (Veasey et al. 2002).[3] These studies typically involved a small number of subjects.

[1] In June 2010, the ACGME issued a report calling for an unprecedented 16 hour limit to shift lengths for interns (Nasca, Day, and Amis 2010).

[2] The major reason controllers fall asleep on the job was found to be related to their weekly work schedule. Air traffic controllers are typically expected to partake in five eight-hour work days per week, yet it is very common that they cram these five shifts into as few days as possible. This compressed schedule is likely to lead to fatigue and can result in serious errors, yet is popular because it allows controllers to have three and a half days off every week. The FAA found midnight shifts, which usually begin at 10 PM and end at 6 AM, to be the most tiring (Harris, Elizabeth. 2011. "F.A.A. to Change Air Traffic Controllers' Schedules." *New York Times*, April 16 and Federal Aviation Administration (FAA), "Press Release—FAA and NATCA Reach Agreement on Fatigue Recommendations" http://www.faa.gov/news/press_releases, July 1, 2011).

[3] The bulk of studies follow a within-subject, lab-based research design, where subjects with different degrees of sleep loss are evaluated using standardized tests, such as: special perception tests, auditory serial addition tests, number connection tests, card sorting tests, reaction time tests, hand-eye coordination tests, and divided attention tests. Similarly, lab-based simulations include: simulated triage tasks, simulated intubation, and simulated driving.

For example, Lockley et al. (2004) found 13 out of 20 interns to experience a decrease in the number of slow eye movements during overnight work (from 11 PM to 7 AM) in longer shifts compared with shorter shifts. Similarly, Arnedt et al. (2005) found reduced sustained attention and poorer performance on a driving simulator after "heavy" rotations compared with "light" rotations for 34 pediatric residents.

Few studies measured clinical performance on actual patients. For example, Goldman, McDonough, and Rosemond (1972) compared videotapes of actual operations performed by five residents and found a 30 percent increase in surgical time in 4 of the 5 residents with little sleep. In a larger retrospective cross-sectional analysis of surgical cases, Haynes et al., (1995) found no increased risk of complications for patients seen by residents that were on call for 24 hours on the day prior to surgery. On the other hand, Rogers et al., (2004) found that nurses working more than 12 hours reported more errors. Our retrospective analysis benefited from a significantly larger sample size, and the richness of our data allows for a within-subject and within-shift analysis, alleviating some concern that the effects of shift length are confounded by time of the day.

Finally, a number of studies focused on the effects of extended work hours on risk of injury and found an association between both work duration and nighttime work and the prevalence of motor vehicle crashes involving medical residents during post-call periods (Steele et al. 1999) as well as percutaneous injuries for interns (Ayas et al. 2006).

Our study contributes to the evidence that performance deteriorates with shift length even in a life-and-death context such as EMS, where there is little room for error. The underlying mechanism is likely fatigue from extended work hours.

I. Data

Our data come from the Mississippi Emergency Medical Services Information System (MEMSIS) and are gathered by the Office of Emergency Planning and Response at the Mississippi Department of Health. MEMSIS provides statewide data, systematically collected through a comprehensive software system enabling real time collection of patient level data by EMS providers and dispatchers.

MEMSIS allows us to track the universe of paramedics' activities between 2001 and 2005, totaling 1,625,000 ambulance runs, including 882,000 inter-facility transfers, and 743,000 trauma and medical incidents. We use all incidents for the purpose of constructing shift schedules, yet to focus on incidents for which time to definitive care is most likely to be important, we limit our attention to EMS incidents for which the initial emergent call was related to trauma (defined as motor vehicle crashes, motorcycle crashes, pedestrian and bicycle injuries, stabbings, assaults, gunshots, or falls) or to a medical emergency (defined as cardiac, gastrointestinal, neurological, psychological, substance abuse, or other), and for which an advanced life support (ALS) unit was dispatched to the scene.[4] We exclude cases of death on arrival as well, because time to hospital's morgue is not important for these incidents. Our

[4] ALS units are more heavily equipped than Basic Life Support units, and offer a wider range of interventions on scene. Interfacility transfers, which are often nonemergent and scheduled in advance, were excluded.

final sample is comprised of 155,392 trauma incidents and 587,617 medical incidents, which involve emergency transport to a hospital.

A. *Construction of Paramedic Shifts*

MEMSIS, which is designed primarily for monitoring, billing, and clinical evaluation, but not for human resources management purposes, does not contain an explicit indicator of shift structure for paramedics. Therefore, we elicit this information from the data. MEMSIS is organized by patient, with each observation corresponding to a single patient, recording the dates and times at which the emergent call was received, an ALS unit was dispatched to the scene, the unit arrived on-scene, the unit left the scene, and the unit delivered the patient to definitive care. For each patient, the paramedic and driver who were dispatched to the incident are identified by unique (and stable) EMT IDs.

We exploit these features and the fact that MEMSIS records every EMS incident in the state—whether emergent or not—to construct paramedic and driver shifts based on their periods of inactivity, which we identify by their absences from the data. Sorting the data first by EMT ID, then by date and time at which they were alerted for each incident, we define the beginning of a new shift every time ten or more hours have elapsed between consecutive observations of the same paramedic.[5] Once shifts are defined, we measure a lower bound for the shift's duration as the difference between the times of the first and last calls of the shift. For simplicity, we refer to this difference as "shift length" and plot its distributions in the trauma and medical data on which we focus our analysis in the upper panel of Figure 1. For both types of incidents, the mode is around nine hours, and the distributions fall off precipitously thereafter, leveling off somewhat around 12 hours. This leveling largely forms the basis for our categorization of shift types. We define long and short shifts as those lasting longer and shorter than 12 hours, respectively. For simplicity, we refer to long shifts as 24-hour shifts, and short ones as 12-hour shifts, though these are admittedly very approximate characterizations. We use the time elapsed between every incident alerted and the first incident in the shift to construct a measure of time on duty. This measure of time-in-shift varies across incidents within shift, and forms the basis for our *within*-shift analysis.

The middle panel of Figure 1 plots the distribution of the paramedics' hours of inactivity between shifts separately for short and long shifts. These distributions are multimodal, with (local) modes occurring roughly at multiples of 12 hours. A large proportion of paramedics on shorter shifts have between 12 and 24 hours off between shifts. The next highest proportions occur in the [36, 48] and [60, 72] hours intervals. In turn, those paramedics starting long shifts are considerably more likely to have been off-duty for longer periods, with a large proportion having been inactive between 48 and 72 hours. These observations are consistent with evidence that paramedics working 24-hour shifts often have two to three days off between shifts.[6]

[5] For robustness, we also used 11 and 12 hours between shifts as cutoffs for defining new shifts. The results presented below were not sensitive to these alternative definitions.

[6] The typical 24-hour shift schedule provides approximately 260 days off per calendar year, a reason many paramedics have a preference for this shift structure (Kuehl 2002). Not surprisingly, a 2006 nationwide survey of paramedics found more than 55 percent of respondents reported working 24-hour shifts.

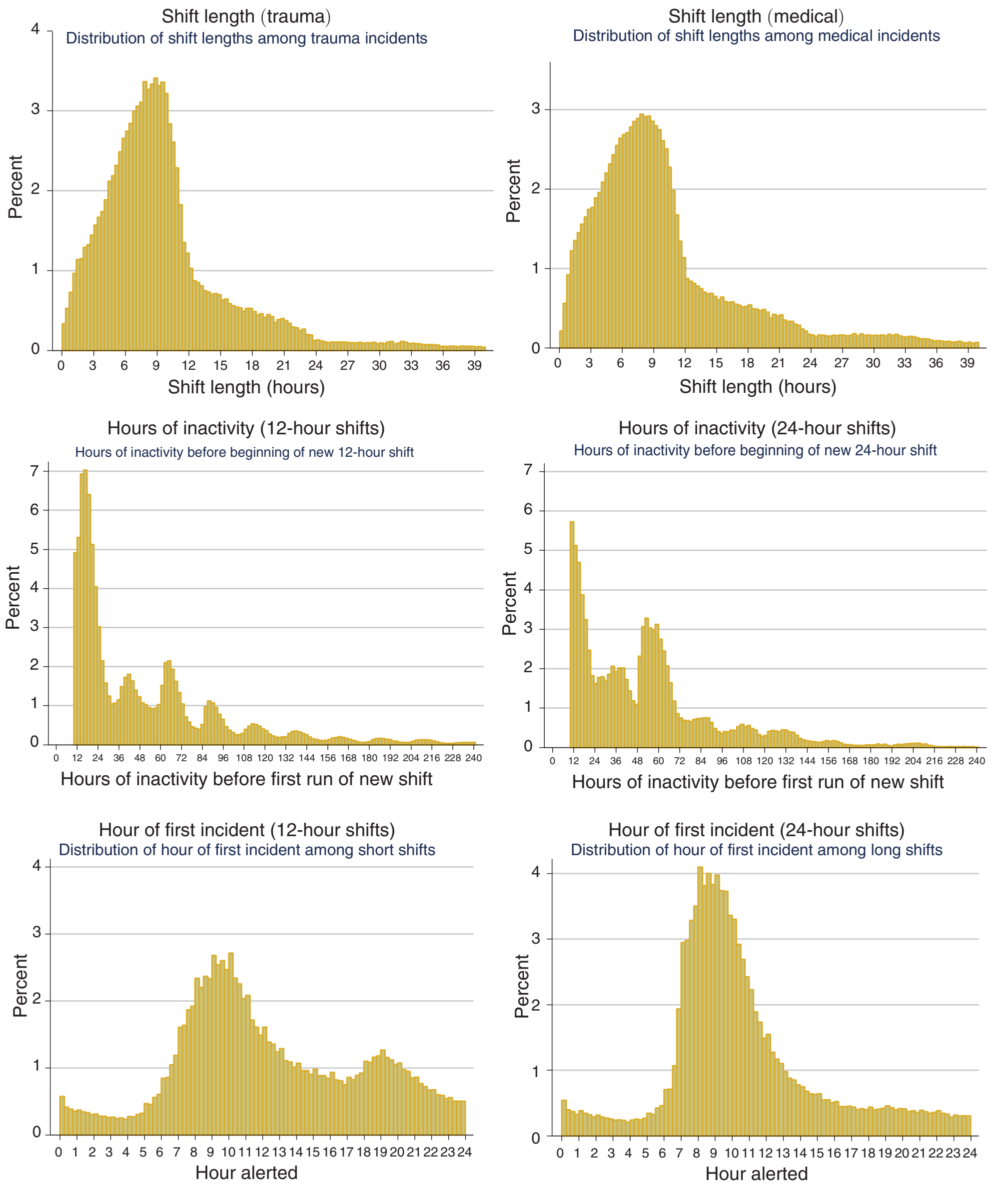

FIGURE 1. DISTRIBUTIONS OF SHIFT LENGTHS, HOURS OF INACTIVITY, AND BEGINNING OF SHIFT

Notes: The top panel of this figure displays the shift length for trauma incidents (left side) and medical incidents (right side). A new shift is defined to begin when a paramedic receives the first call after ten or more hours of inactivity. Shift length is measured as the time from this first incident to the last call of the shift. The middle panel displays the hours of inactivity before a new shift for paramedics on 12-hour shifts (left side) and 24-hour shifts (right side). Because new shifts are defined to begin after at least 10 hours of inactivity, these distributions begin at 10 hours. The bottom panel plots the hour of the first incident in each shift for 12-hour shifts (left side) and 24-hour shifts (right side).

Finally, the lower panel of Figure 1 plots the distribution of the time at which the first incident of a shift occurred separately for short and long shifts. Whereas the vast majority of first incidents occur between 7 AM and 10 AM, for those paramedics starting long shifts,[7] the distribution is bimodal among short shifts, with a large mass between 6 PM and 8 PM. Thus, to provide round-the-clock coverage with short shifts, EMS agencies appear to design an early shift that begins at roughly the same time as those on long shifts, coupled with another that begins in the evening to cover the night. This was also consistent with information collected through interviews with local EMS officials.

Since a beginning of a shift is assigned to the first EMS call following a long break, it is likely measured with error. This measurement error is potentially more severe with greater typical time between incidents. Since the average time between morning incidents is approximately an hour, the true starting point of the shift is likely to precede our assigned starting point by roughly 30 minutes.[8] As we see in Figure 1, there is a mass of shifts with a first incident between 7 AM and 10 AM, suggesting that the dispersion in observed starting time in the morning is real.

The idea behind the ten-hour cutoff between incidents to define a shift is that, given the frequency of incidents in Mississippi, it is unlikely that a paramedic would be on-duty for ten consecutive hours without an incident (these incidents include interfacility transfers, which are more frequent than medical or trauma emergencies). However, this procedure is imperfect, as on-duty paramedics may go inactive for ten or more hours, in which case our procedure will assign them a new shift when in fact they are on the same long shift. Thus, we will inappropriately tend to misclassify such paramedics as being on shorter shifts. Should that be the case, our estimates will be attenuated and might be thought of as lower bounds on the effect of long shifts. Moreover, inactivity is commonly the result of low call volume, which is highly correlated with local characteristics (e.g., population size and density). A second type of misclassification, albeit less likely, may arise if paramedics have breaks between consecutive shifts that last less than ten hours. In this case, we will inappropriately tend to misclassify such paramedics as being on longer shifts. While possible, such instances are not very likely given the structure of shifts in Mississippi (e.g., no agency fits a schedule that consists of three consecutive eight hour shifts).

Nevertheless, it is not conceptually clear that, for the purposes of studying the effects of the variety of fatigue studied here, misclassifications of the first type represent severe threats to validity. While a paramedic may technically be on a long shift, having at least ten hours uninterrupted by an incident implies that she may be well rested for the calls that she does receive (paramedics often manage their fatigue with naps). In essence, since the effect that we aspire to identify arises from fatigue that results from sustained wakefulness, rather than fatigue from chronic sleep loss, such a paramedic would provide little identifying power if her true shift structure were observable.

[7] In the analysis below, we study only those long shifts for which the first call came in the morning (7 AM–12 PM), such that the end of the shift roughly coincides with the midnight–6 AM interval. This corresponds more closely to the clinical literature on the circadian cycle, according to which the natural deterioration in cognition, attention, and focus is most severe between 2 AM and 5 AM (Veasey et al. 2002; Lockley et al. 2004; Arendt et al. 2005; Ayas et al. 2006).

[8] Note that the average out-of-hospital time (36 minutes) places a lower bound on the average time between incidents for a given EMT.

B. *Summary Statistics*

The main performance measure in this study is a process measure that is widely accepted in the EMS community, total out-of-hospital time, which is measured from the moment the ambulance crew is dispatched to a scene to the moment it arrives at the hospital (Carr et al. 2008). We further partition this measure into response time, on-scene time, and transport time. Response time is the most commonly used performance marker in EMS contracting between municipalities and ambulance providers (David and Brachet 2009, 2011). In addition, we track the number of prehospital interventions performed on-scene and minutes-per-procedure. When paramedics are fatigued, they are likely to be slower in performing procedures, such as extrication, spine immobilization, application of oxygen, etc. They may also require multiple attempts before they successfully intubate a patient or place an intravenous line (Cwinn et al. 1987).

While these are all process measures that serve as inputs into a health production function, shorter out-of-hospital time intervals are argued to be an important factor in survival (Feero et al. 1995; Nichol et al. 1996; Sampalis et al. 1993; Institute of Medicine (IOM) 2007; Wilde 2009). In Table 1, we provide summary statistics for medical and trauma runs in our data, broken down by shift structure. In particular, these report the six different dependent variables of interest: total out-of-hospital time and its components (response time, on-scene time, and transport time), number of procedures, and minutes-per-procedure.

Paramedics on 24-hour shifts tend to have shorter out-of-hospital times compared with their 12 hour shift counterparts for both trauma and medical runs (35.17 versus 36.20 minutes for trauma incidents and 35.33 versus 35.86 minutes for medical incidents). These differences arise from longer on-scene and transport times among paramedics on shorter shifts, though they are mitigated by shorter response times in both medical and trauma incidents. In addition, paramedics on 24-hour shifts undertake 0.2 more prehospital interventions in trauma incidents than their shorter shift counterparts, and each procedure is performed 1.33 minutes faster. This relationship is reversed for medical incidents, with those on 12-hour shifts initiating 0.1 more procedures and performing them slightly faster than those on longer shifts.

Table 1 also presents summary statistics for key scene, provider, and patient characteristics. Among trauma incidents, those on long shifts see 2.7 percentage points more motor vehicle crashes, but 1.8 percent fewer falls. This helps explain the discrepancies in incident locations. Long shifters are 3.6 and 3.1 percentage points more likely to attend scenes on county roads and state/federal highways, respectively, but are 3.5 and 3.2 percentage points less likely to be dispatched to incidents located on city streets and other locations (usually residences and nursing homes), respectively.

II. Analysis

We use a difference-in-differences approach to examine whether shift-to-shift changes in shift structure are associated with changes in underlying paramedic performance during the later segments of their shifts.

Table 1—Summary Statistics for Trauma and Medical Incidents for Mississippi, 2001–2005

	Trauma incidents				Medical incidents			
	24-Hour shift		12-Hour shift		24-Hour shift		12-Hour shift	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total out-of-hospital time	35.17	16.92	36.20	16.08	35.33	17.61	35.86	16.87
Response time	8.25	6.15	7.88	5.90	8.88	6.93	8.39	6.69
On-scene time	14.23	8.41	14.81	8.41	12.92	7.79	13.35	8.14
Transport time	12.69	9.75	13.51	9.49	13.53	11.32	14.12	10.60
Number of procedures	2.14	2.28	1.95	2.14	1.95	2.25	2.06	2.39
Minutes per procedure	6.74	5.48	8.07	6.36	5.22	4.38	5.08	4.54
Patient demographics								
White	0.544	0.498	0.568	0.495	0.540	0.498	0.560	0.496
Black	0.419	0.493	0.401	0.490	0.439	0.496	0.421	0.494
Other	0.036	0.187	0.031	0.173	0.021	0.143	0.019	0.137
Age	42.41	24.72	42.42	24.12	56.24	24.93	56.02	24.76
Female	0.556	0.497	0.552	0.497	0.581	0.493	0.567	0.495
EMT characteristics								
Time between shifts	43.12	21.77	37.39	24.87	43.38	21.98	37.86	25.04
EMT-Basic	0.017	0.127	0.023	0.150	0.032	0.177	0.037	0.188
EMT-Intermediate	0.001	0.021	0.001	0.237	0.001	0.024	0.007	0.083
EMT-Paramedic	0.982	0.132	0.966	0.185	0.967	0.216	0.956	0.230
Public/fire-based	0.342	0.474	0.115	0.319	0.311	0.463	0.121	0.326
Hospital-based	0.210	0.407	0.278	0.448	0.235	0.424	0.342	0.474
Private corporation	0.448	0.497	0.607	0.488	0.454	0.498	0.537	0.499
Incident type								
Motor vehicle crash	0.549	0.498	0.522	0.500				
Gunshot	0.015	0.122	0.015	0.121				
Fall	0.305	0.460	0.322	0.467				
Motorcycle	0.013	0.113	0.011	0.102				
Pedestrian	0.016	0.124	0.018	0.132				
Cutting/stabbing	0.022	0.148	0.024	0.152				
Assault	0.081	0.272	0.059	0.285				
Cardio					0.249	0.432	0.266	0.442
Gastrointestinal					0.117	0.321	0.136	0.343
Neuro					0.148	0.355	0.163	0.370
Genitourinary					0.015	0.120	0.013	0.113
Psych/substance abuse					0.038	0.191	0.063	0.243
Constitutional					0.271	0.445	0.301	0.459
Other (medical)					0.162	0.369	0.057	0.232
Incident location								
City street	0.189	0.392	0.224	0.417				
County road	0.115	0.319	0.079	0.269				
Highway	0.255	0.436	0.224	0.417				
Other (trauma)	0.441	0.497	0.473	0.499				
Residence					0.639	0.480	0.611	0.488
Healthcare facility					0.212	0.409	0.234	0.424
Road/highway					0.034	0.181	0.032	0.176
Other (medical)					0.115	0.319	0.123	0.329
Observations	41,052		114,340		159,392		428,225	

Notes: This table summarizes patient and EMT characteristics, as well as incident details, for trauma and medical incidents in the MEMSIS statewide data from 2001 to 2005. Trauma incidents are defined as events where the initial call involved a motor vehicle crash, motorcycle crash, pedestrian or bicycle injury, stabbing, assault, gunshot, or fall. Medical incidents are calls for medical emergencies including cardiac, gastrointestinal, neurological, psychological, substance abuse, or other. All incidents had an advanced life support unit dispatched to the scene and subsequent emergency transport to a hospital. Deaths on arrival were excluded from the sample, as were interfacility transfers.

In our setting, we conceive of paramedics on long shifts as being in the treatment group and those on short (12 hours or less) shifts as being in the control group. We then define an incident as being treated if it takes place in the last quarter of a paramedic's 24-hour shift. Since the vast majority of 24-hour shifts begin in the morning (see Figure 1), it is specifically defined for incidents occurring between midnight and 7 AM. This definition captures the intuition that fatigue may manifest itself after long durations on call and especially at night (Veasey et al. 2002; Lockley et al. 2004; Arendt et al. 2005; Ayas et al. 2006).

There are several reasons to believe that emergent incidents occurring late at night will differ from those occurring during the day. For instance, a motor vehicle accident at 2 AM on a poorly lit county road will likely pose greater difficulties for paramedics than the same accident occurring at midday. Alternatively, the later accident may be more likely to involve an intoxicated driver, or one who has fallen asleep at the wheel, and is therefore likely to be more severe in both observable and unobservable dimensions. These observations suggest that simple night-versus-day comparisons will be inadequate for studying fatigue, as they will be plagued by unobserved severity and complications. For this reason, the late night deteriorations in performance among paramedics on 24-hour shifts are benchmarked to those of paramedics on 12-hour shifts (who started in the late afternoon/early evening; see Figure 1), who experience the same changes from day to night in the nature and characteristics of scenes as their 24-hour counterparts.

Our application of difference-in-differences is further refined by the fact that we can identify individual paramedics, allowing us to adopt a paramedic fixed-effects approach. Our estimates therefore result from *within-paramedic* comparisons, measuring the deterioration in performance that occurs in the last six hours of a paramedic's 24-hour shifts relative to that which she experiences in the second half of her 12-hour evening/night shifts, conditional on observed differences in incident characteristics. The inclusion of paramedic fixed effects implies that our results are not driven by inherent differences between paramedics who are selected for 24-hour shift work and those working shorter shifts. The upper panel of Table 2 indicates that roughly 30 percent of both trauma and medical incidents are served by paramedics on 24-hour shifts, and that approximately a quarter of shifts are 24-hours, with a slightly rising trend over time. However, these 24-hour shifts are unequally distributed across provider types. The lower panel of Table 2 indicates that public, fire-based EMS agencies are almost twice more reliant on long shifts compared to hospital-based and private providers, who employ 24-hour shifts between a quarter and a third of the time. This is consistent with the practice of back-to-back shifts for private providers (such as hospitals and private EMS companies) and the practice of shift splitting for public providers (such as municipal fire departments).

The models we estimate are of the following form:

$$(1)\quad y_{isp} = \mathbf{X}'_{isp}\mathbf{\Pi} + \mathbf{Hour}'_{isp}\beta + \phi \times \mathbf{Shift}_{is} + \gamma \times \mathbf{Night}_{isp} + \alpha_i + \varepsilon_{isp},$$

where y_{isp} is a measure of performance for paramedic i attending patient p during shift s; $Hour_{isp}$ is a vector of 23 indicator variables specifying the time of day of patient p's

Table 2—The Percent of Incidents and Shifts Attended by an EMT on a 24-Hour Shift by Year and across Firm Types

	Trauma		Medical	
Year	Percent incidents served by a paramedic on a 24-hour shift	Percent of paramedic shifts that are 24-hour	Percent incidents served by a paramedic on a 24-hour shift	Percent of paramedic shifts that are 24-hour
2001	23.4	20.7	24.0	18.4
2002	27.2	24.3	27.2	21.4
2003	29.2	25.9	29.3	22.6
2004	29.3	25.7	29.4	22.6
2005	32.0	27.8	32.4	24.4
Total	28.2	24.8	28.5	21.9

	Percent trauma incidents attended by a paramedic on a 24-hour shift			Percent medical incidents attended by a paramedic on a 24-hour shift		
Year	Public/ fire-based	Hospital-based	Private for-profit corp.	Public/ fire-based	Hospital-based	Private for-profit corp.
2001	42.6	19.3	19.0	37.7	18.4	22.2
2002	43.9	20.8	24.9	42.1	21.1	25.6
2003	44.8	23.5	26.5	41.9	22.1	28.9
2004	43.9	23.6	26.8	42.7	23.9	28.2
2005	46.9	27.9	28.9	46.1	25.5	32.1
Total	44.4	22.9	25.3	42.0	22.2	27.7

call; $Shift_{is}$ is an indicator for whether the attending paramedic is in a 24-hour shift; $Night_{isp}$ is an interaction term equaling 1 when the attending paramedic is in a 24-hour shift and patient p's call came between midnight and 7 AM; $\mathbf{X}_{isp}$ are incident, patient, and provider characteristics; and α_i is a paramedic fixed effect.

We first estimate difference-in-differences models for total out-of-hospital time as the dependent variable, then separately for its component parts, first response, on-scene, and transport times, all of which are common EMS process measures. As additional evidence, we also estimate models using the number of pre-hospital procedures performed on-scene by paramedics, as well as the speed of procedures, conditional on at least one such prehospital intervention being performed.

All models control for the certification levels of both the driver and the paramedic (indicators for EMT-Driver, EMT-Basic, EMT-Intermediate, EMT-Paramedic), their tenure in years, and their hours of inactivity before the beginning of the current shift.[9] There are minimum volume restrictions for EMTs to be certified at a higher level, and so the majority of providers in our data switched certification level during their tenure. Moreover, while drivers are less likely to change their certification level (predominantly EMT-Driver), paramedics tend to frequently switch drivers. Controlling for hours of inactivity before the beginning of the current shift may indicate both alertness level at the beginning of the shift and the paramedic's typical

[9] Since paramedics are not exclusively responsible for producing first response and transport times, which might be more readily attributed to the driver of the ambulance unit, all of our models control for the driver's shift structure, certification level, tenure in years, and hours of inactivity before the beginning of their current shift.

shift structure. We do not control for the volume of calls that a paramedic received during a shift leading to the time of each incident to which she was dispatched. While one might argue that fatigue operates not only through sustained wakefulness, but also through the quantity of work she engages in, there are (at least) two arguments against controlling for such a variable. One argument is econometric. There is mechanically limited overlap in the support of this measure between 24-hour and 12-hour shifters, with the former group necessarily accumulating more incidents throughout their longer shifts. For instance, the median call volume for a paramedic in her twentieth hour of a 24-hour shift is 6 calls, which is the ninetieth percentile of call volume for a 12-hour shifter in the last hour of her shift. Controlling for volume would thereby place more of the burden on the linear functional form in the estimation. The second argument is more conceptual. Clearly fatigue can accelerate with call volume, which is itself positively related to duration on duty. Long shifts therefore have a dual effect of forcing paramedics to remain awake for sustained periods and of involving them in more incidents on a per shift basis. By not controlling for call volume within the shift, we are thus identifying a reduced form parameter that combines these two effects.

In addition, all models control for patient characteristics (race, age, gender); the type of incident; the incident location (e.g., residence, state/federal highway, etc.), and a series of indicators for year, month, day of week, and hour of the day. For trauma incidents, we also control for the type (e.g., fracture, burn, laceration, etc.) and location (e.g., head, chest, etc.) of injury, while for medical incidents we control for medical symptoms. For both trauma and medical incidents, we include 30 indicators for procedures performed on scene. These variables primarily control for the severity of trauma and medical scenes, and insure that the effect of the shift length on performance is not confounded by scene characteristics or by reduced patient severity. In the next section, we provide evidence that paramedics on long shifts are not dispatched to less severe incidents, by showing that paramedics' shift lengths are not correlated with scene characteristics and patient acuity.

In Mississippi, EMS is provided by a network of ambulance services organized at the county or city level. These municipalities contract with EMS providers on a sole-provider basis, such that one agency provides all EMS services within the municipality's boundaries. We identify 86 such contracting municipalities, where 56 different EMS providers operate. About 19 percent of agencies are community-based (mostly integrated with local fire departments), 27 percent are hospital-based, and the remaining 54 percent are large private ambulance companies. EMS agencies integrated into and operated by hospitals may have different approaches to prehospital care due to closer medical supervision. Similarly, paramedics working for a large private multi-state company may have access to different training standards, equipment, and operate under more stringent protocols compared to a small, local fire-based agency. In the analysis, we therefore include information about EMS provider type (i.e., private versus hospital-based versus fire-based) to account for those instances of switching between provider types, when municipalities change the type of provider with which they contract. Conversations with EMS directors in Mississippi confirmed that while EMS companies typically subscribe to a specific shift structure (for example, fire-based EMS providers typically organize service delivery around

24-hour shifts), flexibility in scheduling is widespread.[10] The analysis is conducted separately for trauma and medical incidents, which differ in scene, patient age profile, and protocol.[11]

III. Results

The upper panel of Figure 2 shows the total out-of-hospital time by hour of day for trauma and medical runs in Mississippi between 2001 and 2005. These graphs are a representation of the difference-in-differences approach (with no controls) described in the statistical analysis section. Specifically, they show mean prehospital durations by hour of the day, for paramedics on 24-hour (solid line) and 12-hour (dotted line) shifts. The difference-in-differences estimate can roughly be read from the charts as the pre- to post-midnight change in performance that occurs among paramedics on 24-hour shifts minus that of paramedics on 12-hour shifts. There is much less variability in total out-of-hospital time in medical incidents, for which there are almost four times as many observations as there are for trauma.[12] Nonetheless, both charts suggest some deterioration in performance late at night among both short- and long-shifters, though this decline appears steeper among 24-hour paramedics.

The late-night reversals of performance may be mediated by factors other than fatigue. We therefore consider two additional performance indicators that are arguably more sensitive to paramedic fatigue: the number of prehospital procedures performed on-scene and minutes per procedure, with the latter conditioned on at least one procedure being performed. The middle and lower panels of Figure 2 present the number and speed of procedures by hour of day separately for trauma and medical incidents. In the case of trauma, the 24-hour shifters initiate almost 0.3 more procedures during the daytime than their short-shift counterparts, but this gap closes quickly starting around 7 PM and reverses, such that, by midnight, the long-shifters perform 0.1 fewer procedures per incident. Although these differences are raw cell means, they are consistent with fatigue accounting for the decline in paramedic performance.

Figure 2 also highlights differences in performance between short- and long-shifters at baseline. It appears that 24-hour shifters are more expeditious during business hours than their 12-hour counterparts. For trauma incidents, paramedics on long shifts are almost 2 minutes faster at delivering trauma patients to the hospital around noon or 1 PM. For medical incidents, this gap is approximately 48 seconds. These level differences at baseline are likely due to unobserved paramedic heterogeneity, which we analyze systematically in the results section.

[10] For EMTs that worked both long and short shifts, shift-switching occurred rather frequently (every 12 days on average). This is broadly consistent with most EMTs working one long shift and three to four short shifts per week.

[11] As discussed above, MEMSIS collects slightly different information for trauma and medical incidents. For example, the trauma file includes data on the type of injury and the injured body part, while the medical file includes data on medical symptoms.

[12] Note that more than half of trauma incidents involve motor vehicle crashes, which may occur far from urban centers (and therefore require longer travel times) and in complex environments in terms of lighting, weather, and accessibility to victims (and therefore require more time spent on scene). This is another reason for the greater variability in total out-of-hospital time for trauma incidents compared with medical ones.

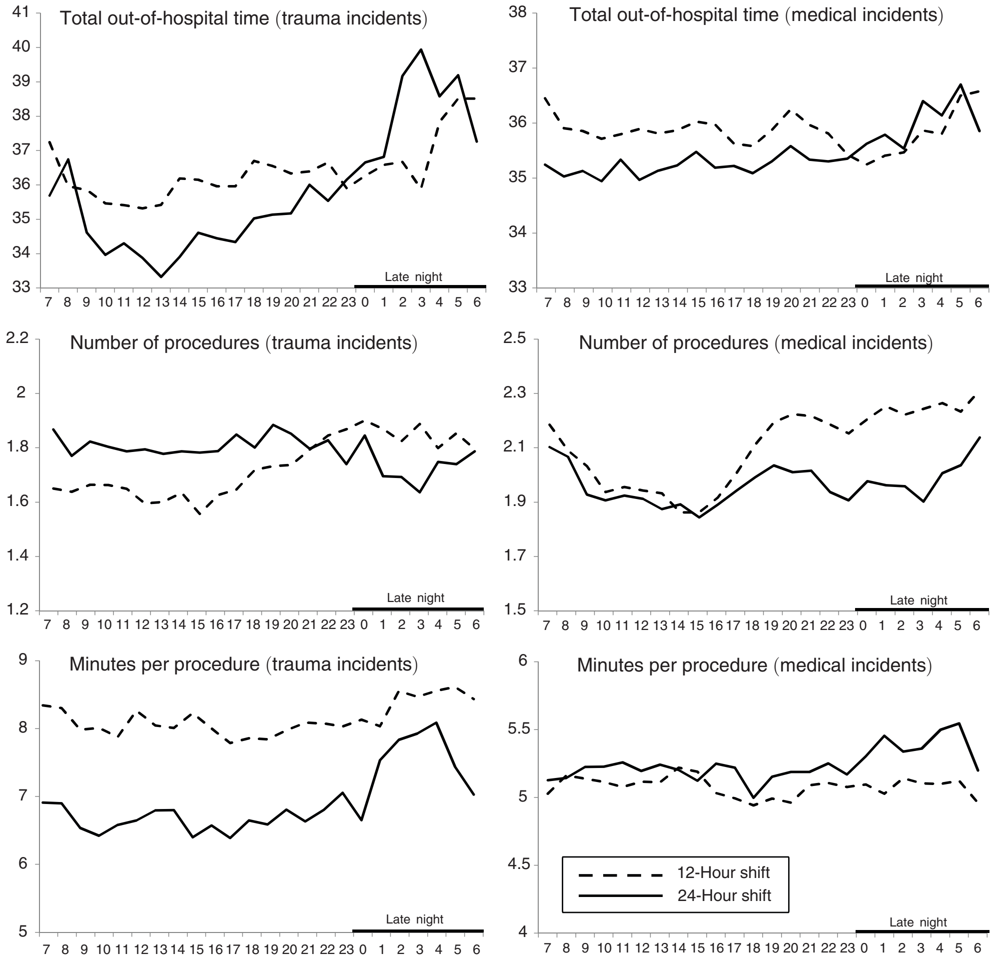

Figure 2. Total Out-of-Hospital Time, Number of Procedures, and Minutes per Procedure by Shift Length and Hour of Day for Trauma and Medical Incidents, Mississippi 2001–2005

Notes: The top panel of this figure shows the average pre-hospital time for incidents at each hour of the day, for trauma incidents (left side) and medical incidents (right side). Paramedics on 12-hour shifts (dashed line) are compared with those on 24-hour shifts (solid line). The middle panel makes similar comparisons between 12- and 24-hour shifts for the number of procedures performed, and the bottom panel compares 12- and 24-hour shifts on the number of minutes per procedure performed. For all panels, the late night falls at the end of the 24-hour period, running from midnight until 7 AM.

To produce a covariate-adjusted version of Figure 2, we followed the specification in (1) separately for incidents during each one hour-block and using all covariates described above as well as paramedic fixed-effects. Figure 3 plots the coefficients on the shift length dummy (24-hour shift = 1; 12-hour shift = 0) and standard errors for each within-hour regression. The trend lines track within-EMT differences in performance between 24-hour and 12-hour shifts, and are consistent with the ones presented in Figure 2. For example, the out-of-hospital time trend line is mostly below zero between 7 AM and midnight and is above zero between midnight and 6 AM, consistent with the late-night reversal patterns observed in Figure 2.

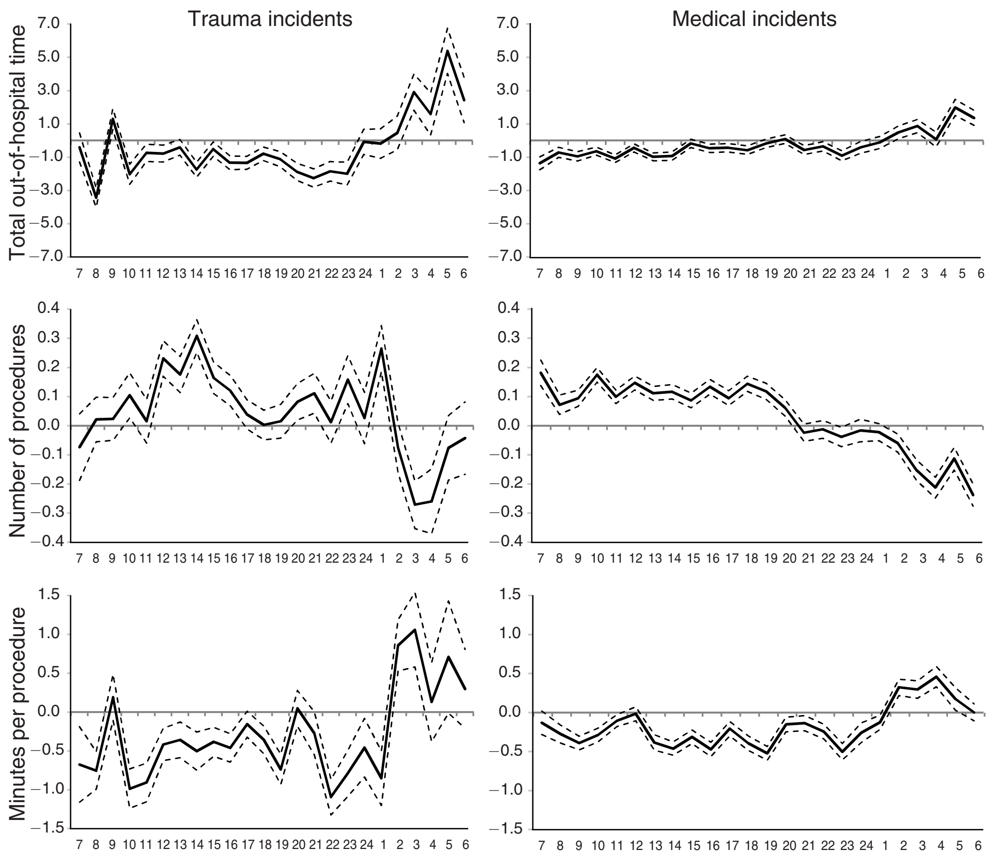

Figure 3. Coefficient Estimates and Standard Errors for within-EMT Differences in Performance across Long and Short Shifts

Notes: This figure displays the coefficients (solid line) and standard errors (dashed lines) on the shift length dummy from the model in equation (1), calculated separately for incidents during each one-hour period. The trend lines track within-EMT differences in performance between 24- and 12-hour shifts. Three outcomes are presented: total out-of-hospital time in the top panel, number of procedures performed in the middle, and minutes per procedure in the bottom panel. The model contains paramedic fixed-effects, an indicator for 24-hour shifts, an interaction term equaling 1 when the paramedic is working a 24-hour shift and the incident occurred between midnight and 7 AM, incident characteristics, patient characteristics, and provider characteristics.

A. *Random Assignment*

To explore the possibility of nonrandom assignment of paramedics to incidents, we regress patient demographics, call type, medical symptoms, trauma injury, and scene characteristics on paramedic shift structure according to specifications that mirror those of the difference-in-difference analysis. In Table 3, we report the coefficients on the indicator for treatment (24-hour shift) and the interaction term (24-hour shift × late at night). The upper panel reports results for medical incidents and the lower panel reports results for trauma incidents. Both panels report results for three models: the first includes paramedic and hour of day fixed

TABLE 3—RANDOM ASSIGNMENT REGRESSIONS WITH PARAMEDIC AND HOUR OF THE DAY FIXED EFFECTS

	Medical incidents ($N = 521,087$)				Trauma incidents ($N = 143,708$)			
	Patient demographics				Patient demographics			
	White	Black	Other race	Female	White	Black	Other race	Female
Model [1]								
Treatment	0.0000	−0.0007	0.0007	0.0020	0.0039	−0.0038	−0.0001	0.0036
	[0.0026]	[0.0026]	[0.0008]	[0.0025]	[0.006]	[0.006]	[0.002]	[0.0055]
Treatment × post	0.0079	−0.0063	−0.0016	0.0093	0.0187	−0.0055	−0.0132	−0.0075
	[0.0072]	[0.0072]	[0.002]	[0.0079]	[0.0162]	[0.0159]	[0.0074]*	[0.0163]
Model [2]								
Treatment	−0.0001	−0.0007	0.0007	0.0021	0.0036	−0.0036	0.0000	0.0036
	[0.0026]	[0.0026]	[0.0008]	[0.0025]	[0.006]	[0.006]	[0.002]	[0.0055]
Treatment × post	0.0078	−0.0063	−0.0016	0.0092	0.0185	−0.0053	−0.0132	−0.0081
	[0.0073]	[0.0072]	[0.002]	[0.0079]	[0.0163]	[0.0159]	[0.0074]*	[0.0163]
Model [3]								
Treatment	0.0000	−0.0007	0.0008	0.0021	0.0036	−0.0036	0.0000	0.0037
	[0.0026]	[0.0026]	[0.0008]	[0.0025]	[0.006]	[0.006]	[0.002]	[0.0055]
Treatment × post	0.0078	−0.0062	−0.0015	0.0093	0.0184	−0.0053	−0.0132	−0.0080
	[0.0072]	[0.0072]	[0.002]	[0.0079]	[0.0162]	[0.0159]	[0.0074]*	[0.0163]

	Location		Symptoms		Location		Type and injured body part	
	County road	Highway	Hemorrhage	Stroke	County road	Highway	Dislocated arm	Back pain
Model [1]								
Treatment	−0.0003	−0.0001	−0.0008	0.0002	−0.0017	−0.0021	−0.0019	−0.0058
	[0.0004]	[0.0007]	[0.0005]	[0.0006]	[0.0042]	[0.0055]	[0.0016]	[0.004]
Treatment × post	−0.0022	−0.0002	0.0019	−0.0012	−0.0064	−0.0022	0.0015	0.0157
	[0.0013]*	[0.0017]	[0.0017]	[0.0013]	[0.0123]	[0.0145]	[0.0046]	[0.0112]
Model [2]								
Treatment	−0.0003	0.0000	−0.0008	0.0002	−0.0018	−0.0021	−0.0020	−0.0058
	[0.0004]	[0.0007]	[0.0005]	[0.0006]	[0.0042]	[0.0056]	[0.0016]	[0.004]
Treatment × post	−0.0022	−0.0002	0.0019	−0.0012	−0.0063	−0.0022	0.0015	0.0157
	[0.0013]*	[0.0017]	[0.0017]	[0.0013]	[0.0123]	[0.0145]	[0.0046]	[0.0112]
Model [3]								
Treatment	−0.0003	−0.0001	−0.0008	0.0002	−0.0017	−0.0022	−0.0019	−0.0056
	[0.0004]	[0.0007]	[0.0005]	[0.0006]	[0.0042]	[0.0055]	[0.0016]	[0.004]
Treatment × post	−0.0022	−0.0002	0.0019	−0.0011	−0.0062	−0.0022	0.0015	0.0161
	[0.0013]*	[0.0017]	[0.0017]	[0.0013]	[0.0123]	[0.0145]	[0.0046]	[0.0112]

(*Continued*)

effects, as well as driver shift structure; the second adds controls for time off between the end of the previous shift and the start of the current one; the third model includes controls for the EMT's tenure. In a few instances (e.g., medical incidents occurring on county roads or trauma incidents involving patients in the "other race/ethnicity" category), the coefficient on the interaction between shift structure and incidents occurring between midnight and 6 AM has some statistical significance, yet the magnitudes of the coefficients are extremely small. The results suggest that paramedic shift structure is unrelated to most patient and scene characteristics across models. This is not surprising, as the unpredictable nature of

Table 3—Random Assignment Regressions with Paramedic and Hour of the Day Fixed Effects (*Continued*)

	Incident type (medical)				Incident type (trauma)			
	Drowning	Smoke	Poison	Overdose	MVC	Gunshot	Fall	Assault
Model [1]								
Treatment	0.0001	−0.0001	−0.0001	0.0001	0.0030	0.0000	−0.0016	0.0022
	[0.0002]	[0.0001]	[0.0002]	[0.0004]	[0.0059]	[0.0012]	[0.0053]	[0.0029]
Treatment × post	−0.0010	0.0006	−0.0002	0.0006	−0.0072	−0.0041	0.0147	−0.0012
	[0.0007]	[0.0006]	[0.0006]	[0.0017]	[0.0182]	[0.0058]	[0.0151]	[0.0138]
Model [2]								
Treatment	0.0001	−0.0001	−0.0001	0.0000	0.0030	0.0000	−0.0016	0.0022
	[0.0002]	[0.0001]	[0.0002]	[0.0004]	[0.0059]	[0.0012]	[0.0053]	[0.0029]
Treatment × post	−0.0010	0.0006	−0.0002	0.0006	−0.0075	−0.0041	0.0148	−0.0010
	[0.0007]	[0.0006]	[0.0006]	[0.0017]	[0.0182]	[0.0058]	[0.0151]	[0.0138]
Model [3]								
Treatment	0.0000	−0.0001	−0.0001	0.0000	0.0030	0.0000	−0.0016	0.0022
	[0.0002]	[0.0001]	[0.0002]	[0.0004]	[0.0059]	[0.0012]	[0.0053]	[0.0029]
Treatment × post	−0.0010	0.0006	−0.0002	0.0006	−0.0076	−0.0041	0.0149	−0.0010
	[0.0007]	[0.0006]	[0.0006]	[0.0017]	[0.0182]	[0.0058]	[0.0151]	[0.0138]

Notes: All models control for paramedic, contract area, and hour of day fixed effects, as well as for the driver's shift structure. Standard errors are clustered at the paramedic level. Model [1]: No controls for either time off between end of last shift and start of current one or EMT tenure. Model [2]: Controls for time off between end of last shift and start of current one. Model [3]: Controls for both time off between end of last shift and start of current one and EMT tenure. Similar results were obtained using age categories, year, month, and day dummies, as well as for additional call, location, destination, trauma type, and medical symptoms. The results are not reported due to space constraints and are available from the authors.

emergencies and the importance of delivering patients to hospitals quickly require the dispatch of units to rely solely on proximity.

B. *Difference-in-Differences Analysis*

Table 4 provides the results of the difference-in-differences analysis, first cross-sectionally with no additional controls, then with upward of 200 scene, patient, and EMT characteristics (as discussed in Section II), and then with paramedic fixed effects. This level of saturation makes it highly unlikely that systematic differences across scenes that are correlated with shift length are responsible for the deterioration in EMT's performance toward the end of long shifts, compared to their performance toward the end of shorter shifts. For each model, we report the coefficient estimate on the interaction between an indicator for whether the paramedic is working a 24-hour shift and an indicator for whether the call occurs between midnight and 7 AM (i.e., γ in equation (1)). In addition, we also report the estimate of ϕ, the coefficient on the 24-hour shift "treatment" indicator.

The interaction term in the first row of Table 4 indicates that trauma and medical patients appear to experience delays between a minute and three minutes in total out-of-hospital time when a paramedic on a long shift is dispatched to their scene relative to when that same paramedic is scheduled for a 12-hour shift, both between midnight and 7 AM. Breaking total out-of-hospital time into its components reveals that paramedics on 24-hour shifts appear to be just under a minute slower in

Table 4—Difference-in-Differences Analysis on the Full Samples of Trauma and Medical Incidents

		Trauma incidents			Medical incidents		
Outcome		No controls	With controls	With EMT FEs	No controls	With controls	With EMT FEs
Full sample							
Out-of-hospital time	T	−1.457***	−1.930***	−0.989***	−0.726***	−0.480***	−0.656***
		(0.101)	(0.109)	(0.159)	(0.056)	(0.060)	(0.086)
	$T \times$ post	2.677***	3.063***	2.261***	1.010***	1.153***	0.792***
		(0.335)	(0.307)	(0.287)	(0.154)	(0.147)	(0.136)
Response time	T	0.208***	0.005	−0.046	0.328***	0.180***	0.027
		(0.037)	(0.041)	(0.064)	(0.022)	(0.024)	(0.036)
	$T \times$ post	1.115***	1.119***	1.071***	0.674***	0.639***	0.575***
		(0.120)	(0.115)	(0.115)	(0.059)	(0.058)	(0.057)
On-scene time	T	−0.588***	−0.877***	−0.444	−0.322***	−0.229***	−0.367***
		(0.050)	(0.054)	(0.081)	(0.025)	(0.027)	(0.039)
	$T \times$ post	0.068	0.364**	0.084	−0.177**	−0.046	−0.068
		(0.182)	(0.169)	(0.162)	(0.075)	(0.070)	(0.068)
Transport time	T	−1.076***	−1.059***	−0.499***	−0.731***	−0.431***	−0.315***
		(0.060)	(0.066)	(0.095)	(0.036)	(0.039)	(0.056)
	$T \times$ post	1.493***	1.580***	1.106***	0.513***	0.559***	0.282***
		(0.182)	(0.174)	(0.158)	(0.095)	(0.091)	(0.083)
Number of procedures	T	0.219***	0.063***	0.096***	−0.111***	−0.031***	0.123***
		(0.014)	(0.014)	(0.020)	(0.007)	(0.007)	(0.009)
	$T \times$ post	−0.294***	−0.257***	−0.173***	−0.169***	−0.122***	−0.072***
		(0.042)	(0.038)	(0.036)	(0.021)	(0.017)	(0.016)
Number of procedures conditional on at least one	T	0.290***	0.117***	0.137***	−0.229***	−0.061***	0.085***
		(0.016)	(0.016)	(0.022)	(0.008)	(0.008)	(0.011)
	$T \times$ post	−0.308***	−0.272***	−0.212***	−0.191***	−0.170***	−0.100***
		(0.048)	(0.044)	(0.042)	(0.024)	(0.021)	(0.019)
Minutes per procedure	T	−1.395***	−0.881***	−0.337***	0.151***	−0.041***	−0.289***
		(0.041)	(0.046)	(0.070)	(0.019)	(0.021)	(0.031)
	$T \times$ post	0.511***	0.497***	0.391***	0.191***	0.159**	0.119**
		(0.146)	(0.142)	(0.139)	(0.052)	(0.050)	(0.049)
N		150,104	150,104	150,104	554,749	554,749	554,749
N (conditional on $>$ 1 procedure)		105,046	105,046	105,046	318,446	318,446	318,446

Notes: $T = 1$(24-hour shift); Post $= 1$(Midnight to 6 AM). Standard errors are clustered at the paramedic level. All models control for the certification levels of the driver and paramedic (indicators for EMT-Driver, EMT-Basic, EMT-Intermediate, and EMT-Paramedic), their tenure in years, and their hours of inactivity before the beginning of the current shift. All models also control for patient demographics (indicators for race, gender, and 12 age categories), location of incident (street, clinic, physician's office, farm, hospice, hospital, county road, industrial site, nursing home, office, public place, residence, restaurant, school, highway, other location), and hour of day, day of week, month of year, and year indicators. We also control for the driver's shift structure in the same (difference-in-differences) manner as the paramedic, though only the latter's coefficients are reported. Trauma models additionally control for indicators of type of trauma (falls, gunshot wounds, cuts or stabbings, assaults, motor vehicle crashes, and motorcycle and pedestrian accidents), and injury characteristics (70 interactions of injured body part and injury type). Medical models control for indicators of incident type (e.g., cardiac event, drowning, poisoning, etc.) and 32 indicators of patient symptoms.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

getting to the scene of medical or trauma emergencies between midnight and 7 AM. For instance, conditional on incident characteristics, it takes paramedics when they are on 24-hour shifts on average 1.07 additional minutes to arrive to the scene of a trauma incident toward the end of their shift, compared with when they are on shorter shifts. These paramedics also take an additional 1.1 minutes transporting trauma patients to a hospital.

Nonetheless, the results along the margins of time markers may be difficult to interpret as being solely attributable to fatigue. For example, EMS agencies may accommodate the longer shifts by allowing on-call paramedics to be asleep when they receive late night calls, which may lead to a slower reaction due to sleep inertia.[13] Although this is clearly a legitimate cost of long shifts, it is not fatigue from sustained wakefulness per se that drives it.

While the difference in time spent on-scene toward the end of a long versus a short shift is indistinguishable from zero, the number and speed of procedures performed on-scene are also affected in trauma and medical incidents. Paramedics on 24-hour shifts engage in 0.17 (or 8.5 percent) fewer procedures during trauma incidents in the closing hours of their shifts. In essence, no discernible difference in on-scene time is achieved by performing prehospital interventions more infrequently toward the end of long shifts. To distinguish whether these results are driven by the extensive versus intensive margins of prehospital interventions, we study the number of procedures conditional on initiating at least one procedure. The results in Table 4 indicate that the intensive margin appears to be driving the results. Conditional on performing at least one procedure, paramedics on long shifts engage in 0.21 (or 10 percent) fewer interventions.[14] Consistent with this result, we find the typical procedure to take 24 additional seconds (0.391×60) to complete for paramedics toward the end of a 24-hour shift.

It is worth noting that the effect on the number of prehospital procedures, while detected for medical incidents, is of smaller magnitude. Ex ante, this may make sense since EMS responses to medical emergencies are standardized to a much greater degree than in trauma incidents. Paramedic training and certification dictates specific responses and interventions for cardiac events, for instance, whereas trauma incidents are much more unpredictable and less standardized. As such, there is more room for paramedic discretion in treating trauma patients.

C. *Robustness*

The difference-in-differences approach provides a useful and simple framework for studying the effects of shift structure. It is not, however, without shortcomings. First, the magnitudes of the effects are attributable not only to performance deficits between midnight and 7 AM, but also to gaps in performance earlier in the day. Second, identification comes from the timing of calls (midnight to 7 AM), rather than from the duration of shifts directly. Lastly, performance deficits from longer shifts

[13] Sleep inertia is defined as incomplete arousal from sleep. It is associated with performance deficits and impaired decision making (Bruck and Pisani 1999). Yet, very little is known about the effects of sleep inertia in health care providers (Veasey et al. 2002).

[14] In more than 96 percent of cases, there is a single emergency medical technician certified as an EMT-paramedic and a driver (certified as either an EMT-driver or an EMT-basic). In less than 1 percent of incidents, the unit is composed of two paramedics. Since only the paramedic is certified to perform the procedures recorded in our data, this measure—number of procedures—is a margin along which fatigue can be more credibly attributed to the paramedic.

may operate in dimensions other than just mean prehospital times. We address these issues below.

Matching on Covariates.—As discussed earlier, observations based on the raw data (Figure 2) as well as those resulting from models controlling for paramedic fixed effects and other covariates (Figure 3) highlight differences in performance between short and long shifters at baseline. However, while the long shifters are, on average, quicker during the day, this relationship is reversed late in their shift (midnight to 7 AM). These disparities suggest that there is nonnegligible selection into 24-hour shifts, and that controlling for unobserved paramedic heterogeneity may be important.

To address this issue we use a within-EMT matching strategy.[15] This strategy seeks to reduce discrepancies in performance within-EMTs. While we cannot observe sleep patterns, we might think that longer breaks between shifts provide better opportunities to mitigate sleep loss.[16] EMTs on 24-hour shifts had longer intervals between shifts compared with those on 12-hour shifts (approximately 43 hours versus 37 hours), which may imply that EMTs coming into a 24-hour shift are more refreshed than 12-hour shifters. The time between shifts varies across shifts and can plausibly account for within-EMT variation in performance earlier into the shift. If the same EMT is more likely to be well rested going into a 24-hour shift than she is going into a 12-hour shift, that could account for the discrepancies in performance at the beginning of shifts.

We matched long and short shifts using propensity score matching with a mix of exact matching on EMT ID and 1-to-1 nearest neighbor propensity score matching without replacement for time between shifts. Our matched sample consists of all incidents that correspond to the matched shifts, where about one-third of 24-hour shifts are on a common support. The resulting matched samples consist of 28,243 trauma incidents and 115,302 medical incidents.

Table 5 reports the results for our three main performance measures for the matched sample within EMTs. For total out-of-hospital time, the results are similar in magnitude and statistical significance to those obtained for the full sample. However, the upper panel of Figure 4 shows greater similarity between 12- and 24-hour shifters in the beginning of their shifts. For minutes per procedure, we find different results for trauma and medical runs. While for trauma the effects are smaller, and for the most part statistically insignificant, the results for medical incidents suggest a 20 second increase in the time it takes a 24-hour shifter to complete a procedure toward the end of her shift (see lower panel of Figure 4). Finally, we no longer find an effect for number of procedures when using this matched sample.

[15] Matching cross-sectionally (across EMTs) on quality related dimensions, such as, tenure, certification level, and time elapsed before the beginning of a new shift, yield similar results to those obtained using the full sample.

[16] Some of the clinical studies surveyed in Veasey et al. (2002) recorded information on sleep patterns between shifts, focusing on longer term sleep loss (for example, the effect of having fewer than six hours of sleep per night, on average, during a one week period). It has been documented that the severity of neurobehavioral impairment is similar in both short-term sleep loss and chronic sleep restriction.

Table 5—Difference-in-Differences Analysis on the Matched Sample for Trauma and Medical Incidents

Outcome		Trauma incidents: No controls	Trauma incidents: With controls	Trauma incidents: With EMT FEs	Medical incidents: No controls	Medical incidents: With controls	Medical incidents: With EMT FEs
Out-of-hospital time	T	−0.669***	−1.059***	−0.801***	−0.621***	−0.778***	−0.718***
		(0.213)	(0.207)	(0.202)	(0.112)	(0.112)	(0.108)
	$T \times$ post	2.157***	2.362***	1.704***	0.936***	0.983***	0.530*
		(0.714)	(0.657)	(0.625)	(0.315)	(0.298)	(0.281)
Number of procedures	T	0.147***	0.086***	0.078***	0.223***	0.102***	0.096***
		(0.028)	(0.027)	(0.025)	(0.014)	(0.012)	(0.011)
	$T \times$ post	−0.017	−0.021	0.043	−0.043	−0.045	−0.026
		(0.084)	(0.075)	(0.071)	(0.041)	(0.033)	(0.031)
Minutes per procedure	T	−0.578***	−0.448***	−0.350***	−0.488***	−0.414***	−0.314***
		(0.085)	(0.087)	(0.087)	(0.040)	(0.039)	(0.039)
	$T \times$ post	0.523*	0.496	0.289	0.419***	0.436***	0.340***
		(0.309)	(0.304)	(0.300)	(0.104)	(0.101)	(0.098)
N		28,243	28,243	28,243	115,302	115,302	115,302

Notes: T = 1(24-hour shift); Post = 1(Midnight to 6 AM). Standard errors are clustered at the paramedic level. See Table 4 notes for the full list of controls. EMTs' 24-hour shifts were matched to within EMT 12-hour shifts. We then used this sample of matched shifts to evaluate the same models as in Table 4.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Within-Shift Analysis.—To complement the within-EMT between-shifts approach, Table 6 repeats the specifications in equation (1) for total out-of-hospital time and number of procedures, replacing the interaction between the "late night" dummy and the 24-hour shift dummy with an interaction between the "late night" dummy and time-on-duty (which measures the time since the beginning of the shift). Since time-on-duty varies within shift, Table 6 offers, in addition to the cross-sectional and EMT fixed-effects analysis, a shift fixed-effects analysis.

The two methods exploit different sources of variation, one being *within*-paramedic variation in shift structure, the other being *within*-shift variation in time-on-call. The identification in the latter case comes from both long shifts and late short shifts that include incidents in both the early (7 AM to midnight) and late (midnight to 7 AM) periods. Based on the lower panel of Figure 1, a typical late short shift would start at 7 PM and end by 7 AM. Identification relies on a comparison of incidents within a given shift, some occurring prior to midnight and others occurring between midnight and 7 AM. The hour of day dummies capture performance changes across time, the time-on-duty variable captures the effects of prolonged shifts, and the [time on duty × late night] interaction captures the differential effect of prolonged shifts during the midnight to 7 AM period.

The within-EMT fixed effects results in Table 6 are smaller in magnitude compared to those in Tables 4 and 5. For example, according to Table 4, a paramedic moving from a 12-hour to a 24-hour shift increases total out-of hospital time between midnight and 7 AM by 1.15 minutes (69 seconds) for a medical incident and by 2.26 minutes for a trauma incident. According to Table 6, adding 12 additional hours of time-in-shift

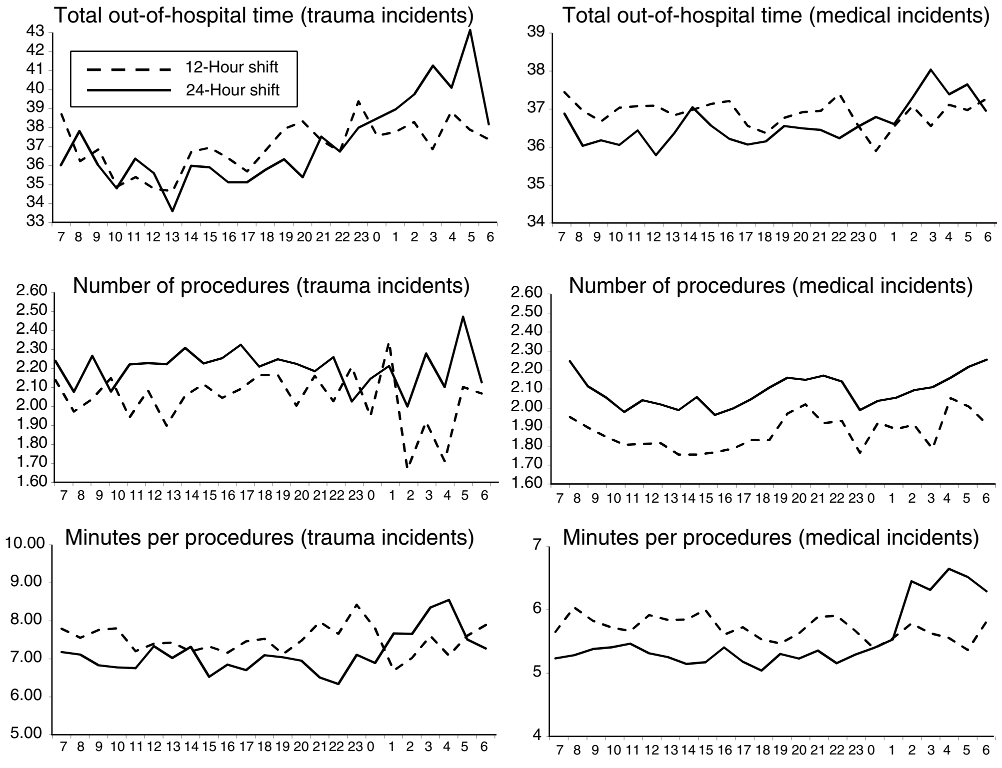

Figure 4. Sample Based on Matching Shifts on EMT ID (Exact Match) and Time Elapsed before the Beginning of a Shift

Notes: The top panel of this figure shows the average pre-hospital time for incidents at each hour of the day, for trauma incidents (left side) and medical incidents (right side). Paramedics on 12-hour shifts (dashed line) are compared with those on 24-hour shifts (solid line). The middle panel makes similar comparisons between 12- and 24-hour shifts for the number of procedures performed, and the bottom panel compares 12- and 24-hour shifts on the number of minutes per procedure performed. For all panels, the late night falls at the end of the 24-hour period, running from midnight until 7 AM.

(the typical difference in time-on-duty between long and late short shifts) increases total out-of hospital time between midnight and 7 AM by 45 seconds (0.063×12) for a medical incident and by 1.06 minutes (0.088×12) for a trauma incident.

The within-shift fixed effects results are smaller in magnitude compared to the within-EMT fixed effects ones and only statistically significant in the case of total out-of-hospital time for medical incidents in the full sample.

While this methodology is appealing, it is far more sensitive to measurement errors, discussed in Section I. The difficulty with undertaking such an analysis is that the precise starting point of shifts is not observed. Measuring the beginning of a shift with error is a potentially important source of bias when separating time-of-day effects from time-in-shift effects and less so when the beginning of the shift is used for the purpose of broadly defining long and short shifts.

Quantile Analysis.—Here we explore the possibility that the performance deficits from longer shifts operate in dimensions other than just mean prehospital times.

Table 6—Difference-in-Differences Analysis Using Time-on-Duty for All Samples

Outcome		Trauma incidents: With controls	Trauma incidents: With EMT FEs	Trauma incidents: With shift FEs	Medical incidents: With controls	Medical incidents: With EMT FEs	Medical incidents: With shift FEs
Full sample							
Out-of-hospital time	H	0.004	0.011	0.017	−0.009*	0.006	−0.007
		(0.010)	(0.009)	(0.025)	(0.005)	(0.005)	(0.007)
	$H \times$ post	0.110***	0.088***	0.045	0.089***	0.063***	0.055***
		(0.022)	(0.020)	(0.057)	(0.010)	(0.009)	(0.014)
Number of procedures	H	−0.003***	−0.002	−0.002	−0.005***	−0.003***	−0.003***
		(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
	$H \times$ post	−0.004	−0.005**	0.001	−0.004***	−0.001	−0.002
		(0.003)	(0.002)	(0.007)	(0.001)	(0.001)	(0.002)
Observations		150,153	150,153	150,140	554,749	554,749	554,718
Matched sample							
Out-of-hospital time	H	−0.046***	−0.012	−0.012	−0.027***	0.001	−0.002
		(0.015)	(0.014)	(0.050)	(0.008)	(0.008)	(0.013)
	$H \times$ post	0.041	0.036	−0.022	0.064***	0.051***	0.039
		(0.047)	(0.044)	(0.133)	(0.021)	(0.019)	(0.030)
Procedures	H	0.007***	0.004**	−0.001	0.004***	0.001	−0.001
		(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)
	$H \times$ post	−0.004	−0.005	0.014	−0.002	−0.001	−0.002
		(0.005)	(0.005)	(0.013)	(0.002)	(0.002)	(0.003)
Observations		28,243	28,243	28,039	115,302	115,302	115,302

Notes: H = Hours since start of shift; Post = 1(Midnight to 6 AM). Standard errors are clustered at the paramedic level. See Table 4 notes for full list of controls. The top section replicates the models from Table 4, but with the interaction between the "late night" dummy and 24-hour shift dummy replaced with an interaction between the "late night" dummy and time-on-duty (time since the start of the shift). The bottom section replicates the models from Table 5 with within-EMT matched pairs, but again replaces the interaction between the "late night" dummy and 24-hour shift dummy with an interaction between the "late night" dummy and time-on-duty. Because time-on-duty varies within shift, this table also displays results from models with shift fixed-effects, in addition to the cross-sectional and EMT fixed-effect analyses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Specifically we posit that sustained wakefulness might flatten out the conditional distribution of our outcome measures. To this end, we employ quantile regression methods, which serve to describe how being on a 24-hour shift late at night affects the entire distribution of total out-of-hospital time and minutes-per-procedure. Table 7 reports the results from quantile regressions estimated cross-sectionally at 7 different percentiles (0.05, 0.15, 0.25, 0.5, 0.75, 0.85, and 0.95).[17] Standard errors for the coefficient estimates are obtained using bootstrapping, which provide robust results (Koenker and Hallock 2001; Hao and Naiman 2007). The results indicate that operating in a 24-hour shift late at night extends the upper tails of the conditional total out-of-hospital time and minutes-per-procedure distributions.[18] For example, being on a 24-hour shift late

[17] EMT fixed effects models, while desirable, are computationally impractical.

[18] The bootstrap standard errors are estimated under the assumption of conditional homoscedasticity and no within-cluster correlation. Therefore, the reported standard errors are likely to understate the true variability of the estimates. Confidence intervals are robust to using Censored Least Absolute Deviations (CLAD) estimator (Powell 1984), which is robust to heteroscedasticity and is consistent and asymptotically normal for a wide class of error distributions.

TABLE 7—EFFECT OF BEING ON A 24-HOUR SHIFT BETWEEN MIDNIGHT AND 7 AM ON QUANTILES OF OUT-OF-HOSPITAL TIME AND MINUTES PER PROCEDURE

Trauma incidents		Quantiles						
		0.05	0.15	0.25	0.5	0.75	0.85	0.95
Out-of-hospital time	T	−2.521***	−2.473***	−2.076***	−1.934***	−1.623***	−1.153***	−0.351
		(0.513)	(0.319)	(0.224)	(0.411)	(0.165)	(0.241)	(0.326)
	$T \times$ post	0.691***	1.082***	2.025***	3.381***	4.148***	4.969***	6.127***
		(0.113)	(0.224)	(0.503)	(0.420)	(0.432)	(0.395)	(0.870)
Minutes per procedure	T	−0.209***	−0.303***	−0.428***	−1.103***	−2.026***	−3.002***	−3.118***
		(0.036)	(0.023)	(0.033)	(0.031)	(0.048)	(0.166)	(0.307)
	$T \times$ post	0.191***	0.183***	0.344***	0.755***	1.014***	1.333***	2.017***
		(0.059)	(0.058)	(0.058)	(0.126)	(0.140)	(0.348)	(0.511)
N		150,104	150,104	150,104	150,104	150,104	150,104	150,104
Medical incidents		Quantiles						
		0.05	0.15	0.25	0.5	0.75	0.85	0.95
Out-of-hospital time	T	−0.627***	−0.615***	−0.516***	−0.493***	−0.404***	−0.287***	−0.087
		(0.194)	(0.120)	(0.085)	(0.155)	(0.062)	(0.091)	(0.123)
	$T \times$ post	0.260***	0.407***	0.762***	1.273***	1.561***	1.870***	2.306***
		(0.054)	(0.107)	(0.241)	(0.201)	(0.207)	(0.189)	(0.417)
Minutes per procedure	T	0.058	0.073	−0.026*	−0.019	−0.065***	−0.051***	−0.061***
		(0.054)	(0.051)	(0.014)	(0.061)	(0.009)	(0.010)	(0.014)
	$T \times$ post	0.041*	0.059***	0.102***	0.212***	0.321***	0.433**	0.748*
		(0.022)	(0.016)	(0.026)	(0.053)	(0.099)	(0.206)	(0.398)
N		554,749	554,749	554,749	554,749	554,749	554,749	554,749

Notes: $T = 1$(24-hour shift); Post = 1(Midnight to 6 AM). The estimated variance-covariance matrix of the estimators is obtained through bootstrapping. See Table 4 notes for list of controls. This table presents the results of quantile regressions estimated cross-sectionally at seven percentiles (0.05, 0.15, 0.25, 0.5, 0.75, 0.85, and 0.95).
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

at night increases the ninety-fifth percentile of total out-of-hospital time for trauma by 6 minutes and for medical incidents by 2.3 minutes, which in both cases is approximately double the median and mean effects. Moreover, being on a 24-hour shift late at night increases the ninety-fifth percentile of minutes-per-trauma-procedure by 2 minutes and the ninety-fifth percentile of minutes-per-medical-procedure by 45 seconds, approximately three times the median and mean effects for trauma incidents and close to five times the median and mean effects for medical incidents.

D. *Calibration Exercise*

EMS are designed to reach and safely transport patients with time sensitive injuries (e.g., excessive blood loss from penetrating or blunt trauma) or medical emergencies (e.g., stroke or cardiac arrest), hence speed is a well-accepted marker of paramedic performance. Nevertheless, speed remains an input into patient outcomes such as mortality, disability, and morbidity. While desirable, we are unable to observe survival directly, as detailed inpatient data is not available for Mississippi during our sample period.

Nevertheless, to quantify our findings on delays in timely arrival to hospitals due to longer shifts, we perform calibration exercises based on clinical evidence linking outcomes to delays in the onset of clinical interventions. We analyze trauma and medical incidents separately. For trauma, we use some general findings from the literature and also focus on the case of massive blood loss. For medical incidents, we look separately at cardiac arrest and stroke.

Penetrating and blunt trauma incidents (e.g., due to motor vehicle crashes, stabbing or gunshot wounds, and falls) may result in both internal and external bleeding, which must be dealt with in a time-sensitive manner or else can quickly become fatal. Massive blood loss occurs when an individual loses blood at a rate of 150 milliliters (ml) per minute (Stainsby, MacLennan, and Hamilton 2000). A Class IV hemorrhage occurs when an individual loses more than 40 percent of blood volume, and such a situation is immediately life-threatening (Manning 2004). The blood volume of an individual weighing 160 pounds is approximately 5 liters (Gutierrez, Reines, and Wulf-Gutierrez 2004). Thus, at a rate of 150 ml of blood lost per minute, it would take less than 13 ½ minutes for this individual to lose 40 percent of his blood volume. Therefore, in the additional 2.26 minutes it takes paramedics on long shifts to deliver trauma patients to a hospital compared with when they are on short shifts, this individual would lose an additional 339 ml of blood, or approximately 6.8 percent of his blood volume.

In general, trauma incidents require quick attention. Out-of-hospital times exceeding 60 minutes for trauma patients have been associated with three times greater odds of dying within 6 days after the incident (Sampalis et al. 1993). In addition to total out-of-hospital time impacting trauma patient outcomes, response time alone may play an important role. A one minute increase in response time has been shown to increase 30-day mortality by 0.71 percent and 1-year mortality by 1.26 percent (Wilde 2009). We find that paramedics on long shifts working in the late night hours have a little over a minute slower response time than when on short shifts. This delay corresponds to a 0.76 percent increase in 30-day mortality and a 1.35 percent increase in 1-year mortality.

For medical incidents, we look specifically at cases of acute myocardial infarction (AMI) and stroke. Guidelines from the American College of Cardiology and the American Heart Association highlight the importance of timely care for AMI patients (Antman et al. 2004). The guidelines state that the time from initial patient contact with paramedics to the initiation of fibrinolytic therapy should not exceed 30 minutes. Similarly, if the patient will receive percutaneous coronary intervention (PCI), the delay from contact with paramedics to PCI should be less than 90 minutes. Our results indicate that from midnight to 7 AM, paramedics working long shifts have 47.5 seconds longer out-of-hospital times for medical patients than when they are working short shifts. Such a delay represents 2.6 percent of the time the guidelines state patients have to receive fibrinolytic therapy and approximately 1 percent of the time patients have to receive PCI before these highly effective, yet very time-dependent, treatments will be of diminished effectiveness.

Also extremely time sensitive is tissue-type plasminogen activator (tPA) therapy for ischemic stroke patients. The therapy has a 1–3 hour treatment window. With every 10 minute delay in treatment, an additional 1 percent of patients given tPA will no longer experience an improved disability outcome (Mitka 2011). The 47.5 second delay for medical patients to reach the hospital caused by paramedics working long shifts during the late night hours accounts for 7.9 percent of this 10 minute period.

While the calibration exercise highlights the importance of timely response and transport to definitive care and its cost in terms of patient outcomes, these calculations have many limitations and should be taken as ballpark estimates. To precisely link fatigue with in-hospital or post-discharge mortality, a far more detailed clinical record of patients must be obtained. For example, it is not inconceivable that gauging the gravity of the patient's situation when arriving at the scene may influence the urgency in which paramedics treat different cases.[19] Secondly, the few studies and guidelines that link time delays to patient outcomes may not be representative of patients in Mississippi.[20]

IV. Discussion

The impact of shift structure on workers' performance is an issue that has received increasing attention by regulatory bodies in manufacturing and service industries.

As we state in the introduction, shift work is common in many industries and is universal in those operating around-the-clock. Oil, natural gas, pipelines, foundries, steel mills, paper, and printing industries schedule shifts to meet increasing global demand and to take advantage of sophisticated and expensive technology. In other industries, such as media, communications, electric utilities, and nuclear power generation, around-the-clock operation and delivery dictates the organization of the workload. Similarly, police and fire departments, emergency rooms, and ambulance services require around-the-clock expert assistance, often on a moment's notice, in situations where lives may be at stake. High degrees of preparedness and service can also be found in just-in-time warehousing, and marine and ports services, where employees work in shifts.

Shift work is also common in many industries with less than 24/7 coverage. In manufacturing, continuous processes exist to manage demand fluctuations. For instance, automotive, electronics, semiconductor, and pharmaceutical industries all organize large parts of their labor force into shifts. Similarly, most retailers organize work in shifts. In aviation, public transit, railroads, trucking, and shipping, shift work results from extended travel durations and government regulation regarding vehicle operation.

In this paper, we offer an evaluation of the effect of shift structure and shift length on workers' performance, by using objective process measures capturing speed and activity. To our knowledge, this is the largest observational study to estimate the effect of shift structure on workers' performance, using a dataset that is collected in real time by paramedics responding to calls. We find that paramedics working longer shifts exhibit poorer performance toward the end of their shift (midnight to 7 AM), as measured by prehospital intervals, number of prehospital interventions, and minutes per procedure compared to their own performance

[19] For example, if the crew cannot control blood loss they may opt to leave the scene earlier and may even drive faster to the hospital.

[20] Mississippi has the highest death rate from both heart disease and motor vehicle accidents in the nation (David and Harrington 2010).

when working 12-hour (or less) shifts. Our results are robust to using samples based on matching paramedics working in different shift structures on covariates, to alternative sources of variation (within-shift versus within-paramedic), and to characterizing the effect of long shifts on different quantiles of the conditional performance distribution. Our results are consistent with the hypothesis that fatigue plays a role in the decline of the performance of paramedics at the end of long shifts.

While our results indicate a social burden from longer shifts, the ultimate choice of shift structure is the result of balancing business requirements (Mayshar and Halevy 1997), employee desires (Kostiuk 1990), and regulatory objectives (Coleman 1995). One such objective can be ensuring certain safety standards for employees working extended hours, such as the 2010 recommendations by the ACGME to cap shift length at 16 hours for interns (Nasca, Day, and Amis 2010) or the 2011 FAA regulation of the minimum number of hours between shifts for air traffic controllers.

While over 80 percent of employees work a daytime schedule, more than 21 million wage and salary workers in the United States (17.7 percent) work alternate shifts that fall at least partially outside of the daytime shift range (McMenamin 2007).[21] Individuals may work extended hours to supplement their income. This will occur, according to neoclassical theory, when the marginal rate of substitution between leisure and income is below the wage rate.[22] Nevertheless, holding labor supply constant, diminishing marginal utility of income does not suggest that individuals would prefer to work shorter shifts. For example, individuals working 48 hours per week can do so in two 24-hour shifts or in four 12-hour shifts, depending on their preferences and the flexibility offered by firms (Altman and Golden 2007).[23] Without the ability to conceptually link shift structure with labor supply decisions, neoclassical theory provides little guidance for understanding employees' preferences for organizing their work schedule. For example, paramedics working 24-hour shifts have two or three days off between shifts and are therefore more likely to hold a second job (Kuehl 2002).[24]

Finally, EMS often relies on volunteers. This may suggest that there are nonpecuniary benefits to working as a paramedic (e.g., serving the community, saving lives, or from thrills embedded in the delivery of emergency care). Nonpecuniary benefits were found to be associated with labor supply (Lazear 1991; Freeman 1997; Akerlof and Kranton 2005; Farzin 2009), but there is no reason to think that these are associated with workforce scheduling.

While more research is needed and while recognizing the inevitable need for health care professionals to work long hours in some circumstances, it appears that greater attention to the design of work schedules may entail benefits to patients relying on emergency medical services.

[21] Similar findings were reported for Canada (Williams 2008) and European countries (Le Bihan and Martin 2004).

[22] In addition, there is some evidence for a "shift premium" (Lanfranchi, Ohlsson, and Skalli 2002).

[23] Because EMS in Mississippi is organized based on sole provider contracts, paramedics residing in a given contracting area may not have much flexibility in affecting the shift structure.

[24] From a measurement perspective, concerns regarding such selection (and others discussed earlier in the paper) highlight the importance of our *within* paramedic approach.

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