Physician Productivity and Organizational Experience in a New Hospital

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VERY PRELIMINARY

Abstract

This paper studies the effects of worker experience on firm productivity analyzing learning by doing among physicians in the emergency department of a new hospital. We measure productivity using total times in the emergency room, medical images, and referrals to specialists. We find large causal effects of physician experience on productivity using other physicians allocation as a source of exogenous variation on current physician assignment. Higher physician experience cause lower visit times, less specialist referrals and less utilization of X-rays. This effect comes from experience acquired both within the emergency department and from other experience, proxied by physician age. We also find that more recent experience has a larger effect than more distant one. Finally, we study how physician productivity relates to organizational learning, and explore the temporal trade-offs of different physician allocation policies.

1 Introduction

Firms become more productive as they grow. Indeed, several papers have documented a volume-outcome relationship, an effect whereby firms use less inputs as they produce more output. A common explanation for the volume-outcome relationship is learning by doing (LBD): firms become more efficient as they perform their tasks repeatedly. However, we still lack an understanding of the exact channels by which LBD occurs, and how employees' experience growth translates into productivity improvements at the firm level. Furthermore, in many settings, such as in healthcare, the evidence available for LBD is correlational rather than causal.

In this paper we study the effects of LBD among physicians in the emergency department (ED). Physician level LBD is important because of the role physicians play in the ED. Physicians are in the center of the hospital production process and interact with nurses and non-medical workers. An inexperienced doctor may be unsure of the diagnostic and make the patient wait, may request medical images, or may refer the patient to a specialist. Hence, as a result of experience growth we should

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expect the doctor to perform better diagnostics and to request less unnecessary lab tests, images, and referrals.

In particular, first we estimate the causal effect of physician experience on total patient time in the ED, use of medical images, and referrals to specialists within the ED. We argue that these outcomes, conditional on a rich set of severity and diagnosis fixed effects, are good proxies for physician productivity. Based on evidence from recent research (Chang and Obermeyer, 2020), we depart from the assumption of the literature of random allocation of physicians to patients by allowing for possible allocation of more experienced doctors to more severe cases. In the presence of such selection, ordinary least squares (OLS) estimates of a regression of productivity outcomes on physician experience are biased. We develop a novel instrument for physician experience that uses the experience of the physician that treated the previous patient as a source of exogenous variation. The "lagged" physician experience is correlated with the current physician experience because the lagged physician is *less likely* to treat the current physician, thus providing a shock to the choice set for the current patient. In addition, we argue that the instrument is uncorrelated with the residual productivity of the current patient's treatment after controlling for a rich set of patient and time fixed effects because the choice of the lagged physician was made before the current physician allocation.

Our results indicate an elasticity of time of attention with respect to experience of roughly -0.065. This is a large effect: a one standard deviation increase in a physician's experience decreases visit times by 9.4 minutes (from a mean time of 1.66 hours). We also find that experience affects negatively the probability of specialist referrals and the probability of requesting X-rays.

Second, we distinguish between experience that is organizational specific from overall physician experience, which we proxy for age. Although age is possibly endogenous as any other physician characteristic, we control for age and instrument for it using the same type of instrument as the one we used for experience, that is, the age of the physician who treated the previous patient. We find that the effect of organizational experience decreases approximately 40 percent when we control for physician age. Yet, the effect of experience remains high and is slightly larger than that of physician age. This result provides evidence that both transitions are relevant to explain firm efficiency gains.

Third, we ask what the implications of physician are for hospital wide LBD. Specifically, we find that average times spent in the ED, conditional on patient characteristics, go down over time. This finding is consistent with a strand of the literature in health that argues that there is a positive volume-outcome relationship, by which larger hospitals have better outcome indicators. We analyze whether this productivity increase is due to pure volume growth, which may lead to managerial interventions, or to physician LBD. We find that physician LBD is more important that hospital volume growth, which conditional on physician experience, actually worsens time indicators. Thus, we provide a *micro-foundation* of the volume-outcome relationship.

Finally, we analyze the hospital's trade off between allocating more patients to experienced physicians so that they receive an effective attention, or allocating more patients to unexperienced physicians in order that the later learn and accumulate experience. This trade off allow us to recover the hospital's discount factor.

1.1 Literature Review and Contribution

This work contributes to the literature on LBD, especially to that in the health industry, by estimating the causal effects of experience. In Industrial Organization the focus of study has been understanding how productivity increases as a result of higher output. See Syverson (2011) for a review. Seminal papers are Benkard (2000, 2004) that show organizational learning in the aircraft industry as a result of increasing production. One feature of the literature is that LBD is very specific. For instance, Levitt et al. (2013) study LBD in car production lines and, while they find large productivity gains in the first weeks of operation, they also find little learning across production lines of different models. Similarly, Kellogg (2011) identifies producer-contractor pair specific LBD in the oil industry, and Haggag et al. (2017) find neighborhood specific LBD among taxi drivers. In the same vein, we find that organizational learning is important regardless of other, previous experience.[1]

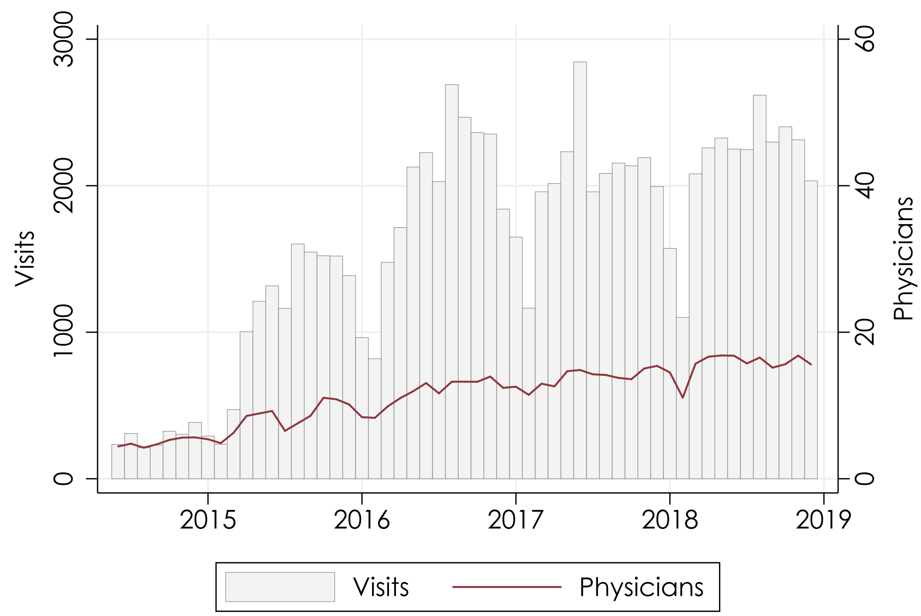
Very few papers focus on worker specific LBD. We study productivity gains at the individual level quantifying the productivity gains of physicians. Our empirical strategy separates these gains from organizational level experience. Moreover, we follow the evolution of physicians' productivity in a hospital since its beginning, studying the causal gains of experience and dealing with selective physician assignment with the use of a novel instrument. Also, we provide a microfoundation of LBD, tying worker LBD to organizational learning.

Furthermore, a strand of the health literature analyzes the volume-outcome relationship, a robust finding by which hospitals that perform a larger number of certain medical procedures tend to have better measures of quality (see Gaynor et al., 2005; and reviews of the literature by Halm et al., 2002; Nguyen et al., 2015; and Mesman et al., 2015). Some articles that study LBD at the physician level (e.g., Huesch, 2009; Contreras et al., 2011) find no correlation between physician experience and patient outcomes (Ho, 2014). On the other hand, some other articles find better outcomes among patients treated by more senior doctors (e.g., Wyatt et al., 1999). Also, Li et al. (2016) find that more senior doctors are associated with longer patient times spent in the ED, less medical tests, lower mortality rates, and lower revisit rates in less severe cases.

In health economics, David and Brachet (2011) study paramedics performance, Hockenberry and Helmchen (2014) and Huckman and Pisano (2006) analyze medical procedures of surgeons; and Bean (2018) studies hospital neonatal intensive care units. To the best of our knowledge, we are the first ones that deal with the endogeneity of experience explicitly. This is important when assignment between workers and task is likely to be not random. In particular, Chang and Obermeyer (2020) provide evidence that allocation between physicians and patients in the ED is a result of physician idiosyncratic preferences and thus not random. We use exogenous variation in the choice set of

[1]Thompson (2001) attributes a large part of the learning effect other papers found in shipbuilding during World War II to capital investments. See also Argote and Miron-Spektor (2011), which reviews contributions in fields ranging from sociology to psychology.

Figure 1 – Number of monthly visits and unique daily physicians



Note: The figure shows the total number of monthly visits and the average number of unique daily doctors in the ED over time.

doctors to deal with selection on unobservable physician and patient characteristics.

2 Institutional Setting and Data

We use administrative data from the hospital of Universidad de los Andes in Chile. This university is a non-profit, private research university that began in 1994. Its medical school ranks among the top 6 in the country.[2] Figure 1 shows the total number of monthly visits and the average number of different physicians in the ED in a day over time.

[2] See `https://www.latercera.com/uncategorized/noticia/percepcion-calidad-carrera/439121`

Table 1 – Summary Statistics

Year	Visits	N. of Daily Physicians	Ratio Patient-Physicians	Time Spent in ED	Specialist (%)	X-Rays (%)
2014	1,742	3.96	3.32	1.93	3.90	25.66
2015	12,415	7.65	6.42	1.68	3.41	26.22
2016	21,844	9.88	7.57	1.79	2.27	23.44
2017	22,893	11.15	6.90	1.55	3.11	23.02
2018	23,486	12.68	6.36	1.61	4.22	24.59
All	82,502	10.67	6.77	1.66	3.30	24.23

Table 2 – Summary Statistics by Severity or Outcome

Outcome	Visits	Time Spent in ED	Specialist (%)	X-Rays (%)
Triage				
Orange	2,175	2.32	2.99	27.54
Yellow	9,069	2.18	8.88	22.80
Green	49,078	1.59	2.74	25.50
Blue	9,413	1.33	1.08	21.98
Staff	54,280	1.62	4.32	25.10
No Staff	28,221	1.73	2.77	22.55
Specialist Referral	2,722	2.76	100	8.71
No Specialist Referral	62,512	1.53	0	24.76
X-Rays	19,990	2.06	1.19	100
No X-Rays	62,512	1.53	3.98	0

Our data include every visit to the ED since the beginning of the hospital's operations in June 2014 until December 2018. We merge different datasets used by the hospital's management. Table 1 shows summary statistics by year. Table 2 presents visit outcomes by triage severity and shows that the visit severity increases time spent in the ED, specialist referrals, and X-ray probability.

We have data on the patient's visit, and patient and physicians' characteristics. We have the triage score, a standardized classification system of the severity of the patient's condition into 5 color categories, which we pool into 4.[3]

In addition, we have timestamps for arrival, triage evaluation, nurse's first visit, doctor's diagnosis, specialist visit, and bill closing. These timestamps allow us to calculate time spent in the different stages of the ED, although we focus on total time. We exclude from our results visits of patients that were ultimately hospitalized, patients that were referred to more than one specialist, and visits that lasted more than 24 hours. Patients are likely less severe on average than those of other hospitals: For example, 81.33 percent of cases in our data are semi-urgent or not urgent, while in the US this figure is only 28.8 percent. The average visit lasted 1.66 hours and the median visit 1.28 hours. [4]

We also have the treating physician's name, the diagnosis code (3 digits ICD-10) and a more aggregated Clinical Classifications Software (CCS) categories,[5] and referral to specialists within the ED. Following the literature, we construct for each doctor a proxy for experience using the log accumulated number of visits (e.g., David and Brachet, 2011). In addition, we have some physician characteristics, as an identifier of whether the physician is part of the regular staff, and the age and gender of staff physicians. We use the physician age to proxy for the physician's overall experience.

[3] The Triage Score System is widely used to classify and prioritize sick and wounded patients when there are not enough resources to treat them at the same time. We pool together the two most severe categories, red and orange, because there are few of the first one. We do not have triage results for 15 percent of the visits.

[4] As a point of comparison, the median ED visit in the US lasted between 2 and 4 hours. Source: National Hospital Ambulatory Medical Care Survey: 2016 Emergency Department Summary Tables.

[5] We use crosswalks from the Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality. We replaced CCS categories for roughly 8,000 visits that we were not able to match to ICD-10 with two digits ICD-10.

Physicians in our sample were relatively young, a common feature of EDs: The mean and median physician ages were 40 and 35 years, respectively. Finally, we have some patient demographics, such as age, gender, address, and an anonymized identifier code.

2.1 Measures of Productivity

We develop measures of productivity at the physician level.[6] The main productivity measure we use is the total time spent in the ER. Time spent is an important outcome because it indicates efficiency in treatment: Given a particular diagnosis and severity, more time in the ED raises costs if only because of the use in space. Moreover, longer treatment times are related to longer waiting times, and patients dislike overspending time in the hospital. Therefore, *conditional* on the patient's severity and diagnosis, visit time is an inverse proxy for productivity. We hypothesize that time in the ED is inversely related to the physician experience: Less experienced doctors may make more initial misdiagnoses, which take more time to treat; may require unnecessary x-rays or laboratory analysis, which are expensive; or may indicate the patient to wait more time before providing a diagnosis, for example, in order to see if the patient develops clearer symptoms.[7]

We also use additional outcomes of the ED visit to proxy for productivity. First, we use specialist referrals. In roughly 5 percent of the cases the ED physician referred the patient to the specialist that was on shift during the patient's emergency visit. The largest share of referrals were to the psychiatrist and to the pediatrician. Our hypothesis is that specialist referrals are negatively correlated with experience.[8] Finally, we use medical images. We have information on X-rays, ultrasound, computerized tomography (CT) scan, and magnetic resonance imaging (MRI). Imaging is generally used as a measure of inefficiency.[9]

We show both experience and average times of attention at the physician level in Figure 2. Panel (a) shows the increase of physicians' experience over time. The dark line in the plot represents the experience of the average physician over time, which mostly increased over time. Panel (b) of the figure shows local linear plots of total time spent in the ED as a function of the experience of the physician. The dark line is a local linear fit of the average time spent of all visits. The fit shows a negative slope. We quantify this drop, controlling for patient and visit outcomes, and dealing with possible bias in the next section.

In addition, we examine the physician assignment mechanism. Using the physician log number of cumulative visits as the main explanatory variable, we run linear probability models of a variable

[6] The most common productivity outcome used in the hospital health literature is deaths (e.g., Propper and Van Reenen, 2010). We do not study deaths because there were very few of them in the hospital the period we study. David and Brachet (2011) studied the time it took to get the patient to the hospital in emergency ambulance services.

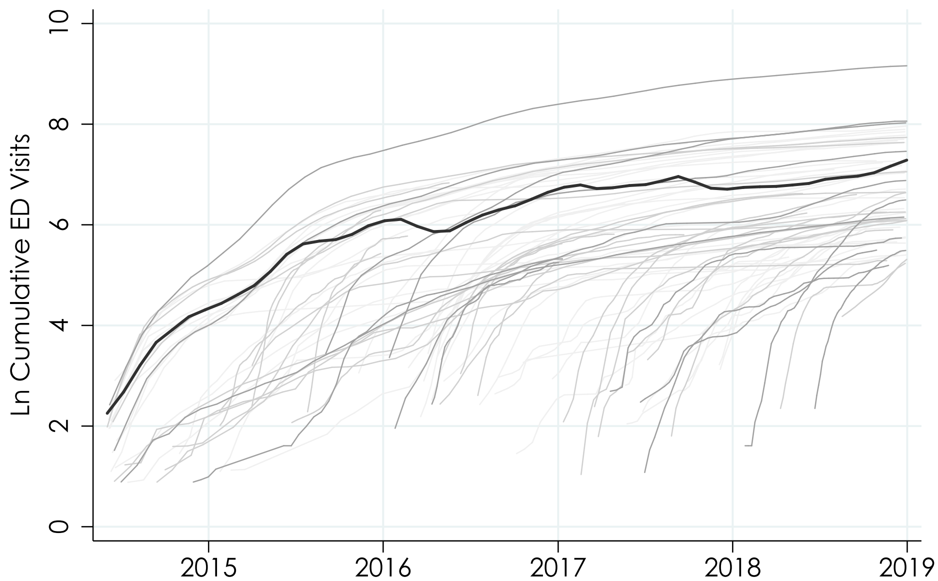
[7] Paley et al. (2011) found 9.5 percent of initial misdiagnoses. The authors also found that the patient's history and a physical examination sufficed to correctly diagnose 60 percent of ED patients, and they did not find differences in misdiagnoses between inexperienced and experienced doctors.

[8] See for example Roland and Abel (2012).

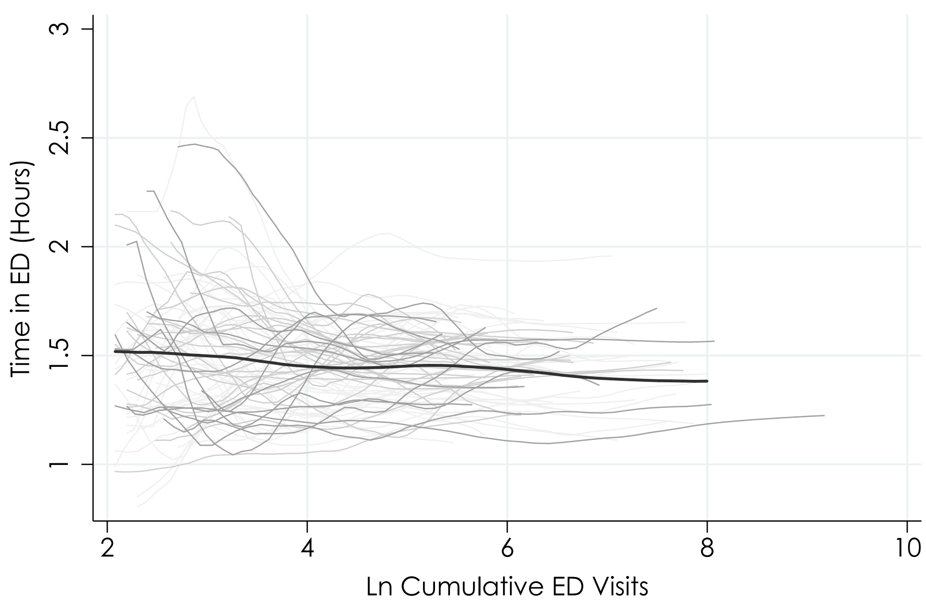
[9] For example, one paper argues that only 1 out of 3 CTs were valuable to determine a disease in the ED (Paley et al., 2011). See also Oren et al. (2019).

Figure 2 – Physician Experience and Productivity

(a) ln Cumulative Number of Visits by Physician over Time



(b) Total Time Spent in the ED



Note: Panel (a) shows local linear plots of time spent in the ED for patients by each physician as a function of the physician's cumulative visits in the hospital. Panel (b) shows local linear plots of physicians' cumulative visits that lasted less than 4 hours in the ED over time. Both panels show physicians with more than 200 visits in the sample period. The dark line shows the local average for all physicians in the sample.

Table 3 – Physician Assignment based on Triage Score

	Dep. Variable							
	Severity						Triage Score	
	OLS						Ordered Probit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Cumulative Visits	-0.004***	-0.002*	-0.001				-0.002	
	(0.001)	(0.001)	(0.001)				(0.003)	
Physician Age				0.001***	-0.000	-0.000		-0.001
				(0.000)	(0.000)	(0.000)		(0.001)
N	69735	67493	67493	45607	45169	45169	67624	45283
Time FE	M-Y	M-Y	M-Y	M-Y	M-Y	M-Y	M-Y	M-Y
Patient Characteristics FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Time of Arrival FE	No	No	Yes	No	No	Yes	Yes	Yes

Note: The table shows regressions of the experience and age of the physician allocated to a patient on the severity of the patient's condition. M-Y indicates month-year fixed effects. Time of Arrival indicates 12 categories for time of arrival to the ED, and day of the week FE. Patient Characteristics include CCS and age category FE. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

indicating more severe cases according to the triage score, and ordered probit models of the triage score. We show the estimation results in Table 3. We also include similar analyses for physician age as a proxy for physician overall experience. The results show some selection on observables that disappears when we add controls. In particular, the estimates indicate that, without conditioning on patient characteristics or time of arrival, less experienced (and younger) doctors saw more severe patients.[10] Despite these findings, we do not rule selection on unobservables because patients could still be allocated to physicians in a non random way, based on other characteristics (Chang and Obermeyer, 2020). Moreover, given an exogenous shock to patient allocation, we can test whether allocation is random by comparing OLS to instrumental variables (IV) results. We will do this in the next section.

3 Empirical Framework

This section provides causal evidence on the gains in productivity as physicians in the ED treat more patients. Let the time spent by patient i in the ED under the care of doctor j at time t (or an alternative visit outcome) be the result of the log-linear production function

$$y_{it} = a_t + \alpha e_{jt} + \beta s_{it} + v_{it} + \xi_{it}, \tag{1}$$

where a_t is a possibly time dependent constant (e.g., hospital's productivity), e_{it} is doctor j's experience at time t, s_{it} is the observed severity of the patient, v_{it} is the unobserved severity (for the econo-

[10]Li et al. (2016) found that more senior doctors saw younger and less urgent patients in their sample.

metrician), and ξ_{it} constitutes an exogenous shock (the lowercase variables denote logs). Only if there is no unobserved severity and if S accounts fully for the physicians' selection mechanism of doctors, then OLS estimation is unbiased. However, it is more likely that the hospital's assignment mechanism is such that physicians are not allocated randomly to patients so that there is selection of experience e_{jt} on patient's unobserved severity v_{it}. For instance, physicians could have been assigned to patients based on unobserved severity. Similarly, as the hospital grew and/or its experience increased, it started receiving patients with more severe diagnoses. More severe cases required more resources and thus productivity would seem to have decreased.

We deal with this omitted variable bias in two ways. First, we proxy for v_{it} with controls for severity to try to account fully for the selection mechanism through selection on observables. In particular, we control for patient diagnosis code (CCS), for the patient triage classification color, which is a measure of severity of the patient's condition; patient age, and time of arrival to the ED (month-year, day of the week, hour of arrival FE). OLS estimates of equation (1) are unbiased if, after controlling for patient characteristics, the unobserved severity does not affect the physician assignment. Notice that physician controls do not help solving the endogeneity problem. On the contrary, physician fixed effects are endogenous controls, because they are also correlated with v_{it}. For this reason, we do not include physician fixed effects in the equation. Likewise, we exclude medical images or specialist referrals because they are endogenous too.[11]

The second way to deal with endogeneity is through the use of an instrument. Our instrument for physician experience is the *lagged* physician experience, that is, the experience of the doctor that treated the patient who was treated immediately before the current patient.[12]

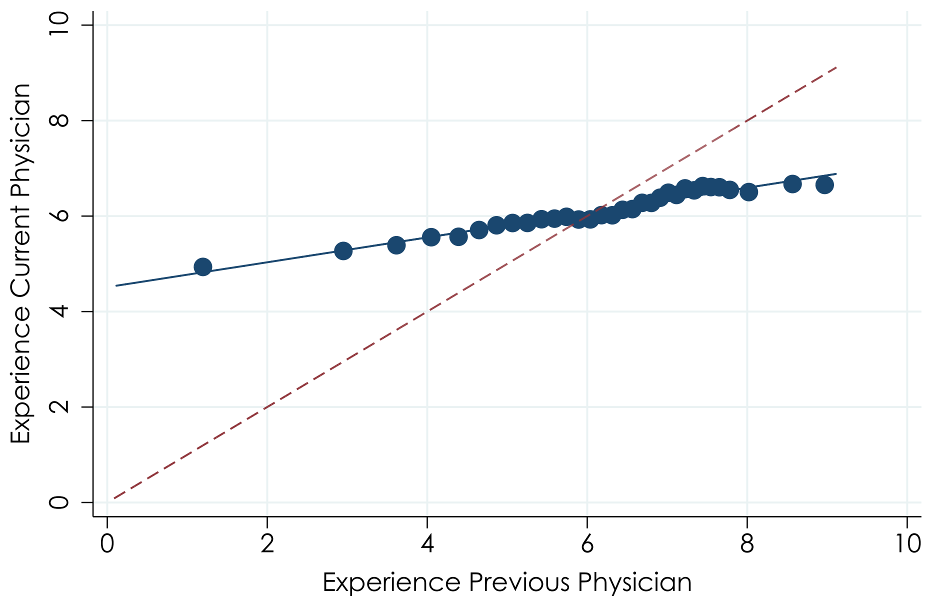
We argue that the instrument is not correlated with the patient's unobserved severity, but it is correlated with the treating physician's experience. First, conditional on controls, the physician experience of the previous patient is not correlated with any characteristic of the current patient and does not have a direct impact on performance measures of the treatment of the current patient because of the time difference between the two visits. That is, the instrument is not a covariate in the reduced form equation. We capture cross related effects that may affect outcomes, such as congestion, using time fixed effects. Second, the correlation between the experience level of the physicians of the current and the previous patients is due to the assignment mechanism itself, and to the fact that the hospital has a fixed set of physicians working at the ED at any given point in time.[13] These factors

[11] Similarly, the main specification of Gaynor et al. (2013) is relatively parsimonious to avoid including endogenous controls.

[12] This is in the spirit of Alé-Chilet and Atal (2019), who use the severity of the previous patient as an instrument for the current patient's severity.

[13] To see the last point more clearly, consider the following. Let the subscript t index the order in which patients started being treated. Hence, patient $t-1$ began her treatment immediately before patient t began hers. Under normal conditions, the physician that treats patient $t-1$ is less likely to be available to treat patient t. As a result, the set of physicians available to treat patient t depends on who is treating patient $t-1$. Because the physician assignment for patient $t-1$ is independent from patient t characteristics, the choice of physician at $t-1$ constitutes an exogenous shock to the choice set of physicians for patient t. For instance, suppose that there are three physicians at the ER, with experience levels low (L), medium (M), and high (H). If physician L treats patient $t-1$, then only physicians M and L may treat patient t. Even though the decision to assign either physician M or L will be related to patient t characteristics, the variation in that choice set is not be determined

Figure 3 – First Stage



Note: The figure shows a binned scatter plot and a linear fit of the lagged physician experience (the instrument) plotted against the current physician experience (the endogenous variable). The figure include a 45 degree dashed line .

generate a change in the *choice set* of the doctors available to the current patient.

We plot a binned scatter plots between the lagged and the current physician experience in Figure 3. The figure shows a linear relationship between the two variables. The curve's slope is less than one, as the dashed line indicates. The curve also indicates that if a more inexperienced doctor saw the previous patient then the current patient is expected to be seen by a more experienced doctor, while the opposite is also true. Notice that if the allocation was random, then we would also observe a similar "regression to the mean" pattern. Yet, if that is the case, then the OLS and the IV estimates would be the same, which is something we can empirically test.

The lagged experience has no statistical power as an instrument in the following scenarios: (i) when there is only one physician, (ii) when all physicians have the same experience, and (iii) when there are no patients waiting for being treated. In these situations there is no variation in the experience of the current patient's physician and that of the previous patient's physician. In our data these conditions do not hold often. For instance, in around 13 percent of cases the lagged physician is the same as the current one. We do not drop these observations because this would introduce selection in our source of exogenous variation.[14]

One possible further concern with our estimation strategies is hospital selection: If there are still unobserved patient or disease characteristics that confound hospital selection and performance mea-

by those characteristics. Thus, we use this exogenous variation in the choice set as an instrument.

[14]Note also that the power of the instrument decreases as the number of physicians is close to one or tends to infinity.

sure, we can use as a further control the distance between the hospital and the patient's residence address. As severity of illness and comorbidity increase, that distance should decrease. Thus, in life threatening conditions we expect the patient to go to the closest hospital.[15]

4 Results

The results of the estimation of Equation (1) show large and significant effects of physician experience on patient's time spent in ED. Our preferred specifications include month-year fixed effects. The inclusion of time controls entails that the identification comes from the cross section—as opposed to the time series—by comparing across doctors with different levels of experience in the same month or week. Hence, these estimates separate physician LBD from shocks at the institutional level.

Columns (1)-(4) of Table 4 show the OLS estimates of increasing additions of time, diagnosis (CCS), and patient controls, respectively. Patient controls include dummies for 6 age group categories, 12 hour of arrival bins, and day of the week. Column (5) adds physician fixed effects. We think these variables are endogenous because they are correlated with the unobserved patient severity. The size of experience the effect decreases, which is consistent with this endogeneity issue. Column (6) and (7) show that using week-year and ICD-10 fixed effects, respectively, does not result in different estimates. The specifications provide an elasticity of -0.042, that is, a 1 percent increase in the number of cumulative visits reduce the total time of a visit in 0.04 percent. An alternative interpretation is that a one standard deviation (1,786 treated patients) increase in the average doctor experience (1,235 treated patients) results in a 6 minute drop in the visit time.

If there are still unobserved sources of physician assignment the OLS estimates are biased. Consequently, we show IV estimates in Table 5, where the instrument is the experience of the physician that treated the patient previous to the current one. The IV estimates are 50 percent larger than the OLS. The elasticity of -0.065 implies a 9.4 minute drop as a result of a one standard deviation increase in the average doctor experience. The Angrist Pischke F-statistic is large, which indicates no weak instrument issues. Columns (6) and (7) of Table 5 show the results of the first stage. Also, Hausman endogeneity tests reject the null hypothesis that the log number of visits is exogenous and, thus, that the OLS and the IV estimates are the same.

Table 6 presents the effect of experience on other outcomes. We focus on referrals to specialist and X-rays. We include the same fixed effects as in our preferred specifications above. We find slightly different results when controlling for the CCS or for the ICD-10 diagnosis codes and, thus, we present results for both. We find marginally significant effects that imply that a one standard deviation increase in experience raises the probability of referring to a specialist by 1 percent (or 0.03 percentage points), and the probability of requesting X-rays by 2 percent (or 0.56 percentage points).

[15] Other papers have estimated a hospital demand model (e.g., Geweke et al., 2003; Bean, 2018; Prager, Forthcoming). Due to data limitations we cannot take this approach.

Table 4 – Fixed Effect Regressions

	Dep. Variable: ln Time Spent in ED						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln Cumulative Visits	-0.042***	-0.045***	-0.045***	-0.042***	-0.028***	-0.042***	-0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
N	63737	63737	63737	63737	63115	63737	63158
N Days	1671	1671	1671	1671	1671	1671	1671
R-sq adjusted	0.01	0.02	0.19	0.21	0.23	0.21	0.22
Time FE	No	M-Y	M-Y	M-Y	M-Y	W-Y	M-Y
Diagnostic FE	No	No	Yes	Yes	Yes	Yes	Yes*
Patient Characteristics FE	No	No	No	Yes	Yes	Yes	Yes
Physician FE	No	No	No	No	Yes	No	No

Note: Diagnostic FE indicates CCS categories and triage color FE, except for the star symbol (*) that indicates ICD-10 and triage color FE. M-Y and W-Y indicate month-year and week-year fixed effects, respectively. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 5 – Instrumental Variable Results

	Dep. Variable: ln Total Time ER						ln Cumulative Visits	
	OLS	IV					First Stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Cumulative Visits	-0.042***	-0.045***	-0.066***	-0.061***	-0.065***	-0.068***		
	(0.002)	(0.007)	(0.014)	(0.015)	(0.016)	(0.018)		
Lag ln Cumulative Visits							0.099***	0.096***
							(0.007)	(0.007)
N	63736	63736	63736	63736	63157	63157	63736	63157
N Days	1671	1671	1671	1671	1671	1671	1671	1671
R-sq Adjusted	0.21	0.01	0.00	0.00	-0.02	-0.02	0.20	0.23
AP F-stat		806.35	253.23	218.65	214.49	184.60		
Hausman Test p-value		0.639	0.055	0.092	0.047	0.049		
Time FE	M-Y	No	M-Y	M-Y	M-Y	W-Y	M-Y	M-Y
Diagnostic FE	Yes	No	Yes	Yes	Yes*	Yes*	Yes	Yes*
Patient Characteristics FE	Yes	No	No	Yes	Yes	Yes	Yes	Yes

Note: Diagnostic FE indicates CCS categories and triage color FE, except for the star symbol (*) that indicates ICD-10 and triage color FE. M-Y and W-Y indicate month-year and week-year fixed effects, respectively. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 6 – Other Outcomes

	Dep. Variable: Probability of							
	Specialist				X-Rays			
	OLS		IV		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Cumulative Visits	-0.005***	-0.004***	-0.005	-0.007*	-0.007***	-0.005***	-0.017*	-0.016*
	(0.001)	(0.000)	(0.004)	(0.004)	(0.001)	(0.001)	(0.009)	(0.009)
N	63157	63157	63157	63157	63157	63157	63157	63157
N Days	1671	1671	1671	1671	1671	1671	1671	1671
AP F-stat			216.50	214.62			216.50	214.62
Mean Dep. Var.	0.03	0.03	0.03	0.03	0.25	0.25	0.25	0.25
Diagnostic FE	CCS	ICD-10	CCS	ICD-10	CCS	ICD-10	CCS	ICD-10

Note: Diagnostic FE include either CCS or ICD-10 code fixed effects. All specifications include M-Y, triage color, patient age category, hour of arrival, and day of the week FE. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

5 Extensions

5.1 Previous Experience

A main caveat of the previous analysis is that we only considered physicians' institutional experience, that is, the experience within the hospital.[16] We study whether previous experience is driving the effect we find by using physicians' age as a proxy for previous experience. In order to do so, we have to deal with the same endogeneity issues for age that result from patient allocation. Hence, we instrument for physician visits and physician age using the visits and the age of the physician that treated the previous patient. We include in our regression sample only observations for which both the current and the lagged physician were part of the staff because we only have the age for staff physicians.

Our results show that among staff physicians the effect of institutional experience is larger than what we previously found (Columns 1 and 3 of Table 7).[17] The main results (Columns 2 and 4 of Table 7) indicate that the LBD effect is still important after controlling for physicians' age, although the coefficient is smaller when doing so. Moreover, the age sign is consistent with our previous results that older, more experienced doctors are more productive. We interpret the magnitudes of the two effects by analyzing the result of a 1 standard deviation in each variable. We find that such an increase in organizational experience entailed a 9.6 minute decrease in patient time spent in the ED, while a similar increase in physician age (9.36 years) lead to a 6.7 minute decrease. Thus, organizational experience was more important for productivity gains in time spent.

[16] Huckman and Pisano (2006) find that within hospital experience significantly improves surgeons' performance, although the effect of experience acquired in other hospitals is not significant.

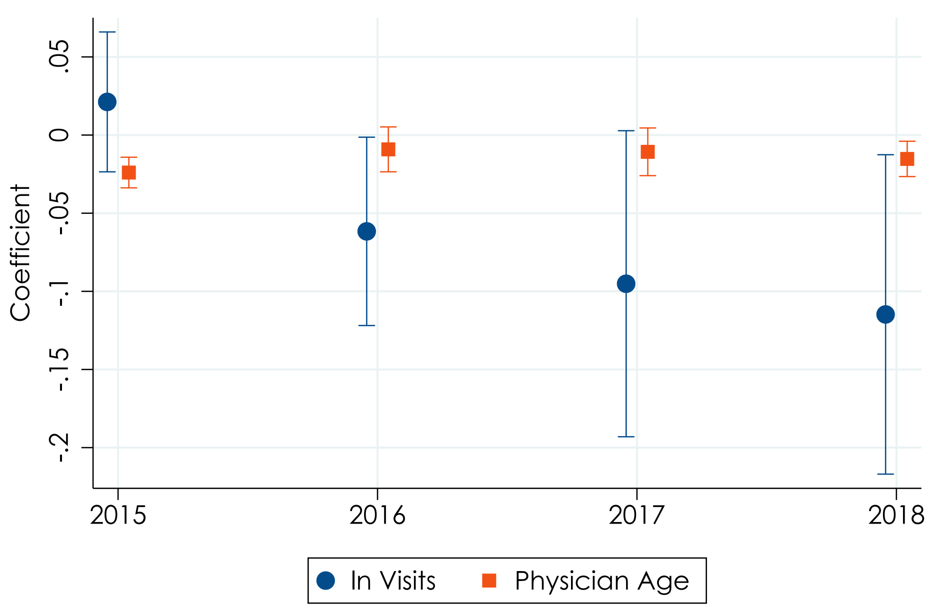
[17] We explore the differences between staff and non staff physicians in Subsection 5.2.

Table 7 – Previous Experience

	Dep. Variable: ln Total Time ER				ln Cumulative Visits	Physician Age
	OLS		IV		First Stage	
	(1)	(2)	(3)	(4)	(5)	(6)
ln Cumulative Visits	-0.056***	-0.033***	-0.115***	-0.071***		
	(0.004)	(0.005)	(0.023)	(0.022)		
Physician Age		-0.006***		-0.012***		
		(0.001)		(0.003)		
Lag ln Cumulative Visits					0.182***	-0.142**
					(0.012)	(0.068)
Lag Physician Age					-0.004***	0.145***
					(0.001)	(0.009)
N	28821	28821	28821	28821	28821	28821
N Days	1623	1623	1623	1623	1623	1623
R-sq adjusted	0.21	0.22	-0.02	-0.01	0.49	0.31
AP F-stat			226.31	246.29		
				331.13		

Note: All specifications include diagnostic, M-Y, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Figure 4 – The Effect of Physician Experience and Age on Patient Time Spent in the ED



Note: The figure shows the ln visits and age coefficients and their 95 percent confidence intervals of year by year regressions, where the dependent variable is the total patient time spent in the ED (See Column 4 of Table 7). All regressions include diagnostic, M-Y, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week.

Table 8 – Staff vs. Non-Staff Experience

	Dependent Variable:					
	ln Time in ED		Specialist		X-Rays	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Staff * ln Cumulative Visits	-0.026***	-0.099***	0.004***	0.014*	0.001	-0.013
	(0.004)	(0.031)	(0.001)	(0.008)	(0.002)	(0.017)
ln Cumulative Visits	-0.029***	-0.012	-0.007***	-0.015**	-0.007***	-0.007
	(0.003)	(0.025)	(0.001)	(0.006)	(0.002)	(0.013)
Staff	0.148***	0.583***	-0.024***	-0.071	-0.005	0.052
	(0.028)	(0.187)	(0.007)	(0.045)	(0.013)	(0.099)
N	63737	63736	67497	67496	67497	67496
N Days	1671	1671	1672	1672	1672	1672
AP F-stat 1		120.00		120.48		120.48
AP F-stat 2		25.90		26.72		26.72
AP F-stat 3		38.92		40.42		40.42

Note: All specifications include diagnostic, M-Y, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

5.2 Staff vs. Non-Staff Physicians

Staff ED physicians account for 65 percent of the visits in our sample, but for 13 percent of the physicians (40 out of 312). The demographics between the two groups may be different. Moreover, the fact that some physicians may work outside the hospital's ED is a potential confounder of LBD, as non staff physicians may gain experience elsewhere. However, this issue is less relevant for staff physicians. Finally, the results for the staff physicians subsample in Table 7 shows larger LBD effects of staff physicians. Hence, we account for these differences with a staff dummy and its interaction with the log number of cumulative visits in the ED. As explained before, these two variables are endogeneous and, similarly, we use the previous physician staff status and its interaction with log visits as instruments. Table 10 presents the results. We find that the LBD effect in time spent in the ED comes from staff physicians. This result changes for specialist referrals where LBD is due mainly to non staff physicians. Moreover, the staff dummy is quite large and negative, although not significant. These facts suggest that the specialist referrals decision is more related to the hospital internal practices and instructions, which may take more time to deliver to non staff physicians.

5.3 Patient Fixed Effects

A large share of the patients were at the ED more than once (we show the distribution of visits by patient in the Appendix). We take advantage of this fact and control for patient time invariant characteristics with patient fixed effects. Table 9 presents both OLS and IV results. We control for month of the year and for triage results. The point estimates are slightly larger than , but statistically indistin-

Table 9 – Patient Fixed Effects

	Dep. Variable: ln Time Spent in ED					
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Cumulative Visits	-0.045***	-0.046***	-0.045***	-0.059***	-0.083***	-0.072***
	(0.002)	(0.002)	(0.003)	(0.010)	(0.019)	(0.021)
N	57978	57978	47491	57978	57978	47491
N Days	1666	1666	1663	1666	1666	1663
R-sq adjusted	0.09	0.10	0.14	-0.36	-0.37	-0.40
AP F-stat				748.10	235.16	203.33
Patient FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Severity FE	No	No	Yes	No	No	Yes

Note: The time fixed effect is month of the year. Severity FE corresponds to triage color FE. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

guishable from those of the main results.

5.4 Different timestamps

Our main visit outcome is the total time the patient spent in the ED. We check next our main specification when we use different time intervals as the proxy for productivity. We find that increased physician experience decreases all time intervals except for the arrival-triage time that is the only one where the physician does not intervene.

5.5 Recent experience and forgetting

Recent experience should be more important than past one if physicians *forget* more distant visits (Benkard, 2004; David and Brachet, 2011). We check the presence of "organizational forgetting" regressing log total time spent in ED on the log number of visits the physician had only in recent months, beginning from 0-4 months up to 0-24 months, and comparing these to all visits in the hospital. Table 11 shows the results for both OLS and IV models. The estimates indicate that the effect is largest for visits that took place in the first 8 months. To test whether the 0-8 months coefficients are different from all experience, we run regressions of log time spent in the ED on log number of physician visits in the first 8 months and log number of total physician visits and instrumenting for these variables using their respective lags. We show the results in Table A2 of the Appendix. We find that almost all the effect was due to visits in the first 8 months.

Table 10 – Alternative Time Intervals

	Dependent Variable: Log Time between					
Model	Arrival-Close (1)	Arrival-Triage (2)	Arrival-Registry (3)	Arrival-Diagnosis (4)	Registry-Diagnosis (5)	Diagnosis-Close (6)
OLS	-0.042***	0.002	-0.049***	-0.047***	-0.077***	-0.036***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
IV	-0.064***	-0.001	-0.052***	-0.064***	-0.117***	-0.055**
	(0.015)	(0.018)	(0.018)	(0.016)	(0.026)	(0.025)
Mean Indep. Var.	1.67	0.14	0.51	0.72	0.20	1.07

Note: Each coefficient represents the estimate of a different regression, where the dependent variable is the log cumulative number of physician visits. All specifications include diagnostic, M-Y, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week. The number of observations is 63,060, except for Arrival-Triage specifications, where is 62,923. The independent variable average is 6.16. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 11 – The Effect of Recent Experience vs. Past Experience

	Independent Variable: ln Cumulative Recent Visits						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time Range (months):	0-4	0-8	0-12	0-16	0-20	0-24	All
OLS	-0.052***	-0.048***	-0.044***	-0.041***	-0.040***	-0.038***	-0.036***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IV	-0.097***	-0.111***	-0.106***	-0.098***	-0.090***	-0.087***	-0.079***
	(0.028)	(0.026)	(0.024)	(0.023)	(0.022)	(0.022)	(0.020)
AP F-stat (IV)	121.87	116.65	109.68	109.31	111.58	111.53	114.91

Note: Each coefficient correspond to a different regression. N=73,644; and the number of days equals 730. The sample corresponds to the years 2017 and 2018. All specifications include diagnostic, month-year, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

6 Microfoundations of Organizational LBD

In the previous sections we showed that physicians that treated more patients in the university hospital's ED performed more productively. Thus, it is natural to ask whether increased *hospital wide* physician experience is related to overall hospital productivity. In this section we show how physician-level productivity relates to organizational productivity changes. This is important to microfound organizational LBD.[18]

We want to answer two questions. The first question is how the cumulative experience of the *average* physician translates into productivity gains at the institutional level. This issue is important to understand how microlevel gains in productivity translates into aggregate, organizational wide productivity gains. Panel (a) of Figure 5 presents a binned scatter plot and a polynomial fit of the average visit time as a function of the experience of the average doctor. The panel shows that increased experience of the average physician had an effect on hospital productivity. The second question is related to the volume outcome relationship in health of whether larger hospitals are more efficient. Given our previous findings we want to know whether visit time changes were due to productivity gains at the physician level or to other institutional factors that made the hospital more efficient as the *total* number of visits increased. Panel (b) of Figure 5 presents the relationship between hospital total ED visits and time spent in the ED. This relationship is negative, as also was the relationship between physician experience as hospital productivity. Thus, we would like to know whether the average physician experience or the hospital total experience were more important in decreasing visit times.

We present the results in Table 12. An observation in these analyses is a day. Panel (a) of the table shows regressions of the average daily time spent in the ED on the average physician productivity with various time effects, which control for differences in patients composition. The effect is negative and similar to our results on the physician level experience. In Panel (b) we add the hospital cumulative volume as a second explanatory variable. The effect of the average physician experience becomes larger, but the effect of the total hospital experience is positive. The result suggests that the volume outcome relationship in our context was due to physician level increase in experience rather than organizational growth. Moreover, the positive sign of the hospital volume suggests a congestion effect, which the growth in physician experience offset.

7 A Model of Physician-Patient Allocation (Incomplete)

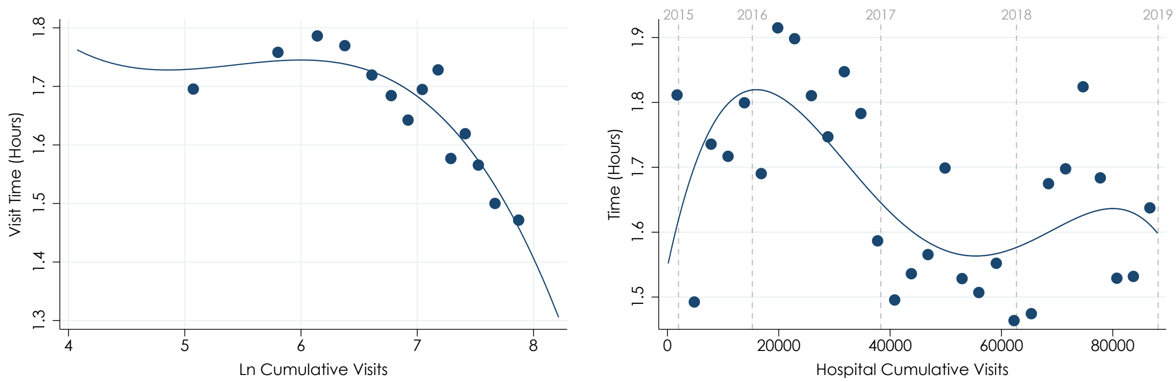
In this section we develop a physician-patient allocation model. We analyze the intertemporal tradeoffs of different allocation policies of physicians to patients and calibrate the hospital preferences for the future.[19]

[18] Aggregation of productivity has been discussed by Foster et al. (2001), Melitz (2003) and Hulten (2010), among others.

[19] Joskow (1980) develops a queuing model of patients arrival under uncertainty to calculate the optimal number of beds in a hospital.

Figure 5 – Experience Accumulation and Hospital Productivity

(**a**) Average physician experience (**b**) Hospital experience



Note: The figure shows the relationship between hospital productivity and the experience of the average physician (Panel a) and between hospital productivity and the total hospital experience (Panel b).

Table 12 – Physician vs. Hospital LBD

	Dep. Variable: ln Time Spent in ED			
Panel (a)	(1)	(2)	(3)	(4)
Average Physician ln Cumulative Visits	-0.024***	-0.047***	-0.040***	-0.066***
	(0.006)	(0.008)	(0.010)	(0.010)
N	1674	1674	1674	1674
R-sq adjusted	0.02	0.03	0.03	0.13
Time Effects	No	Linear	Year	M-Y
Panel (b)				
Average Physician ln Cumulative Visits	-0.074***	-0.073***	-0.073***	-0.066***
	(0.010)	(0.010)	(0.010)	(0.010)
Hospital ln Cumulative Visits	0.042***	0.039***	0.064***	-0.002
	(0.008)	(0.013)	(0.016)	(0.044)
N	1674	1674	1674	1674
R-sq adjusted	0.04	0.04	0.05	0.13
Time Effects	No	Linear	Year	M-Y

Note: Each observation corresponds to a different date. M-Y indicates month-year fixed effects. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

To fix ideas, consider two extreme cases of a possible hospital allocation strategy. Assume there is overcapacity of physicians and that there is no patient heterogeneity. One strategy is that the hospital allocates first the most experienced physicians because they are the ones that treat patients in the lowest time. An alternative strategy is that the hospital allocates first the less experienced physicians because the hospital wants that they improve their treatment times in the future.

Hence, conditional on the existence of LBD and on preference for the future, there are incentives to prioritize low experience doctors rather than high experienced doctors when a patient arrives and when multiple physician are available. Moreover, the trade-off between the treatment time of the current patient and the long-term gains due to physician experience increases is determined by the hospital's discount factor. Below we provide a model of the hospital's allocation problem which, after calibrating it, will allow us to obtain the hospital's discount factor.

Model

We model the physician allocation decision made by the hospital ED management. Time t is discrete and there is a set of physicians indexed by $j \in \{1, ..., J\}$. Each physician j is characterized at time t by (i) its experience E_{jt}, which is measured by the number of treated patients, and (ii) T_{jt} for how many periods starting at t the physician j is not available to treat new patients. Patients arrive to the ER following a random process. Each period, a new patient (one and only one) comes into the ER with probability p. Each patient is characterized by (i) t_i, arrival time, (ii) s_i observed severity of illness, and (iii) x_i other patient characteristics.

The time that a physician j takes to treat patient i is given by:

$$g(s_i, E_{jt}) + \epsilon_{ijt} \tag{2}$$

where the function $g(\cdot)$ gives the expected treatment time conditional on s_i and E_{jt}, and ϵ_{ijt} is a idiosyncratic shock that is not observed by the hospital manager when making the allocation decision. The idiosyncratic shock ϵ_{ijt} encompasses any unexpected treatment difficulty that arises during patient treatment. The index t denotes the time at which the treatment started. Even though patient i arrived at period t_i, it can be the case that its treatment started at $t' > t_i$.

There is a queue Y of patients waiting to be assigned a physician (i.e., the number of patients in the waiting room). Every period that queue is sorted by patient severity, where the most severe patient is sorted in the first position. Every period that at least one physician is available (i.e., $T_{jt} = 0$ for some j), the hospital manager has to decide to what patient allocate a physician. The manager follows an allocation rule F which assigns the most severe patient to one and only one physician. In case that there are two or more patients with the same severity in the queue, one patient is randomly selected. If a patient in the queue is not assigned, she stays in the queue to the next period.

Two features make the allocation problem dynamic. First, any given physician becomes more efficient as he treats more patients. Thus, any allocation made at time t might affect treatment times of patients treated at any time $t' > t$. Second, the allocation decision at a given period determines the available physicians for subsequent periods. There is a value of having an available physician (in case multiple patients with higher severity arrives in the subsequent periods). Even though a given physician is available at time t, it might be optimal not to assign a patient to him.

The key dynamic effect we are interested in is the trade off of whether assigning a given patient to a low-experienced physician or to a high-experienced one. Prioritizing the low-experienced physicians increases the overall long-run experience and efficiency of the ER, but implies that the treatment time of the current patient will be longer.

We define the state S of the ER at a given period t as:

1. Physicians' experience: $\{E_{1t}, ..., E_{Jt}\}$
2. Physicians' availability: $\{T_{1t}, ..., T_{Jt}\}$
3. Patient queue x_t: $\{(s_1, t_1), (s_2, t_2), ...\}$

The allocation rule is a function which maps state S to a S'. Because an actual allocation decision happens only when a physician is available, if there is no available physician at the beginning of period t, then only T_{jt} change at that period.

The timing of the problem is the following:

1. Physicians' state (experience and availability) is updated
2. Patient arrival stage. The patient arrival is realized and the patient's severity is drawn.
3. The patient queue is updated (both the patients in the queue and patient order within the queue)
4. Patient assignment stage. Patient assignment is sequential following patient order in the queue and conditional on physician availability. Whenever there are no more available physicians, the assignment stage ends. The process is the following:
   (a) The decision maker checks whether there is any available physician. If there is no available physician, this stage ends.
   (b) The decision maker decides whether or not to assign the first patient in the queue. If the decision is not to assign the first patient, the assignment stage ends.
   (c) If the decision maker decides to assign the first patient, then she decides the assignment. The assigned patient is taken out of the queue and the relevant physician is no longer available.
5. The ϵ_{ijt} of the recently assigned patients are realized.

In future work we will calibrate such a model of physician-patient allocation.

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Appendix

Table A1 – Number of visits by Patient

Visits	N
1	14,457
2	14,407
3	9,056
4	5,885
5	3,886
6	2,553
7	1,818
8	1,331
9	926
10+	2,561
Total	56,880

Table A2 – Recent vs. Past Experience

	Dep. Variable: ln Time Spent in ED	
	OLS	IV
	(1)	(2)
Ln Cumulative 0-8 months	-0.033***	-0.121**
	(0.008)	(0.061)
Ln Cumulative Visits All	-0.012*	0.009
	(0.006)	(0.048)
N	37644	37644
N Days	730	730
AP F-stat 1		43.68
AP F-stat 2		38.90

Note: All specifications include diagnostic, month, and patient characteristics FE. Diagnostic FE indicates CCS categories and triage color FE. Patient characteristics include age categories, hour of arrival, and day of the week. Standard errors clustered at the daily level in parentheses. * p<0.10, ** p<0.05, *** p<0.01