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On the Determinants of Organizational Forgetting†

By Guy David and Tanguy Brachet*

Studies of organizational learning and forgetting identify potential channels through which the firm's production experience is lost. These channels have differing implications for efficient resource allocation within the firm, but their relative importance has been ignored to date. We develop a framework for distinguishing the contributions of labor turnover and human capital depreciation to organizational forgetting. We apply our framework to a novel dataset of ambulance companies and their workforce. We find evidence of organizational forgetting, which results from skill decay and turnover effects. The latter has twice the magnitude of the former. (*JEL* D23, D83, J24, J63)

Several recent studies have estimated organizational forgetting rates for firms in specific industries (Linda Argote, Sara L. Beckman, and Dennis Epple 1990; Eric Darr, Argote, and Epple 1995; Epple, Argote, and Kenneth Murphy 1996; C. Lanier Benkard 2000; Peter Thompson 2007; Gautam Gowrisankaran, Vivian Ho, and Robert Town 2006). Organizational forgetting occurs when the firm's stock of production experience depreciates over time (Argote, Beckman, and Epple 1990).

The depreciation of organizational knowledge is thought to involve a number of factors, including individual, technological, environmental, and work force changes (Argote 1999). We argue that these factors lead to organizational forgetting through their effects on the value of human capital. In particular, there are two broad channels through which forgetting at the firm level may occur: the depreciation of human capital (Winfred Arthur, Jr. et al. 1998) and labor turnover, whereby experienced employees are replaced by new ones.

These channels of organizational forgetting are important when there is technological change or failure to record firm experience. When human capital is imperfectly transferrable across technologies, technological change lowers the value of individual experience and hence leads to smaller negative turnover effects, as new technologies render existing human capital obsolete. Similarly, a failure to record

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firm experience may exacerbate both human capital depreciation (as existing workers lack records to refresh their memories or reinforce routines) and turnover effects (as new workers do not have access to an organizational body of knowledge).

Distinguishing between human capital depreciation and labor turnover effects is important for resource allocation within firms. However, because existing studies have relied on organizational level data, they cannot make this distinction.

There is an extensive literature on skill decay and skill retention among individuals (Arthur et al. 1998; Argote 1999). Most broadly, skill decay refers to the deterioration of acquired skills over time. The amount learned and the passage of time are the two most important determinants of skill decay (Charles D. Bailey 1989). Individual competence is commonly measured in terms of either speed or accuracy, with speed being more prone to depreciate over time (Susan Bodilly et al. 1986). The distinction between speed and accuracy is important since most studies of organizational forgetting focus on industries in which production processes are characterized by fixed-sequence tasks (e.g., following a protocol), for which skill decay has been shown to be most pronounced (Joseph D. Hagman and Andrew M. Rose 1983).

The empirical evidence on the effect of labor turnover on organizational forgetting is mixed (Argote, Beckman, and Epple 1990; Argote 1999; Thompson 2007). Labor turnover effects are potentially important when the human capital acquired by former workers is less valuable to current performance than that of current employees. However, without data on the employment histories of workers, previous studies had to measure a firm's experience stock as the accumulated experiences of all workers, whether currently employed or not.

A combination of task, market, and industry-specific characteristics govern the relative importance of skill decay and labor turnover in shaping organizational forgetting. The two channels imply different strategies to mitigate organizational forgetting. For instance, retention policies to reduce labor turnover may include improved compensation packages or safe working environments. On the other hand, skill decay may be slowed by limiting periods of inactivity or frequent refreshers. For example, more flexibility in scheduling may appeal to workers and so lessen turnover rates. But strict scheduling designed to reduce periods of inactivity may slow skill decay.

We provide a framework for studying the relative contributions of labor turnover effects and skill decay to organizational forgetting. Most studies of organizational learning and forgetting have focused on large scale industrial settings. In contrast, this paper focuses on a setting in the service sector. We study trauma-related ambulance runs in Mississippi between 1991 and 2005. The nature of emergency medical services (EMS) allows us to attribute performance to individual paramedics, and thus measure human capital depreciation in a profession in which individual skills may decay, and in an industry with high labor turnover rates. Indeed, we find that both human capital depreciation and turnover contribute to organizational forgetting, with turnover effects having twice the magnitude of individual skill decay.

Because we can track individual performance, we can study individual human capital depreciation directly. We consider the effects of individual production inactivity and the scope of tasks (interference), two mechanisms commonly associated with skill decay.[1]

The paper is organized as follows: Section I describes our framework for measuring human capital depreciation and labor turnover effects in the context of organizational forgetting. In Section II, we adapt the framework to the EMS setting to measure the contributions of individual production inactivity and the scope of tasks to human capital depreciation. In Section III, we describe the data and other determinants of performance. In Section IV, we discuss our results. Section V concludes.

I. Framework

The human capital of individual i may be defined as the total stock of past production experiences, $e_{i,t} = e_{i,t-1} + \phi_{i,t}$ where $\phi_{i,t}$ is the experience accrued by individual i between $t - 1$ and time t and $e_{i,t}$ the experience accumulated by t.[2] However, this formulation does not allow for forgetting, nor for the greater salience (or, perhaps, relevance) of recent experience. The drawback of this approach is that an experience from the distant past is treated as perfect substitute for a recent one.

A more flexible definition of human capital, referred to as the *forgetting model* (Argote, Beckman, and Epple 1990; Benkard 2000; Gowrisankaran, Ho, and Town 2006; Thompson 2007), defines experience by

$$e_{i,t} = \lambda e_{i,t-1} + \phi_{i,t}. \tag{1}$$

The parameter λ allows for forgetting (i.e., $\lambda < 1$) and captures the intuition that less recent experiences may be less relevant for today's performance. Here $(1 - \lambda)$ can be viewed as the rate of human capital depreciation.

Let N_t be the number of employees in the firm in period t, such that $N_t \equiv N_{t-1} - m_t + n_t$, where m_t and n_t are the number of employees exiting and entering the firm between $t - 1$ and t, respectively.

We partition the firm's experience in period t into three mutually exclusive groups: $\left[\lambda \sum_{i=1}^{N_{t-1}-m_t} e_{i,t-1} + \sum_{i=1}^{N_{t-1}-m_t} \phi_{i,t}\right]$ is the human capital of $N_{t-1} - m_t$ stayers, corresponding to equation (1); $\mu\left[\sum_{i=N_{t-1}-m_t+1}^{N_t} \phi_{i,t}\right]$ is the recent experience accumulated by the n_t entrants, where the parameter μ represents the value to the firm of new employee experience; and $\left[\gamma \sum_{j=1}^{t-1} \sum_{k=1}^{m_j} \hat{e}_{k,t-1}\right]$ is the value of past experience of all exitors, allowing the firm to retain a different proportion, γ, of exitors' human capital, where j indexes the exit period of individual k, and the value to the firm of former employee k's human capital evolves according to $\hat{e}_{k,t} = \gamma\, \hat{e}_{k,t-1}$.[3]

[1] Individual level data is not sufficient for studying individual skill decay. One must also attribute performance to individuals, as in the case of EMS.

[2] In large scale manufacturing settings, experience is measured in production units, such as the number of aircraft produced (Benkard 2000), the number of ships built (Thompson 2007), etc. In EMS, experience is measured as the volume of emergencies.

[3] Note that for simplicity, we assume no employee reentry to the firm.

The sum of the three components, presented in equation (2), is the value of the firm's cumulative experience in period t,

$$(2)\qquad E_t = \left[\lambda \sum_{i=1}^{N_{t-1}-m_t} e_{i,t-1} + \sum_{i=1}^{N_{t-1}-m_t} \phi_{i,t}\right] + \left[\gamma \sum_{j=1}^{t-1}\sum_{k=1}^{m_j} \hat{e}_{k,t-1}\right] + \left[\mu \sum_{i=N_{t-1}-m_t+1}^{N_t} \phi_{i,t}\right].$$

Individual worker identifiers, as in equation (1), are essential for decomposing organizational forgetting into human capital depreciation and turnover effects. In the absence of individual level data, the distinction between forgetting that arises through the loss of human capital accumulated by individuals who left the firm and human capital depreciation of workers still employed by the firm cannot be made. Similarly, the distinction between the contribution of recent experience of veterans and that of new employees cannot be made.

These limitations impose strong assumptions on the sources for organizational forgetting. Specifically, they assume perfect exchangeability of past experience on current performance across all employees, including those who are no longer in the firm.

To see this, we can write the cumulative experience profiles for the firm as:

$$(3)\qquad \tilde{E}_t = \lambda \underbrace{\left[\sum_{i=1}^{N_{t-1}-m_t} e_{i,t-1} + \sum_{j=1}^{t-1}\sum_{k=1}^{m_j} \hat{e}^{*}_{k,t-1}\right]}_{\tilde{E}_{t-1}} + \underbrace{\left[\sum_{i=1}^{N_{t-1}-m_t} \phi_{i,t} + \sum_{i=N_{t-1}-m_t+1}^{N_t} \phi_{i,t}\right]}_{q_t},$$

where $\tilde{E}_t$ is the value of aggregate experience of all current and past employees in period t. The first bracketed term on the right hand-side of equation (3) is the sum of experience accumulated by individuals up to (and including) period $t-1$ (i.e., $\tilde{E}_{t-1}$). This term is determined by individuals who are still employed by the firm in period t and those who were no longer with the firm as of $t-1$, terms that are impossible to construct separately without individual level data.[4] The second bracketed term, q_t, is the sum of the recent experiences accumulated between $t-1$ and t by individuals who joined the firm prior to $t-1$ and by new employees who joined the firm between $t-1$ and t. Equation (3) imbeds the assumption that the value of recent experiences of both new employees and veterans are identical from the firm's perspective.

Equation (3) highlights the implicit restrictions on the parameters of equation (2) when individual level data is unavailable. Specifically, equations (2) and (4) coincide when the human capital of exiting workers is as valuable for current production as that of current employees (i.e., $\lambda = \gamma$) and when new employees' current experience is as valuable for production as that of established workers (i.e., $\mu = 1$).

When employee-level data is unavailable, as in Benkard (2000), Gowrisankaran, Ho, and Town (2006), and Thompson (2007), entrants, stayers, and exitors are indistinguishable and are therefore treated as contributing equally to current production.

[4]Note that $\tilde{E}_t \neq E_t$ in part since $\sum_{j=1}^{t}\sum_{k=1}^{m_j} \hat{e}^{*}_{k,t} = \sum_{j=1}^{t}\sum_{k=1}^{m_j} \lambda^{t-j}\cdot\hat{e}_{k,j}$ while $\sum_{j=1}^{t}\sum_{k=1}^{m_j} \hat{e}_{k,t} = \sum_{j=1}^{t}\sum_{k=1}^{m_j} \gamma^{t-j}\cdot\hat{e}_{k,j}$, where j is the exit period for individual k.

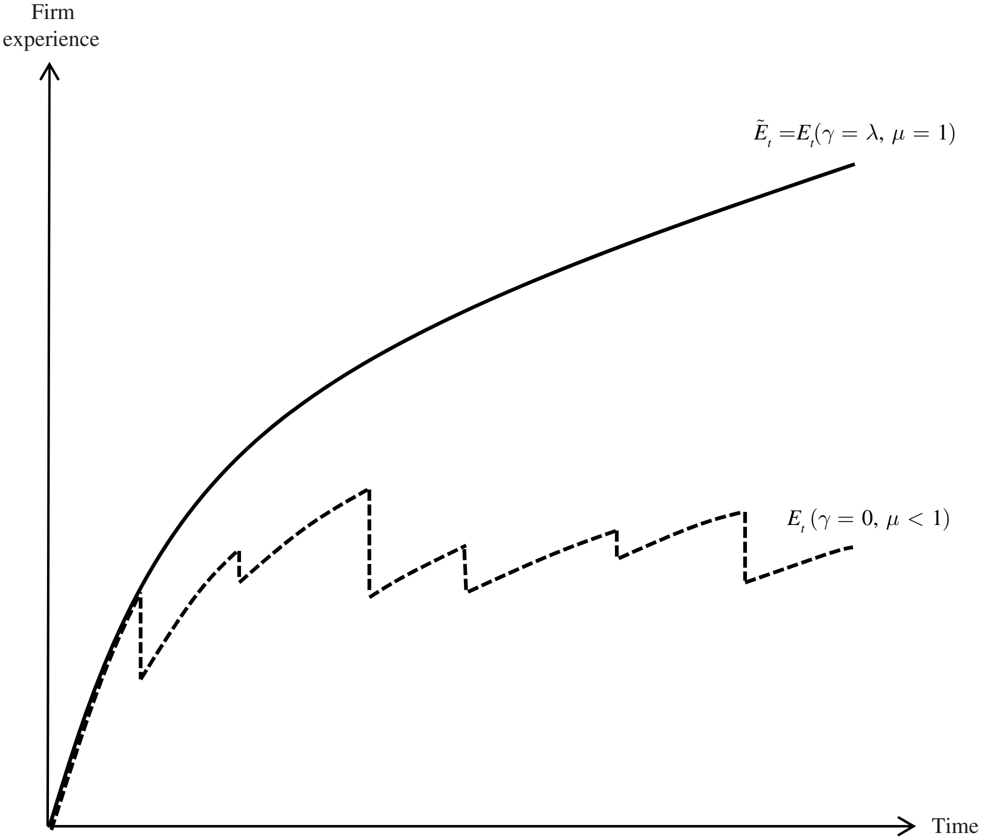

Figure 1. Measures of Accumulated Firm Experience Over Time

Hence, forgetting is measured from the firm's stock of experience in period t, and under the following law of motion for the organization's experience stock:

$$\tilde{E}_t = \lambda \tilde{E}_{t-1} + q_t. \tag{4}$$

Figure 1 depicts the evolution of a hypothetical firm's accumulated experience over time. The solid line tracks the evolution of all experience ever accumulated in the firm ($\tilde{E}_t$), with the underlying assumption that past experiences of individuals currently in the firm and those of individuals who left it are equally valuable to current production (i.e., $\lambda = \gamma$). The dotted line tracks the aggregate human capital of the firm's current employees (E_t) in each period t, restricting μ to 1 and the human capital accumulated by individuals who left the firm to have zero value in current firm production (i.e., $\gamma = 0$, such that $E_t = \sum_{i=1}^{N_{t-1}-m_t} e_{i,t}$). The magnitude of the discrete drops in the dotted line reflects the human capital lost (instantaneously) when workers exit. When $0 < \gamma < \lambda$, the evolution of the firm's accumulated experience over time would fall between the solid and the dotted lines, with the magnitude of the drops depending on γ. When $\mu < 1$, the dotted line becomes flatter as current employees represent a mixture of new and seasoned workers. The gap between the two lines would therefore increase the smaller μ and γ are.

The ability to measure the magnitude of skill decay from firm level data depends on the extent of turnover as well as its cost to the firm. Equation (5) highlights the effects that are confounded in equation (4) when studying skill decay, expressed in the form of an omitted variable.[5]

$$(5)\ E_t = \lambda \tilde{E}_{t-1} + q_t - \left[\sum_{j=1}^{t} \sum_{k=1}^{m_j} (\lambda^{t-j} - \gamma^{t-j}) \hat{e}_{k,j} + (1 - \mu) \sum_{i=N_{t-1}-m_t+1}^{N_t} \phi_{i,t} \right].$$

As made explicit in equation (3), the term $\sum_{j=1}^{t-1} \sum_{k=1}^{m_j} \hat{e}^*_{k,j}$ is a component of $\tilde{E}_{t-1}$, and is therefore highly correlated with it. Omitting this term from a regression model will bias the coefficient on $\tilde{E}_{t-1}$ (towards zero when $\lambda > \gamma$). The gap between the lines in Figure 1 corresponds to the bracketed term in equation (5), which illustrates the loss of information when only aggregate firm data are available.

Define $\overline{\phi}_t$ and $\overline{e}_{t-1}$ as the current and past experience of the average employee at time t. When evaluating the cost of human capital depreciation between $t - 1$ and t, the benchmark is the case of no forgetting. Therefore, the contribution of the average employee's human capital depreciation to organizational forgetting is $\overline{e}_{t-1}(1 - \lambda)$, where $(1 - \lambda)$ is the rate of human capital depreciation. The effect of turnover on organizational forgetting is a combination of two components; the first is the cost to the firm of losing an experienced employee relative to retaining that experience inside the firm, $\overline{e}_{t-1}(\lambda - \gamma)$, and the second is the cost to the firm of hiring a new employee relative to an experienced one, $\overline{\phi}_t(1 - \mu)$.

The joint effect of human capital depreciation and turnover for the average employee, measured in performance terms, is $\overline{e}_{t-1}(1 - \gamma) + \overline{\phi}_t(1 - \mu) = [\overline{e}_{t-1}(1 - \lambda)] + [\overline{e}_{t-1}(\lambda - \gamma) + \overline{\phi}_t(1 - \mu)]$. The relative contribution of turnover to organizational forgetting is $\left(\overline{e}_{t-1}(\lambda - \gamma) + \overline{\phi}_t(1 - \mu)\right)/\left(\overline{e}_{t-1}(1 - \gamma) + \overline{\phi}_t(1 - \mu)\right)$, while that of employee human capital depreciation is $\overline{e}_{t-1}(1 - \lambda)/\left(\overline{e}_{t-1}(1 - \gamma) + \overline{\phi}_t(1 - \mu)\right)$. When $\mu = 1$, new employees contribute as much to firm experience as established ones, and the relative contributions of turnover and skill obsolescence to firm forgetting are constant at $(\lambda - \gamma)/(1 - \gamma)$ and $(1 - \lambda)/(1 - \gamma)$ respectively. However, when μ differs from 1, the relative importance of each channel depends on average current-period experience and that of exiting employees and therefore on the speed of turnover within the firm. The greater the turnover rate, the lower is $\overline{e}_{t-1}$, and the lesser the importance of human capital depreciation in organizational forgetting. This confirms the intuition that human capital depreciation loses its relative importance when employment spells are short and the scope for erosion of individual human capital is limited.

[5] To derive the first term in the bracketed expression in (5), note that since $\hat{e}^*_{k,j} = \hat{e}_{k,j}$ at the time of exit, where j marks individual k's date of exit, the difference between the value of exitors' human capital retained at rate λ relative to rate γ is $\lambda \sum_{k=1}^{X_t} \hat{e}^*_{k,t-1} - \gamma \sum_{k=1}^{X_t} \hat{e}_{k,t-1} = \sum_{j=1}^{t} \sum_{k=1}^{m_j} (\lambda^{t-j} - \gamma^{t-j})\, \hat{e}_{k,j}$.

II. Empirical Application

We apply our framework to the universe of trauma-related ambulance runs in Mississippi between 1991 and 2005. Trauma patients, who are involved in such incidents as automobile accidents, injuries from falls, and criminal violence, are stabilized, treated, and transported to definitive care by EMS providers.

Demand conditions are important in EMS. Specifically, the unpredictable nature of emergencies and the importance of speed require ambulance units to be dispatched based on proximity and availability. This limits the firm's ability to match task and talent, which weakens the role of organizational capital in mitigating forgetting (Edward C. Prescott and Michael Visscher 1980).

Both human capital depreciation and turnover effects are likely to play roles in EMS. On the one hand, the EMS provider's performance depends on acquired skills (e.g., closed-loop tasks), which are subject to skill decay. On the other hand, for EMS companies, retention of paramedics is a persistent issue due to concerns regarding personal safety, stressful working conditions, irregular hours, excessive training and requirements, limited mobility, and low wages (Institute of Medicine Committee on the Future of Emergency Care in the United States Health System 2007).

The medical literature provides little guidance as to the right approach for managing out-of-hospital trauma victims. Yet, conditional on the characteristics of patients, paramedics, injury, medical interventions performed, and of the scene, and since care provided in the field by emergency medical technicians is not definitive, there is no dispute that a shorter out-of-hospital time is preferred to a longer one.[6] In the case where care is rendered on-scene, better diagnostic and therapeutic expertise is essential in reducing pre-hospital intervals. In this application, we therefore identify additional experience as participation in additional ambulance runs and performance as the total out-of-hospital time for a trauma incident, which is considered a key marker of EMS performance (Brendan G. Carr et al. 2006). The importance of getting the patient to definitive care as soon as possible, allowing only for the performance of essential procedures, is widely accepted, as shorter out-of-hospital EMS time intervals represent an important factor in survival (Stan Feero et al. 1995).[7] As such, contracts between municipalities and EMS organizations almost universally specify standards for pre-hospital duration. In many cases, these are the only standards mentioned and enforced (Institute of Medicine 2007; Theodore R. Delbridge et al. 1998).

As paramedics become more proficient in identifying faster routes, diagnosing patient acuity, identifying the appropriate procedures, mastering protocols and techniques, and exercising better judgment in crisis situations, shorter out-of-hospital times result. Moreover, skilled paramedics require less outside communication and medical oversight, which in turn contribute to lowering out-of-hospital time.

[6] Total out-of-hospital time is defined as the time (in minutes) from the moment the unit is alerted of an incident to the moment it delivers the patient(s) to the hospital/trauma center.

[7] Mississippi does not systematically collect patient discharge data, rendering it impossible to match EMS incidents to mortality or other patient health outcomes.

We develop models linking the human capital accumulated by paramedics to out-of-hospital time. The input of interest is the human capital of paramedics, as measured by their recent and past experiences as of the date of the incident.

Formally, consider a trauma scene at date t in which injured patient k requires some pre-hospital intervention(s) by paramedic i. Out-of-hospital time may be written as

$$\ln OHT_{ikt} = \beta_e \ln e_{it} + \beta_X X_{kt} + \beta_W W_{it} + \varphi_t + \eta_i + \varepsilon_{ikt}, \tag{6}$$

where OHT_{ikt} is the out-of-hospital time for patient k attended by paramedic i. $e_{i,t}$ is paramedic i's experience as of date t. X_{kt} capture the characteristics of the patient, such as her age, sex, race, and all interactions of injury type and injured body part. It also captures characteristics of the incident, such as type and location of trauma. In addition to paramedic experience, W_{it} includes paramedic characteristics, such as their certification levels, the certification level and experience of the driver that is paired with them, the team's joint experience, and the type of firm they work for. φ_t is a vector of indicators for hour of day, day of the week, month and year. η_i are individual paramedic fixed effects and ε_{ikt} is a random disturbance. The parameter β_e measures the degree of paramedic learning.

The law of motion in (1) calls for estimating equation (6) by nonlinear least squares according to the following specification:

$$\ln OHT_{ikt} = \beta_e \ln(\lambda e_{i,t-1} + \phi_{i,t}) + \beta_X X_{kt} + \beta_W W_{it} + \varphi_t + \eta_i + \varepsilon_{ikt}. \tag{7}$$

Our measure of recent paramedic experience, ϕ, accumulates experience over running 3-month windows, recording paramedic volume at a given date as the number of trauma runs accumulated during the prior 91 days.[8] This measure is more precise than fixed calendar quarters, used extensively in the learning literature applied to health care providers, as it responds instantaneously to any changes in the recent experience profile.[9] We construct similar measures of experience for drivers and driver-paramedic pairs.

Individual paramedic fixed effects are introduced to mitigate concerns that the relationship between experience and performance observed in the cross-section is driven by composition effects. For example, low quality paramedics might participate in fewer runs whereas more able paramedics may accumulate more experience by working more intensely and/or staying in the profession longer. Paramedic fixed effects therefore ensure that the experience parameters in (7) are identified from improvements in performance *within* paramedic.

[8] For each incident, we look back 91 days, tallying the number of trauma incidents attended by the paramedic sent to a particular scene ($\phi_{i,t}$). Similarly, we count the trauma incidents attended in the 91-day window starting 182 days ago ($\phi_{i,t-1}$), then 273 days ago ($\phi_{i,t-2}$), then 364 days ago ($\phi_{i,t-3}$), and so on. The parameter λ should therefore be interpreted as quarterly retention rate. While the definition of time interval over which to accumulate volume is somewhat arbitrary, three-month windows turn out to be computationally convenient given the size of the dataset used in our application. Shrinking the size of the look-back window would add to the computational burden.

[9] Experience accumulation with moving windows can be viewed as smoothing the calendar quarter step function and alleviating the imprecision which increases the further incidents are from the beginning of the quarter.

The study of human capital accumulation among paramedics is particularly well suited for studying learning and forgetting as the unpredictable nature of emergencies does not lend itself to the type of selection on unobserved quality that exists whenever the choice of producers is driven by the quality of their products or services. Ambulance units are dispatched based on proximity and not on reputation, and trauma victims do not choose the providers of emergency pre-hospital care.[10]

Specifically, conditional on observables and on fixed effects, ε_{ikt} is unlikely to be related to paramedic characteristics, be they quality, ability or, importantly, experience as selection on such unobservables is unlikely to occur given the current design of the EMS system. This is a major benefit of studying learning and forgetting in the context of emergency medical services, and as a result, the parameters in (7) can be consistently estimated by (nonlinear) least squares.

In turn, organizational forgetting is estimated using the definition of firm experience in (4), which corresponds to the case where individual data are not available.

$$\ln OHT_{kt} = \beta_{\tilde{E}} \ln(\lambda_{\tilde{E}} \tilde{E}_{t-1} + q_t) + \beta_X X_{kt} + \varphi_t + \varepsilon_{kt}. \tag{8}$$

Our measure of recent firm experience, q_t, accumulates trauma incidents served by the responding firm over the 91 days preceding each incident. Thus, we ignore the detail in our data about which paramedic and driver were sent to which scene, and aggregate the firm's quarterly volume over the set of paramedics it employs, counting each incident as one experience.

Following Thompson (2007), in equation (8) we estimate including and excluding hiring and separation rates. Additional information on hiring and separation rates creates an intermediate case between having no ability to track individuals and having an individual-level panel, as it tracks turnover-related dynamics in addition to firm-level experience accumulation.[11] The measure of firm experience, represented by the solid line in Figure 1, ignores any information on individual providers and therefore excludes time varying paramedic characteristics such as certification level and experience as well as paramedic fixed effects.

Finally, we estimate organizational forgetting using the definition of firm experience in (5). For comparability, we use the same set of controls as in (8).

$$\begin{aligned} \ln OHT_{kt} = \beta_E \ln\Bigg(\lambda_E \tilde{E}_{t-1} + q_t - \Bigg[\sum_{j=1}^{t}\sum_{k=1}^{m_j} (\lambda_E^{t-j} - \gamma^{t-j})\,\hat{e}_{k,j} \\ + (1-\mu)\sum_{i=N_{t-1}-m_t+1}^{N_t} \phi_{i,t}\Bigg]\Bigg) + \beta_X X_{kt} + \varphi_t + \varepsilon_{kt}. \end{aligned} \tag{9}$$

In equation (9), we exploit the unique paramedic identifiers in our data to define hiring and separation dates using each paramedic's first and last ambulance run,

[10] While in Table 4 we provide evidence in support of random assignment, matching scene acuity to paramedic experience will lead to conservative estimates of the effect of experience on performance, as it will bias our results towards zero.

[11] Technically, even if data on exit dates of employees were available, introducing dummies to mark the date of an employee's exit will not recover λ_E, as $\sum_{j=1}^{t-1}\sum_{k=1}^{m_j} \hat{e}_{k,j}$ is time varying by virtue of human capital depreciation.

respectively. Using these definitions, we construct measures that track the experience of paramedics in their first quarter on the job, and record that of paramedics no longer in the firm as of the date of their exit.

The variation originating from the drops in the dotted line (in Figure 1) allows us to disentangle γ from λ_E. It is important to note that the coefficient estimate of organizational forgetting, $\lambda_{\tilde{E}}$, obtained from estimating equation (8) is a weighted average of λ_Es and γs as the overall effect of organizational forgetting depends on both the rate of turnover and the magnitude of human capital lost to it.

III. Data

Our data were obtained from the Office of Emergency Planning and Response at the Mississippi Department of Health. Since 1991, this office has systematically collected incident-level EMS data through the Mississippi Emergency Medical Services Information System (MEMSIS). The raw data are recorded at the individual patient level by local EMS providers.

We limit our attention to emergency incidents for which the initial call was related to trauma (defined as motor vehicle crashes, motorcycle crashes, pedestrian injuries, stabbings, assaults, gunshots, or falls).[12] To focus on EMS runs where time to definitive care is most likely to be important, we exclude cases of death on arrival and limit the sample to calls involving at least one patient injury and ending in transport to hospitals by ground transportation.[13]

Detailed data on medical interventions and procedures are available only for the 2001–2005 period. While we restrict our analysis to this latter period, we use data for all years (1991–2005) to construct the history of paramedics' experiences, encompassing approximately 613,000 trauma runs. Our data allows us to follow 1,740 uncensored paramedics (85 percent of paramedics in our data) from their entry into the profession and construct measures of their tenure and cumulative experience. The final sample includes approximately 177,000 observations (or 146,000 observations, excluding censored paramedics).

With the Emergency Medical Services Systems Act of 1973, Congress delegated the responsibility for overseeing EMS provision, financing, and organization to municipalities (Delbridge et al. 1998). Local governments can provide these services in-house, usually through their fire department or, alternatively, contract with local hospital-based or other ambulance companies (David and Arthur J. Chiang 2009). Mississippi encompasses 86 contracting municipalities (82 counties and four cities). Each contracting area corresponds to a single EMS provider, with some serving multiple contracting areas.[14] We control for the type of agency providing EMS in our analysis.

[12] Given the highly skewed nature of reported interval times, and the possibility of extreme values due to miscoding, we exclude calls for which either the reported time from dispatch to arrival on the scene or the reported time from leaving the scene to arrival to a hospital exceeds 60 minutes. This criterion excluded less than one percent of trauma observations.

[13] A number of companies in Mississippi provide air ambulance services. We exclude less than 400 such observations, in which helicopters and fixed wings were dispatched. Therefore, all runs in our data involve ground transportation.

[14] All contracting municipalities in Mississippi operate on sole provider agreements, which assign a single advanced life support (ALS) provider to each contracting municipality. The local ALS provider (the "firm" in our

Local and national guidelines require advanced life support teams responding to trauma calls to be composed, at a minimum, of one driver and one paramedic (EMT-P).[15] Paramedics can engage in advanced airway management, cardiac monitoring, drug therapy and/or advanced techniques that exceed the level provided by technicians with lower certification levels. Team composition may therefore affect total out-of-hospital time through the quantity and complexity of procedures performed on scene. In addition to the experience of the paramedic, we control for the driver's experience and certification level as well as for the experience accumulated jointly by the paramedic-driver pair (i.e., the team).

To proxy for the underlying severity, we control for the number and types of procedures, the type of trauma and patient characteristics. In addition, our data include detailed information on the injured body part (i.e., arm, leg, chest, hip, back, neck, head, face, abdomen, and eye) and the type of injury (i.e., pain, burn, laceration, soft tissue, blunt, fracture or dislocation, penetrating trauma, and amputation). We control for all possible combinations of these indicators, as they are likely to be correlated with the severity of the injury which, in turn, is likely to be an important determinant of total out-of-hospital time.

While we are interested in the effect of firm experience on total out-of-hospital time, there are many other factors that may affect this marker of performance. These confounders, presented in Table 1, include the type of trauma, the incident location, patient characteristics, the number and types of procedures performed, the month and year, the certification level of the EMTs, the company that employs them, the municipality they operate in, and the number of victims.[16]

The timing of the call may affect total out-of-hospital time as well. Weather conditions, varying by season, may also affect the time needed to reach, access, stabilize, and transport patients. Potential lack of artificial lighting and fatigue, especially at night, could affect the speed of operation at the scene. Therefore, in our analysis, we control for year, month, day of week, and hour of the day.

IV. Results

In this section, we begin by presenting estimates of organizational forgetting, turnover effects and human capital depreciation in EMS at the firm level. We then present analyses of potential mechanisms leading to skill decay at the individual paramedic level.

analysis) may compete with other firms for the exclusive contract, yet faces no competition in dispatching once they secure the contract.

[15] The three national standard levels of training for Emergency Medical Technicians (EMT) are: EMT-Basic (EMT-B), EMT-Intermediate (EMT-I), and EMT-Paramedic (EMT-P). The US Department of Transportation (DOT) provided the basis for the education of EMTs and Paramedics. In addition, Mississippi requires operators of ambulance vehicles to be EMT-Driver certified (EMT-D), by participating in a training program in operation of emergency vehicles.

[16] Approximately 75 percent of trauma incidents involved a single patient and 98 percent involved at most three individuals.

Table 1—Summary Statistics

Variable	Mean		SD
Out-of-hospital time	36.05	minutes	16.62
Paramedic number of runs in last 3 months	18.02	trauma runs	12.35
Firm number of runs in last 3 months	458.91	trauma runs	530.69
Paramedic total number of runs (uncensored)	409.37	trauma runs	298.96
Paramedic-driver pair total number of runs	27.81	trauma runs	57.11
Number of procedures			
Number of EMS procedures in incident	1.99	procedures	2.19
Demographics and people in incident			
Patient age	42.12	years	25.10
Patient race: African American	40.67%		0.491
Patient race: white	56.00%		0.496
Patient gender: female	55.08%		0.497
Number of victims in incident	1.33	victims	0.743
EMS times and trauma characteristics			
Type of trauma: fall	31.49%		0.464
Type of trauma: motor vehicle crash	53.00%		0.499
Type of trauma: motorcycle accident	1.15%		0.106
Type of trauma: pedestrian accident	1.69%		0.129
Type of trauma: cut/stabbing	2.34%		0.151
Type of trauma: assault	8.83%		0.284
Type of trauma: gunshot	1.51%		0.122
Location of trauma: city street	20.66%		0.405
Location of trauma: county road	9.33%		0.291
Location of trauma: state/federal highway	23.69%		0.425
Location of trauma: residence	30.53%		0.461
Location of trauma: other	15.80%		0.365
Year, month, day of week, hour of the day			
Year 2001	19.61%		0.397
Year 2002	21.55%		0.411
Year 2003	19.66%		0.397
Year 2004	19.75%		0.398
Year 2005	19.43%		0.396
January	7.54%		0.264
February	7.78%		0.268
March	8.76%		0.283
April	8.79%		0.283
May	9.15%		0.288
June	8.54%		0.279
July	8.78%		0.283
August	7.90%		0.270
September	7.99%		0.271
October	8.20%		0.274
November	8.33%		0.276
December	8.24%		0.275
Certification levels			
Cerification level: EMT-Basic	2.55%		0.158
Cerification level: EMT-Intermediate	0.57%		0.075
Cerification level: EMT-Paramedics	96.12%		0.193

Table 2—Determinants of Organizational Forgetting with Hiring and Separation Rates Pre-Hospital Trauma Incidents, Mississippi 2001–2005

Dependent variable: Log(total out-of-hospital time)			Model I	Model II	Model III	Model IV	Model V
Reduced form organizational forgetting (Eq. (8) with hiring & separation rates)	Cross-section	$\lambda_{\tilde{E}}$	0.6970 [0.00822]***	0.6908 [0.00801]***	0.6911 [0.00718]***	0.6933 [0.0047]***	0.6946 [0.00478]***
	Contract-area fixed effects	$\lambda_{\tilde{E}}$	0.7089 [0.00268]***	0.7010 [0.00555]***	0.7130 [0.00499]***	0.7109 [0.00444]***	0.6995 [0.02679]***
	Cross-section	$\lambda_{\tilde{E}}$	0.6700 [0.00713]***	0.6805 [0.00748]***	0.6959 [0.00719]***	0.6934 [0.00465]***	0.6893 [0.00461]***
		Separation	0.2640 [0.02064]***	0.2983 [0.02035]***	0.3096 [0.02025]***	0.2921 [0.01968]***	0.3058 [0.01983]***
		Hiring	0.3793 [0.0183]***	0.3126 [0.01809]***	0.3112 [0.01803]***	0.3134 [0.01757]***	0.3045 [0.01761]***
	Contract-area fixed effects	$\lambda_{\tilde{E}}$	0.7523 [0.00282]***	0.7079 [0.00644]***	0.7055 [0.00559]***	0.7028 [0.00485]***	0.6990 [0.03443]***
		Separation	−0.0188 [0.01961]	−0.0169 [0.01893]	−0.0234 [0.01875]	−0.0150 [0.01814]	−0.0093 [0.01835]
		Hiring	0.0687 [0.01767]***	0.0154 [0.01711]	0.0240 [0.01694]	0.0288 [0.0165]*	0.0212 [0.01649]
Firm turnover and skill decay (Eq. (9) with hiring & separation rates)	Cross-section	$\lambda_{\tilde{E}}$	0.6807 [0.00769]***	0.6915 [0.0079]***	0.7176 [0.00764]***	0.6882 [0.00455]***	0.6533 [0.00384]***
		γ	0.4906 [0.00451]***	0.4155 [0.02353]***	0.4526 [0.01391]***	0.4664 [0.00523]***	0.3135 [0.02037]***
		μ	0.4596 [0.25649]*	0.2471 [0.14136]*	0.6358 [0.27885]**	1.4657 [0.25987]***	5.9486 [0.51753]***
		Separation	0.2616 [0.02068]***	0.2958 [0.02038]***	0.3068 [0.02027]***	0.2881 [0.01968]***	0.3009 [0.0198]***
		Hiring	0.3818 [0.01826]***	0.3156 [0.01802]***	0.3138 [0.01798]***	0.3166 [0.01752]***	0.3021 [0.01755]***
	Contract-area fixed effects	$\lambda_{\tilde{E}}$	0.7585 [0.00202]***	0.7575 [0.00552]***	0.8012 [0.00463]***	0.7810 [0.00344]***	0.7707 [0.02705]***
		γ	0.4984 [0.00136]***	0.4456 [0.01086]***	0.3841 [0.02516]***	0.3630 [0.00657]***	0.3687 [0.07357]***
		μ	1.7565 [0.17636]***	1.7901 [0.47801]***	1.3273 [0.40484]***	1.5867 [0.35761]***	1.3373 [1.67305]
		Separation	−0.0184 [0.01964]	−0.0154 [0.01897]	−0.0206 [0.0188]	−0.0118 [0.01819]	−0.0120 [0.01839]
		Hiring	0.0681 [0.01764]***	0.0139 [0.0171]	0.0216 [0.01694]	0.0260 [0.0165]	0.0218 [0.01651]
	Observations		139,651	139,651	139,651	139,651	139,651
Controls	Number of procedures			X	X	X	X
	Demographics and people in incident				X	X	X
	Trauma characteristics				X	X	
	Year, month, day of week, hour						X

Notes: Heteroskedasticity-robust standard errors are reported in brackets below the estimated coefficients. Significance levels for estimates of μ are for tests against the null of $\mu = 1$ (i.e. new and seasoned paramedics make equal contributions to firm recent experience). Patient demographics include indicators for race, gender, and 12 age categories. Trauma characteristics include the type of trauma, location of incidents, and injury characteristics. The types of trauma are falls, gunshot wounds, cuts or stabbings, assaults, motor vehicle crashes, and motorcycle and pedestrian accidents. Locations of incidents include residences, city streets, county roads, and state or federal highways. Injury characteristics include 70 interactions of injured body part and injury type.

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

A. *Firm-Level Analysis*

We estimate equations (8) and (9), first with no controls (Model I), then successively add possible confounders, as discussed in the previous section.[17] All models are estimated by nonlinear least squares with heteroskedasticity-robust standard errors.

Table 2 reports estimates of organizational forgetting for the full sample, first cross-sectionally, then with contract-area fixed effects to account for unobserved differences in geography and severity across areas.[18] The upper panel reports estimates based on equation (8), which represents a reduced form of organizational forgetting, as it ignores the distinction between human capital depreciation and turnover effects. The estimates suggest that about a quarter of the stock of experience existing at the beginning of the year survives to the end of the year (0.699^4). When forgetting is identified only from changes over time within contract-area, the measure of forgetting is stable and tightly estimated, with 70 percent of a firm's experience being carried over from a quarter ago to today's performance.

Due to data limitations, previous studies of organizational forgetting could only address turnover effects by adding hiring and separation rates as regressors (Argote 1999; Thompson 2007). This approach is valid and useful for eliciting organizational forgetting net of turnover effects under certain limiting scenarios. These include cases where there is no learning; there is learning but none of it is lost (i.e., the human capital accumulated by those leaving the firm stays with the firm); or human capital is lost due to exit, but is perfectly predicted by turnover rates. Nevertheless, it is unlikely that separation rates embody all information regarding the human capital accumulated by those leaving the firm. For instance, consider two identical firms, one which replaces a highly experienced paramedic while the other replaces a relatively inexperienced one. Both firms will record the same turnover rate yet may differ in their production experience.

To test this empirically, the middle panel of Table 2 includes hiring and separation rates as regressors. In the cross section, hiring and separation rates have large adverse and significant effects on performance. However, when controlling for unobserved contract-area characteristics, these effects disappear. One possible explanation is that the magnitude of hiring and separation rates reflect the size of firms, with observed turnover rates decreasing in firm size. In our application, small firms are common in rural areas, in which total out-of-hospital times are inherently longer.

The lower panel of Table 2 reports estimates based on equation (9), in which firm experience is separated into human capital accrued by individuals still in the firm and by those who left the firm. We discuss the estimates of skill decay $(1 - \lambda_E)$ and turnover effect $(\lambda_E - \gamma)$ from the most saturated model (Model V) with contract-area

[17] Sample size is slightly decreasing across models due to missing information on EMT certification levels and time stamps totaling less than 850 observations and resulting in approximately 174,000 in Model VI for the full sample.

[18] Note that since equations (8) and (9) mimic the case in which data on paramedics are missing, it makes little sense to estimate models that include indicators for individual paramedics.

fixed effects. We find the turnover effect to be roughly twice as large as the effect of human capital depreciation (0.402 compared with 0.229).

As indicated by our framework, the reduced form coefficient estimate of organizational forgetting estimated from equation (8) and reported in the upper panel of Table 2 (0.699) is a weighted average of λ_E (0.771) and γ (0.369) from the lower panel.

In turn, the estimate of μ in equation (9) is unstable and imprecisely estimated across specifications. Model V with contract area fixed effects suggests that the hypothesis that a new paramedic is comparable to a seasoned one in terms of performance cannot be rejected. While this null (i.e., $\mu = 1$) implies that new and seasoned paramedics make equal contributions to firm *recent* experience, it does not imply that replacing an experienced paramedic by a new one is costless since a fraction $(\lambda - \gamma)$ of the former's past human capital, $\overline{e}_{t-1}$, would be lost entirely during replacement.

Put together, $(\overline{\phi}_t(1 - \mu) + \overline{e}_{t-1}(\lambda_E - \gamma))/(\overline{\phi}_t(1 - \mu) + \overline{e}_{t-1}(1 - \gamma))$ is a measure of the relative importance of the cost of turnover. Assuming the average paramedic in our sample is replaced by one with no experience (i.e., $\overline{\phi}_t \cong 18.02$ and $\overline{e}_{t-1} \cong 209.44$) we find that about 62 percent of organizational forgetting is attributable to turnover.[19]

Adding hiring and separation rates to equation (9) has no effect on the estimates of λ_E, γ, and μ. This suggests that hiring and separation rates provide inadequate information in our application, as they are correlated neither with the recent experience of entrants nor with the value of human capital of employees no longer with the firm.

B. *Individual-Level Analysis*

In our application, we find both human capital depreciation and turnover effects to be important channels through which organizational forgetting comes to bear. The detail of our data, which tracks individual employee activity, allows us to further investigate mechanisms that may be responsible for individual skill decay by considering specifications that attribute performance entirely to paramedic-driver teams. More specifically, our data follows paramedics over 15 years. For 85 percent of paramedics, we observe their entry into the profession and onwards, and can therefore study learning and forgetting within individuals. For each incident, we control for time varying paramedic characteristics such as changes to their certification-level as well as the experience and certification-level of the driver with which they are paired. Note that individual level data is not sufficient for studying individual skill decay. One needs an application that allows for attributing performance to individuals.[20] In EMS, out-of-hospital time is produced by paramedic-driver pairs. Therefore, in addition to controlling for the driver characteristics, we control for the joint experience of each paramedic-driver pair.

[19] $\overline{e}_{t-1} = f(\lambda_E)$ is calculated assuming $\lambda_E = 0.771$ (as estimated in the most saturated contract area fixed effects specification in Table 2) for the uncensored paramedics sample.

[20] The inability to attribute performance to individuals poses a measurement challenge in large scale manufacturing, where production often requires joint assembly and coordination. In this regard, the applicability of the individual-level analysis, outside of the service industry, may be limited.

TABLE 3— RANDOM ASSIGNMENT REGRESSIONS WITH PARAMEDIC FIXED EFFECTS

	Patient characteristics							
	Age indicators							
Dependent variable:	5–14	14–18	18–25	25–35	35–45	45–55	55–65	65–75
Log quarterly volume (91 days)	0.001	−0.001	−0.001	0.002	0.001	−0.003	0.0004	−0.001
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Log cumulative volume (excl. left-censored paramedics)	−0.002	0.002	0.002	0.002	0.005	0.0005	−0.001	−0.0004
	[0.002]	[0.003]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.002]
Log cumulative volume (incl. left-censored paramedics)	−0.001	0.001	0.002	0.002	0.005	0.00005	−0.0004	−0.001
	[0.002]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]	[0.002]

	Patient characteristics (cont.)			Scene characteristics				
	Age (cont.)			Number of				
Dependent variable:	75–85	White	Female	injuries	Street	Road	Highway	MVC
Log quarterly volume (91 days)	0.0004	0.006	0.004	0.002	0.008	−0.005	0.005	−0.012
	[0.002]	[0.003]*	[0.003]	[0.013]	[0.003]**	[0.002]**	[0.003]*	[0.002]***
Log cumulative volume (excl. left-censored paramedics)	−0.005	0.007	0.001	0.001	−0.007	−0.005	−0.004	0.016
	[0.003]*	[0.006]	[0.004]	[0.024]	[0.006]	[0.004]	[0.006]	[0.007]**
Log cumulative volume (incl. left-censored paramedics)	−0.005	0.008	0.001	−0.006	−0.007	−0.006	−0.003	0.016
	[0.003]*	[0.006]	[0.004]	[0.023]	[0.006]	[0.004]*	[0.006]	[0.007]**

	Scene characteristics (cont.)							
							Hour indicators	
Dependent variable:	Gunshot	Fall	Motorcycle	Pedestrian	Cut/stab	Assault	18–20	21–23
Log quarterly volume (91 days)	−0.001	0.006	0.001	0.001	−0.0004	0.005	−0.001	0.0004
	[0.001]	[0.002]***	[0.001]	[0.001]	[0.001]	[0.002]***	[0.003]	[0.003]
Log cumulative volume (excl. left-censored paramedics)	0.001	−0.013	−0.0001	−0.0004	−0.002	−0.002	0.004	−0.005
	[0.001]	[0.005]**	[0.001]	[0.001]	[0.002]	[0.003]	[0.005]	[0.005]
Log cumulative volume (incl. left-censored paramedics)	0.001	−0.014	0.0001	0.0001	−0.002	−0.002	0.002	−0.007
	[0.001]	[0.005]***	[0.001]	[0.001]	[0.002]	[0.003]	[0.005]	[0.005]

Notes: Paramedic fixed effects are included in all models since subsequent learning/forgetting models are estimated with fixed effects; and to allow for the possibility of paramedic sorting across time and across the firm's coverage areas in a manner that matches their ability to the expected severity of scenes. Standard errors are reported in brackets below the estimated coefficients, and are clustered at the paramedic level.

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

Consistent estimation by nonlinear least squares of individual skill decay models relies on random assignment of paramedics to scenes. In particular, it requires unobserved patient and scene characteristics to be unrelated to paramedic experience conditional on paramedic fixed effects. Table 3 reports estimates of models in which incident characteristics are regressed on paramedic experience, controlling for paramedic fixed effects. The results indicate that paramedic experience is unrelated to most observable patient and scene characteristics, providing some validation for our research design. In the few instances in which experience has some statistical significance, the magnitudes of the coefficients are extremely small.[21] This is not surprising, as the unpredictable nature of emergencies and the importance of total out-of-hospital time require ambulance units to be dispatched based solely on proximity.

To control for potential heterogeneity in productivity, we estimated specifications with paramedic fixed effects. These capture any time-invariant factors that affect individual performance and may be related to experience. For example, firms may require their most able paramedics to be on call during times when and/or locations where the volume and severity of trauma are expected to be high. This type of sorting is absorbed into the fixed effect.[22]

The individual skill decay models are presented in Table 4, which reports estimates of individual learning, β_e, and skill retention, λ, based on equation (7).[23] Individual skill decay measured at the paramedic level is comparable in magnitude to the estimates from the firm analysis, presented in Table 2. The upper panel reports the results for the full sample including all paramedics, and the lower panel reports results for the subsample that excludes paramedics who appeared in the data in 1991, and are therefore potentially left-censored.[24] Each panel contrasts estimates from cross-sectional, contract-area fixed effects, and paramedic fixed effects specifications, with successively more incident characteristics being controlled for moving from Model I to VI. As mentioned above, paramedic experience profiles are calculated on a rolling-quarters basis such that, for instance, $\varphi_{i,t}$ is the number of runs in which paramedic i was involved over the 91-day period ending at date t. Standard errors are clustered at the paramedic level to allow for correlation in out-of-hospital times across incidents within the same paramedic.

The similar magnitudes in the upper and lower panels suggest that the problem of censored regressors, studied by Roberto Rigobon and Thomas M. Stoker (2009), does not appear to be severe in this context. Given the estimated magnitude of quarterly individual forgetting, this similarity most probably stems from the irrelevance of experiences accumulated prior to 1991 to performance after the beginning of our sample, in 2001. Focusing on the uncensored sample and the paramedic fixed effects specifications, the estimates of β_e are relatively insensitive to the set of controls and imply statistically significant learning on the part of paramedics. All else constant, a 50 percent increase in paramedic experience is associated with roughly 40 seconds shorter total-out-of-hospital duration. Finally, Table 5 indicates that there is a consistent and statistically significant degree of skill decay, and is larger in magnitude than the aggregate skill decay reported in Table 2. While both equations (7) and (9) produce strong evidence of skill decay, the discrepancy in magnitudes

[21] The largest effect is for the incidents of motor vehicle crashes (MVC), where a 1 percent increase in cumulative experience is associated with a 0.00016 percentage point increase in the likelihood being dispatched to a MVC scene.

[22] Bias may result from evolutionary forces such as learning about match quality, which has implications for separation decisions. To test for potential attrition bias, we perform a version of the Marno Verbeek and Theo Nijman (1992) variable addition test described in Jeffrey M. Wooldridge (2002) in which leads and lags of selection indicators are added as regressors. This approach is attractive in this context since it is implementable in a fixed effects specification. We find no evidence of attrition bias.

[23] Note that individual forgetting is $1 - \lambda$.

[24] Note that the full sample was used for the firm analysis (Tables 2 and 3), as censoring would not be possible to infer absent individual identifiers.

Table 4—Paramedic-Level Learning and Forgetting
Pre-Hospital Trauma Incidents, Mississippi 2001–2005

Dependent variable: Log(total out-of-hospital time)		Model I	Model II	Model III	Model IV	Model V	Model VI
Including left-censored paramedics							
Cross-section	Learning (β_e)	−0.00924	−0.02986	−0.02787	−0.00156	−0.00271	−0.00530
		[0.00541]*	[0.00678]***	[0.00676]***	[0.00063]**	[0.00183]	[0.00368]
	Retention (λ)	1.74084	0.55551	0.55610	140.90450	14.10342	3.92207
		[0.98028]*	[0.09076]***	[0.09429]***	[188.2986]	[25.81297]	[4.75924]
Contract-area fixed effects	Learning (β_e)	−0.02856	−0.02877	−0.02862	−0.02778	−0.02612	−0.02669
		[0.00381]***	[0.00379]***	[0.00372]***	[0.00364]***	[0.00368]***	[0.00376]***
	Retention (λ)	0.69670	0.58178	0.58155	0.59285	0.60616	0.60837
		[0.04093]***	[0.04857]***	[0.04752]***	[0.04611]***	[0.04828]***	[0.04739]***
Paramedic fixed effects	Learning (β_e)	−0.02784	−0.02925	−0.02867	−0.02447	−0.03437	−0.03539
		[0.00662]***	[0.00642]***	[0.00632]***	[0.00635]***	[0.00877]***	[0.0088]***
	Retention (λ)	0.49701	0.48027	0.47164	0.49441	0.69686	0.70002
		[0.10903]***	[0.10528]***	[0.1092]***	[0.12045]***	[0.0789]***	[0.07677]***
Observations		177,455	177,455	177,455	177,455	177,455	176,508
Number of clusters		2,044	2,044	2,044	2,044	2,044	2,022
Excluding left-censored paramedics							
Cross-section	Learning (β_e)	−0.01020	−0.03354	−0.03157	−0.00114	−0.00291	−0.00637
		[0.00646]	[0.00725]***	[0.00718]***	[0.00038]***	[0.00242]	[0.00468]
	Retention (λ)	1.56288	0.58284	0.56785	1171.24900	8.76735	2.67375
		[0.81404]*	[0.08794]***	[0.09379]***	[1261.453]	[16.89843]	[2.64565]
Contract-area fixed effects	Learning (β_e)	−0.03088	−0.03153	−0.03146	−0.03098	−0.02971	−0.03026
		[0.00415]***	[0.00415]***	[0.00408]***	[0.00402]***	[0.00406]***	[0.00414]***
	Retention (λ)	0.72453	0.61603	0.61440	0.62318	0.64005	0.63925
		[0.04175]***	[0.04602]***	[0.04486]***	[0.04364]***	[0.04505]***	[0.04455]***
Paramedic fixed effects	Learning (β_e)	−0.02963	−0.03065	−0.03025	−0.02624	−0.03617	−0.03727
		[0.00694]***	[0.00676]***	[0.0066]***	[0.00657]***	[0.00877]***	[0.00876]***
	Retention (λ)	0.51765	0.49851	0.49030	0.51431	0.71150	0.71269
		[0.10731]***	[0.10814]***	[0.1101]***	[0.1197]***	[0.07867]***	[0.07605]***
Observations		146,969	146,969	146,969	146,969	146,969	146,185
Number of clusters		1,738	1,738	1,738	1,738	1,738	1,718
Controls	Number of procedures		X	X	X	X	X
	Demographics and people in incident			X	X	X	X
	Trauma characteristics				X	X	X
	Year, month, day of week, hour					X	X
	Certification level						X

Notes: All models control for driver and paramedic-driver pair experiences. Patient demographics include indicators for race, gender, and 12 age categories. Trauma characteristics include the type of trauma, location of incidents, and injury characteristics. The types of trauma are falls, gunshot wounds, cuts or stabbings, assaults, motor vehicle crashes, and motorcycle and pedestrian accidents. Locations of incidents include residences, city streets, county roads, and state or federal highways. Injury characteristics include 70 interactions of injured body part and injury type. Standard errors are reported in brackets below the estimated coefficients, and are clustered at the paramedic level.

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

of human capital retention may be driven by differences in volatility of the two measures of experience. Paramedic-level experience profiles are more volatile than their firm's experience profile, which tracks the demand for emergency trauma care, and are therefore more likely to generate lower (and less tightly estimated) retention coefficients.

Table 5—Mechanisms for Skill Decay and Falsification Test
Pre-Hospital Trauma Incidents, Mississippi 2001–2005

Dependent variable:	Specifications with periods of inactivity					
Log(total out-of-hospital time)	Model I	Model II	Model III	Model IV	Model V	Model VI
Learning (β_e)	−0.03564	−0.03551	−0.03438	−0.02970	−0.04284	−0.04322
	[0.00862]***	[0.00835]***	[0.00805]***	[0.00796]***	[0.01083]***	[0.01083]***
Retention (λ)	0.55049	0.52433	0.50996	0.52801	0.73962	0.73974
	[0.10319]***	[0.1074]***	[0.11228]***	[0.12382]***	[0.07806]***	[0.07781]***
Days since last run	0.00072	0.00072	0.00068	0.00061	0.00069	0.00069
	[0.00021]***	[0.00021]***	[0.0002]***	[0.00019]***	[0.00019]***	[0.00019]***
Observations	146,012	146,012	146,012	146,012	146,012	145,248
Number of clusters	1,657	1,657	1,657	1,657	1,657	1,644
	Specifications including experience with medical incidents					
Log(total out-of-hospital time)	Model I	Model II	Model III	Model IV	Model V	Model VI
Learning (β_e)	−0.01892	−0.04548	−0.04457	−0.03837	−0.04335	−0.02927
	[0.01272]	[0.01594]***	[0.01551]***	[0.01498]**	[0.0195]**	[0.00886]***
Retention (λ)	0.48310	0.61104	0.60049	0.61268	0.72616	0.64383
	[0.26701]*	[0.08771]***	[0.08835]***	[0.10046]***	[0.12479]***	[0.10711]***
Learning (β_e^M)	−0.01105	0.02396750	0.02536	0.020915	0.00936	−0.00129
	[0.01218]	[0.0160294]	[0.01593]	[0.01526]	[0.01867]	[0.00191]
Retention (λ^M)	0.48929	0.85149	0.87804	0.90076	0.75880	34.44258
	[0.38699]	[0.14122]***	[0.14152]***	[0.17695]***	[0.52887]	[157.4546]
Observations	146,970	146,970	146,970	146,970	146,970	146,191
Number of clusters	1,738	1,738	1,738	1,738	1,738	1,718
	Falsification test					
Log(time alerted)	Model I	Model II	Model III	Model IV	Model V	Model VI
Learning (β_e)	−0.001575	−0.001543	−0.001641	−0.001978	−0.003000	−0.003692
	[0.00527]	[0.00454]	[0.00386]	[0.00314]	[0.00337]	[0.00509]
Forgetting (λ)	0.00000	0.00070	0.00004	0.00006	0.00005	0.00113
	[0.00001]	[0.00776]	[0.0004]	[0.00027]	[0.00025]	[0.00825]
Observations	147,061	147,061	147,061	146,993	146,993	146,209
Number of clusters	1,741	1,741	1,741	1,740	1,740	1,720
Controls						
Number of procedures		X	X	X	X	X
Demographics and people in incident			X	X	X	X
Trauma characteristics				X	X	X
Year, month, day of week, hour					X	X
Certification level						X

Notes: All models are estimated with paramedic fixed effects, exclude left-censored paramedics, and control for driver and paramedic-driver pair experiences. Patient demographics include indicators for race, gender, and 12 age categories. Trauma characeristics include the type of trauma, location of incidents, and injury characteristics. The types of trauma are falls, gunshot wounds, cuts or stabbings, assaults, motor vehicle crashes, and motorcycle and pedestrian accidents. Locations of incidents include residences, city streets, county roads, and state or federal highways. Injury characteristics include 70 interactions of injured body part and injury type. Standard errors are reported in brackets below the estimated coefficients, and are clustered at the paramedic level.

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

In all of our specifications, it is important to note that even if our controls for interventions on scene, injury profile, trauma characteristics, and patient demographics reflect severity only to a limited extent, concerns regarding omitted variables are not likely to be important given the current EMS system design. It is difficult to argue for a correlation between severity and experience, due to the fact that dispatching is determined by proximity to the scene and not by paramedic reputation. However, even if dispatch matched paramedic experience with patient severity, it is unlikely that indications of higher acuity would result in the dispatching of the least experienced crews, which is the only mechanism that would account for our results. If there is matching between paramedic experience and patient severity, our coefficient estimates of β_e underestimate the true degree of learning.

While our regressions control for the count of procedures performed on-scene, one might worry about selection on the complexity of procedures performed by paramedics. For example, if inexperienced paramedics choose simpler procedures, which require relatively fewer minutes, we might infer that less experience results in shorter on-scene times conditional on the number of procedures. This would lead us to underestimate the magnitude of the experience premium. To address this concern, we replaced the procedure counts with a set of 33 procedures indicators. Our results are insensitive to this replacement and, for brevity, are not reported here.

As individual skill decay accounts for approximately 38 percent of organizational forgetting in EMS, it is important to better understand how individual paramedic forgetting may come to bear. We test two potential mechanisms for skill decay: production breaks through periods of inactivity and interference through a wider set of tasks; in our application, the performance of non-trauma (medical) tasks.

We extend the analysis presented in Table 4 by recording the number of days elapsed since the last trauma run for each paramedic and adding it as a regressor to equation (7). Under this mechanism of skill decay, pre-hospital times that follow longer periods of inactivity may be lengthier. The results, reported in the upper panel of Table 5, indicate that additional days of trauma inactivity carry a small but statistically significant cost, suggesting that an additional day of inactivity is associated with pre-hospital intervals that are on average one second longer. Comparing estimates of β_e and λ in Tables 4 and upper panel of Table 5, omitting length of inactivity does not appear to confound our estimates.[25]

In general, periods of inactivity encompass two alternative time uses: one includes activities that are at least partially relevant to performance, while the other includes irrelevant tasks. In EMS, non-trauma events such as stroke or cardiac arrest may have relevance to trauma performance to the extent that they involve similar clinical interventions and/or patient interaction.

From a learning perspective, adding paramedics' experience histories with medical incidents to the specification allows for productivity spillovers in experience across medical and trauma incident types.[26] Greater experience with medical incidents may confer some benefits at the scene of trauma if mechanically similar

[25] Note, however, that paramedic volume already captures some of the information contained in our measure of paramedic inactivity: as the average number of inactive days inversely corresponds to the number of trauma incidents in a given quarter. Nevertheless, the point estimates in the upper panel of Table 5 indicate slightly more learning and less forgetting, as expected when controlling for the confounding effect of recent inactivity.

[26] Robert S. Huckman and Gary P. Pisano (2006) study same-task transferability for surgeons across different hospitals and its effect on patient mortality. Our analysis studies potentially heterogeneous skills and their effect on performance in a single setting.

tasks are performed in both types of incidents or learning about patient management accrued over medical scenes is transferable to trauma scenes. The middle panel of Table 5 presents results from estimating equation (7′) below, in which medical experience is added to trauma experience in (7), and is parameterized as in (1):

$$(7') \qquad \ln OHT_{ikt} = \beta_e \ln(\lambda e_{i,t-1} + \phi_{i,t}) + \beta_e^M \ln\left(\lambda^M e_{i,t-1}^M + \phi_{i,t}^M\right) + \beta_X X_{kt} + \beta_W W_{it} + \varphi_t + \eta_i + \varepsilon_{ikt},$$

where an "M" superscript indicates a variable or parameter relating to medical runs. Using this specification, we find little evidence of transferability across incident types, as estimates of β_e^M are indistinguishable from zero across all models. This may result from EMS protocols being more well-established for medical events relative to trauma events (Carr et al. 2006).

In addition to studying transferability of human capital, equation (7′) simultaneously explores interference of experience accumulated from medical incidents with performance at the trauma scene. The scope of tasks that each individual carries out may interfere with their performance on a given task through weaker memory retrieval, which may contribute to skill decay (Arthur et al. 1998). The seven percentage point drop in the retention parameter, λ, in the middle panel of Table 5 (relative to Table 4) could be interpreted as evidence of task interference.

Finally, we implement a falsification exercise by estimating the same models described by equation (7), in which we replace the dependent variable, total out-of-hospital time, with an alternative marker of system performance, dispatch time. Dispatch time is defined as the length of time between a 9-1-1 call and the moment paramedics are notified and dispatched to the scene. This measure provides the basis for a credible falsification test as, unlike time spent en route and on-scene, paramedics have no influence on it. Therefore, we do not expect to find a relationship between individual paramedic experience and dispatch time. The lower panel of Table 5 validates our performance measure as we find no evidence of learning or skill decay in the case of dispatch time, lending credibility to our results.

V. Conclusion

Studies of organizational learning and forgetting identify potential channels through which the firm's production experience is lost. While the ability to distinguish between these channels has implications for efficient resource allocation within the firm, to date, their relative importance has largely been ignored. This paper develops a framework for eliciting the contributions of the two most salient channels, labor turnover and human capital depreciation, to organizational forgetting. When applying our framework to ambulance companies and their workforce, we find evidence of organizational forgetting, which results from skill decay and turnover effects. The latter has twice the magnitude of the former.

Similar to shipbuilding, automobile and aircraft manufacturing, and pizza franchises, where forgetting has been documented, emergency medical services are labor intensive, subject to high labor turnover, and learning-by-doing is thought to be important at the individual worker level.

In some cases, organizational forgetting is associated with breaks in production and demand volatility. However, organizational forgetting may occur even under continuous production if individual skills depreciate over time and/or the human capital of employees is lost to labor turnover. For instance, high observed turnover rates were hypothesized to cause organizational forgetting in pizza franchises (Darr, Argote, and Epple 1995). EMS is characterized by high labor turnover as personnel face a difficult, often hazardous, work environment.[27] In our application, we find that labor turnover accounts for 62 percent of organizational forgetting.

To test whether the large turnover effects we find in EMS are a feature of the industry or a feature of our framework, we follow Thompson (2007) by adding hiring and separation rates to the standard reduced form organizational forgetting specification. In our application, hiring and separation rates neither capture the true effect of labor turnover nor refine the estimates of organizational forgetting. The inadequate information embedded in hiring and separation rates suggests that other studies that lacked the ability to track individuals and therefore relied on firm-level measures of hiring and separation may have understated turnover effects.

While the bulk of firms and employment in developed countries is concentrated in the service sector,[28] studies of organizational learning and forgetting focus almost exclusively on large scale industrial settings, such as commercial aircrafts (Benkard 2000), automobile production (Epple, Argote, and Murphy 1996) and ships (Argote, Beckman, and Epple 1990; Thompson 2001; Rebecca Achee Thornton and Thompson 2001; Thompson 2007). In these large-scale production endeavors, organizational forgetting is the result of a mixture of firm and employee level experience depreciation. This is, therefore, a reduced-form phenomenon that encompasses a number of mediators including turnover, literal forgetting by individuals, and adaptation to technological innovations. Hence, a benefit of studying production of services is the ability to attribute performance to individuals. This is true in our application; emergency medical services are universal and involve measures of performance that are attributable to individual paramedics. As discussed earlier, the ability to track individuals is necessary for eliciting the contributions of labor turnover and human capital depreciation to organizational forgetting.

The ability to attribute performance to individuals in emergency medical services speaks not only to the richness of our data but also to the nature of production in service industries, which relies heavily on individual performance (e.g., a mailman, a dentist, a plumber, or a customer service representative). This, in turn, imposes limitations for generalizing our findings to settings where there is reliance on joint production.

[27] Paramedics are exposed to potentially infectious bodily fluids, for instance through contact with contaminated needles, and to the hepatitis B virus (Delbridge et al. 1998). Moreover, they are frequently exposed to the threat of violence, incur injuries associated with lifting or falling, and face oncoming traffic at the scene of motor vehicle crashes. Occupational fatality rates for paramedics are comparable to those of police and fire personnel. There are 12.7 fatalities per 100,000 EMS workers annually, which compares with 14.2 for police and 16.5 for firefighters, and a national average of 5 fatalities across all professions (Brian J. Maguire et al. 2002).

[28] For example, the Bureau of Labor Statistics reports that 75 percent of total US employment in 2006 was concentrated in the service industry.

While services and manufacturing differ in their production environments, ambulance companies do resemble manufacturers in their responsibility for hiring, training, contracting, maintenance of equipment, scheduling, and strategic planning. EMS companies provide service elements that individual paramedics are not able to provide in isolation. For example, around-the-clock coverage is a key contractible feature of emergency services. Our analysis suggests that about a quarter of the firm's stock of experience existing at the beginning of the year survives to the end of the year. This reduced form estimate is lower than recent findings for an aircraft manufacturer (about 60 percent according to Benkard 2000), close to the 35 percent for Liberty shipbuilders (Thompson 2007), and higher than the 5 percent estimated by Darr, Argote, and Epple (1995) in the case of pizza franchises. This may suggest that a firm's ability to mitigate organizational forgetting is weaker in the tertiary sector, and calls for additional studies of service delivery.

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