Received: 5 April 2019 | Revised: 4 November 2019 | Accepted: 6 November 2019

DOI: 10.1002/hec.3984

RESEARCH ARTICLE

WILEY Health Economics

Capacity constraints and time allocation in public health clinics

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Summary

Unlike in the production of most goods, changes in capacity for labor-intensive services only affect outcomes of interest insofar as service providers change the way they allocate their time in response to those capacity changes. In this paper, we examine how public sector service providers respond to unexpected capacity constraints in the specific context of public health clinics. We exploit an exogenous reduction in public health clinic capacity to quantify the trade-off between patients treated and time spent with each patient, which we treat as a proxy for a quality versus quantity decision. We provide evidence that these small and generally insignificant effects on nurse time favor public sector employees prioritizing quality of each interaction over clearing the patient queue.

KEYWORDS

health care production, nurse staffing, quality of care

1 | INTRODUCTION

Health care providers, like suppliers of other services, face inherently stochastic demand but cannot store inventory. Suppliers therefore tend to carry excess capacity on a median day; however, identifying the appropriate amount of excess capacity and quantifying the effects of policies that may reduce capacity (e.g., staffing or general budget reductions) require an understanding of how providers respond to more restrictive capacity constraints. In this paper, we examine how public health clinicians respond to unexpectedly tight time constraints created by exogenous temporary reductions in staff. When short-staffed, how much time with the average patient are providers willing to trade-off to see as many patients as possible?

The answer to this question helps to predict the optimal amount of median excess capacity built into the provision of public clinical services. For example, if providers are reluctant to reduce the time spent with patients, and leaving patients untreated has a high social cost, then ensuring median day excess capacity in the public provision of clinical services can yield significant welfare gains (Hughes and McGuire, 2003). Whereas leaving patients untreated creates obvious negative externalities, particularly if they are in the clinic for communicable illness, a reduction in time spent with each patient may also negatively affect the quality of care.[1]

We identify the causal effects of capacity reductions through a series of repeated, but not periodic, exogenous temporary reductions in the number of nurses working in a given clinic on a given day. Our data were provided by the Knox County Health Department (KCHD) in Tennessee and are comprised of time records for each patient visit in five public health clinics over 16 months. In addition to providing certain types of health care in the clinic, KCHD is

[1]See, for example, Whittington and McLaughlin (2000), Tai-Seale et al. (2007), Munyisia et al. (2011), and McCloskey et al. (2014), among others.

responsible for administering FluMist vaccines in public schools. On days when KCHD is administering FluMist, two nurses are removed from typical clinical duties and sent to the particular school for the morning, leaving clinics short-staffed with reduced operating capacity for the first half of the day.

The selection and timing of FluMist administration is plausibly exogenous to the demand or expected patient volume for a given clinic. For example, all scheduling decisions were made by the KCHD central office without consulting the clinics and with no compensating actions taken by the central office. Clinics that were selected for FluMist on a given day were instructed to keep all scheduled visits and were prohibited from otherwise increasing their staffing levels on FluMist days. We expand on these institutional details and provide empirical evidence on the exogeneity of FluMist days in Section 2.

Our empirical analysis exploits these reductions in clinic staff, along with unexpectedly high-demand days, to quantify the trade-off between patients seen versus time with each patient. First, we quantify the effects of reductions in clinic staff on provider behaviors and specific components of the clinic visit.[2] A simple event study of daily clinic visits and other aggregate measures of clinic behaviors surrounding FluMist days shows an abrupt reduction in capacity on FluMist days. Our regression analysis of nurse days further confirms that nurses removed for FluMist administration see significantly fewer patients, thereby reducing overall clinic capacity. We also find that nurses in affected clinics (who are not administering FluMist) decrease their share of walk-in patients, indicating a prioritization of patients with scheduled appointments. At the visit level, when clinic capacity is reduced, average total visit time significantly decreases by 7% (or about 5 min). This primarily occurs through a reduction in administrative aspects of the visit, with small (and insignificant) reductions in time with nurses.

There are two general ways in which time with nurses may be unaffected by a reduction in clinic capacity. First, there could be deliberate efforts by clinics and nurses to maintain some minimum amount of time per patient. Alternatively, our estimates could simply reflect existing excess clinic capacity, such that any reduction in capacity is nonbinding. One way we separate these mechanisms is to estimate unconditional quantile regressions at the nurse level, allowing for differential effects along the support of daily visit volumes. From this analysis, even on the busiest days (upwards of the 75th percentile of visit volume) when capacity constraints are likely binding, we find that nurses never reduce their time with each patient by more than 5%. Alongside additional empirical analysis, we interpret the inelasticity of time spent with patients as indicative of a prioritization of time with nurses over the number of patients seen. However, it is also likely that there is some minimal amount of time in which the provider can conduct the necessary activities to respond to patient needs, and this constraint partially drives the inelasticity we observe in the data.

Our study offers three distinct contributions to the literature. First, our investigation of how public service workers adjust their time allocation in response to reductions in capacity is novel.[3] Most prior relevant work in the health sector focuses on excess capacity and provider response to stochastic demand in the hospital and long-term care settings (Friedman and Pauly, 1981; Gaynor and Anderson, 1995; Keeler and Ying, 1996; Hughes and McGuire, 2003; Sharma et al., 2008) or providers' acceptance of patients and time spent with each patient in emergency departments (Chan, 2016; Chan, 2018). Recent work from Freedman et al. (2018) examines changes in physician behavior due to increased time pressures in the clinic, exploiting variation in patient volumes to identify responses of primary care physicians within the day. Our analysis is similar in spirit, albeit with a different source of identification (a reduction in nurse staffing levels in the clinic) and a different care setting (public vs. private). There are also reasons to suspect that workers in the public and private sectors may respond very differently to reduced capacity. For example, Dixit (2002) discusses how incentives and competition can inefficiently distort worker effort and performance in the public sector.[4]

Second, most prior work on exogenous capacity changes in health care settings focuses on increased rather than reduced capacity. There have been a number of studies examining the effects of regulatory changes in required staffing/patient ratios, with mixed findings.[5] Additionally, previous studies that prompted such regulation change have been criticized

[2]We use the term "provider" to refer to both the clinic and nursing staff collectively.

[3]In studies of other industries, understaffing has been found to be related to lower levels of performance at the group level in professional and trade occupations (Ganster and Dwyer, 1995), a decline in the positive experiences and increased workload stress in an educational service setting (Yoe, 1988), and less than optimal sales and profitability in stores (Mani et al., 2015).

[4]The public health setting is important in its own right as over 20 million people currently receive primary and preventative health care at community health centers (Kaiser Family Foundation, 2013). Additionally, capacity constraints may have differential effects when the constraint is on labor, rather than capital (beds), or when the need for treatment is more/less urgent. Unlike emergency departments, most patients to public health clinics will survive until the next day if untreated, in which case, providers in health clinics may place more weight on time with patients over maximizing the number of patients seen in a timely manner.

[5]Chen and Grabowski (2015), Bowblis (2011), Park and Stearns (2009), Tong (2011), Aiken et al. (2010), and Lin (2014) found quality of care increased in at least one dimension, whereas Evans and Kim (2006), Matsudaira (2014), and Cook et al. (2012) found no change in quality of care.

for problems including omitted variable bias and endogeneity of staffing levels (Evans and Kim, 2006). To our knowledge, this is the first study to investigate the effects of exogenously *decreased* staffing levels on time spent with patients and number of patients seen.

Finally, whereas prior work often examines *permanent* regulation-induced changes in staffing levels, we study the effects of temporary staffing decreases. Understanding the effects of permanent changes are of course important for policy and budget considerations (e.g., previous studies have linked “lower than target” nurse staffing levels and higher patient turnover with higher mortality rates (Needleman et al., 2011; Schilling et al., 2010)); however, the effects of permanent changes may be quite different than temporary changes, in which case, existing studies of permanent capacity changes may be uninformative to settings with more temporary effects. Indeed, our results indicate that effects of staff reductions were strongest on days with the largest patient volume, which suggests that estimates derived from a permanent capacity change may mask larger effects on critical days.

2 | DATA AND INSTITUTIONAL DETAILS

Data were provided by the KCHD in Tennessee and are composed of time records for each patient visit in five public health clinics over 16 months and two flu seasons. A clinic visit is observed in our data when the visit is initiated within the electronic patient record, which means that a patient must officially check in; the extent where patients enter the clinic and leave without checking in is unobserved in our data. Each individual record was documented by clinic staff in an electronic patient record, where we observe the date of the visit, the initiation of the visit (scheduled or walk-in), the location (clinic) of the visit, patient age, and the unique nurse ID for each visit. For each visit, we also observed detailed time stamps for different stages of the visit, including (a) check-in time (time between signing in and being taken to a treatment room), (b) ready nurse time (time spent in the treatment room awaiting a nurse), (c) nurse time (time spent from the start of the consultation to the conclusion of treatment), and (d) ready check-out time (time between the conclusion of treatment and when the patient leaves).

KCHD provides many services, including health education, awareness, vaccinations, and clinical services. Clinical services, the focus of this paper, are provided almost exclusively by registered nurses rather than physicians. For a public health organization serving a population of approximately 600,000, KCHD is fairly representative in terms of the scale of operations and set of clinical services offered (National Association of County & City Health Officials, 2016). In the median month, KCHD employs 40 providers compared with an average of 35 for public health organizations serving populations of 500,000–999,999. KCHD offers adult and child immunizations (as do 90% of all local public health departments), women, infants, and children programs (66%), tuberculosis screening and treatment (79%), sexually transmitted disease (STD) testing (65%), screening for human immunodeficiency virus /acquired immunodeficiency syndrome screening (62%), and family planning (53%). KCHD also offers some services that are less common overall but more typical for larger urban public health organizations (e.g., treatment for human immunodeficiency virus /acquired immunodeficiency syndrome and other STD's, oral health, and prenatal care to certain populations).

KCHD also administers FluMist vaccines to public school children in Knox County, typically between October and December. On a calendar day when FluMist vaccines are administered, more than one school is usually scheduled to receive vaccines, and more than one clinic is usually selected to administer the vaccines (on average, three clinics are selected to administer FluMist vaccines on a FluMist day). If a clinic is selected, two nurses are typically pulled from the selected clinic to administer FluMist in schools, thereby reducing capacity in those clinics during that time.

On a FluMist day, nurses on FluMist duty are away for the morning and return to work in the clinics in the afternoon. The average clinic has around six staffed nurses on any given day, such that the loss of two nurses in the morning is equivalent to a 17% reduction in clinic capacity. Note that the clinics are almost entirely nurse run with fixed hours each day. As such, there is no opportunity for nurses to work overtime or otherwise extend clinic hours on FluMist days. Nurses also share administrative and patient care duties in the clinic, and nurses are not restricted to work in just one clinic—about 35% of nurses work in two or three clinics over our panel.

In total, our data consist of 37,748 visits to five public health clinics over 303 business days from October 2014 to January 2016. FluMist was administered on 25 days in our data (8.3% of all business days) during which there were 2,713 total visits (7.2% of all observed visits). Summary statistics are provided in Table 1, where we present statistics for all visits in the first column and statistics by FluMist/Non-FluMist days in columns 2 and 3, respectively.[6] Statistics on individual components

[6]We measure FluMist at the clinic-day level. Non-FluMist days therefore include visits to nonselected clinics on days for which some other clinic(s) may have been selected for FluMist administration.

TABLE 1 Summary statistics for clinic visits (full sample)

Components of visit length	Overall	FluMist	Non-FluMist	t stat
Total visit time	71.88	66.35	72.25	4.805
	(49.80)	(43.22)	(50.19)	[<0.001]
Check-in time	11.34	10.23	11.41	4.068
	(14.38)	(10.03)	(14.62)	[<0.001]
Ready nurse time	10.47	9.76	10.53	2.714
	(17.94)	(13.54)	(18.24)	[0.007]
Nurse time	30.40	30.09	30.42	0.642
	(28.42)	(24.71)	(28.68)	[0.521]
Ready check-out time	14.44	14.35	14.45	0.162
	(29.09)	(28.90)	(29.11)	[0.872]
Visit/patient characteristics (%)				
Age range (years)				
0-10	18.37	20.32	18.22	
11-20	20.91	17.18	21.20	
21-30	26.44	26.40	26.44	
31-40	15.66	15.86	15.65	
41-50	7.97	7.89	7.98	
51-60	5.43	6.23	5.37	
61-70	3.39	3.87	3.35	
71-80	1.42	1.55	1.41	
81+	0.40	0.70	0.38	
Reason for visit				
Immunization	32.96	37.82	32.58	
STD screen/treat	16.72	22.12	16.31	
Depo-Provera	5.88	4.83	6.07	
Back-to-school immunization	5.67	n/a	5.96	
Travel immunization	4.91	4.57	4.94	
Day of visit				
Monday	21.41	22.74	21.31	
Tuesday	21.90	18.43	22.16	
Wednesday	18.53	12.75	18.98	
Thursday	19.28	22.67	19.02	
Friday	18.88	23.41	18.53	
Clinic visited				
CDC	24.12	32.10	23.51	
KCTE	10.06	7.96	10.22	
KCWE	18.27	16.48	18.41	
KCWH	22.03	16.00	22.50	
TIC	25.51	27.46	25.36	

Note. Standard deviations in parenthesis. Summary statistics based on 37,748 total visits and 2,713 FluMist observations. Limited to the five most common reported reasons. Abbreviations: n/a, not applicable; STD, sexually transmitted disease; CDC, Main Clinic; KCTE, Knox County Teague Clinic; KCWE, Knox County West; KCWH, Knox County Women's Health; TIC, Travel Immunization Clininc.

of each visit are presented in panel 1 of Table 1, and statistics on general patient/visit characteristics in panel 2. We also provide t statistics and p values of a test of differences in FluMist versus non-FluMist days for the variables in panel 1.[7]

From panel 1 of Table 1, clinic visits last around 72 min on average but only 66 min on FluMist days. Time spent with nurses is the most time-consuming aspect of a visit, with average nurse times of around 30 min. Nurse time and ready

[7]We observe FluMist days in 2014 from the KCHD schedules, but we do not observe the specific nurses or clinics affected in that year. Because our analysis is at the visit and provider levels, we drop the 2014 FluMist days from the analysis to ensure that our treatment indicator is accurately measured. We find similar results when dropping 2014 entirely.

check-out times were comparable between FluMist and non-FluMist days, whereas check-in times and ready nurse times were shorter.[8]

Panel 2 of Table 1 also presents the percentage of patients in different age groups as well as the percentage of different reasons for the visit, the day of the visit, and the clinic. A Pearson's χ^2 test applied to the different groups of variables in panel 2 reveals statistically significant differences between FluMist and non-FluMist days (p<.01 in all cases); however, as evident by the table, the magnitude of these differences is relatively small. Moreover, some differences between FluMist and non-FluMist days are expected as part of a potential response to capacity reductions. For example, if scheduled patients are prioritized over walk-in patients (a hypothesis we explore in our empirical analysis), then we should expect a relative reduction in the reasons for visits that are more common among walk-in patients (such as STD screening/treatment). Because nurses are removed from clinics to administer FluMist in schools, it is also unsurprising to see a reduction in visits from children on FluMist days and a corresponding relative increase in visits from older patients.

Importantly, panel 2 of Table 1 also shows that FluMist days are not isolated to specific days of the week or a subset of clinics. FluMist days therefore do not appear to be heavily periodic, which offers some evidence that clinics could not fully predict when they would be selected for FluMist administration. The data further suggest that FluMist days are not periodic within clinic. For example, every clinic experienced at least one FluMist day on each day of the week over our panel.

2.1 | FluMist administration

Two key features of the administration of FluMist vaccinations are useful in establishing FluMist as an exogenous source of temporary reductions in clinic capacity. First, nurses pulled from the clinic to administer FluMist in schools were not replaced by nurses from other clinics or temporary staff. Second, all scheduling decisions of FluMist days were made by the KCHD central office without consulting the clinic. Clinics were notified of being selected for FluMist administration just 1 or 2 days prior, and when a clinic was selected, the nurses who remained in the clinic were instructed to maintain their scheduling patterns and staffing levels. In other words, clinics that had registered nurses out at schools were told to treat the day like a normal day—but with fewer clinicians. There were no compensating actions taken in any way by the central office. In fact, we were asked to examine the visit-level data from KCHD because the consequences of these short-staffing days with respect to quality of care or production of public health were unknown. The central office wanted to know what (if any) compensating actions should be taken.

Although the institutional details of FluMist administration suggest that staffing reductions were indeed exogenous, it is, of course, possible that clinics anticipated FluMist days and adjusted accordingly. We therefore consider a series of event studies examining daily clinic patterns for the days immediately surrounding a FluMist day. By design, our event studies are not regression based and instead reflect basic descriptive statistics over time. The purpose of these event studies is twofold: (a) illustrate the reduction in capacity from FluMist administration and (b) examine whether clinics anticipated the staffing reductions and adjusted their behaviors leading up to FluMist days. Figure 1 summarizes the results, presenting statistics for clinic visits (total, scheduled, and walk-in) and total nurse visit time for each day within 2 business days of a FluMist day.

Figure 1a depicts total daily visit volume at the clinic level for ±2 business days surrounding a FluMist Day. For each of the 2 days before and after a FluMist day, the clinic sees an average of 25.8 patients. On FluMist days, the clinic sees an average of 21.8 patients, representing more than a 15% decrease in total patient volume. Figure 1b,c plots total daily visit volume for scheduled visits and walk-in visits, respectively. There is some descriptive evidence that providers in FluMist clinics may anticipate these FluMist days by scheduling (on average) one fewer appointment on FluMist days than neighboring days; however, clinics selected for FluMist see 3.5 fewer walk-in patients on a FluMist day than neighboring days. The fact that the reduction in total visits is primarily driven by decreased walk-in volume suggests that clinics indeed experience a binding reduction in capacity on (at least some) FluMist days. Moreover, if the clinic could fully anticipate FluMist days in advance, then there should be a proportional reduction in scheduled visits, but instead, we see relatively small reductions in scheduled visits. This empirical finding is therefore consistent with the clinic having relatively little time to adjust their scheduling patterns in advance of a FluMist day.

[8]A referee suggested that we take into account seasonality for a more direct comparison of visit component lengths between FluMist and non-FluMist days. Summary statistics from the sample restricted to flu season (months where there was at least one FluMist day for at least one clinic) can be found in Table S1. Results are qualitatively and quantitatively similar.

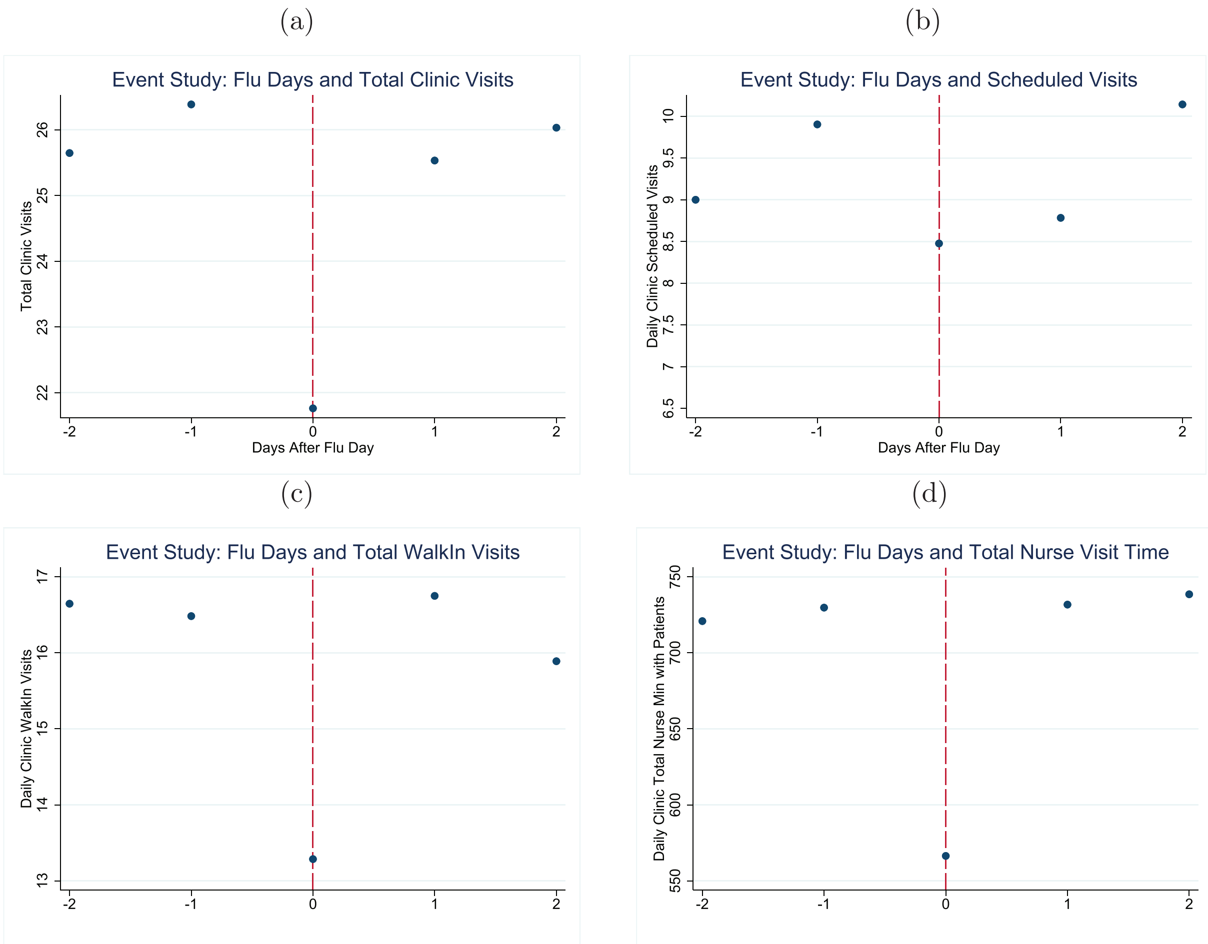

FIGURE 1 Event study: Daily clinic total activity around FluMist days. Each figure represents daily clinic totals of a given visit type or minutes of activity for all days within ±2 business days from a day when nurses from that clinic went to administer FluMist [Colour figure can be viewed at wileyonlinelibrary.com]

We also examine how FluMist days differ from adjacent days in terms of total time patients spend with nurses. Figure 1d shows that on FluMist days, patients collectively spend a total of 570 min with nurses throughout the day compared with 725 min with nurses on adjacent days. Consistent with the overall reduction in total visits, this abrupt decrease in total nurse–patient minutes on FluMist days is reflective of a reduction in clinic capacity.

In summary, these figures provide descriptive evidence that FluMist days reduce total clinic capacity. To the extent that providers anticipate the effects of FluDays, they are only able to slightly adjust the demands placed on the clinic via small reductions in scheduled visits. Walk-in visits account for about two thirds of total visit volume, whereas three fourths of the drop in patients seen on FluMist days is from decreases in walk-in patients. Nonetheless, these preliminary takeaways are purely descriptive and based on simple clinic-day means. Next, we employ regression methods to examine how visits are affected by reduced clinic capacity and tighter time constraints, controlling for patient, clinic, visit, and nurse characteristics.

3 | INITIAL EVIDENCE ON THE EFFECTS OF CAPACITY REDUCTIONS

In this section, we first provide evidence on the average effect of FluMist days on various activities at both the nurse and visit level. This analysis provides more rigorous evidence that FluMist administration does indeed reduce clinic activity among those nurses directly impacted. We then show the effects of FluMist days on nurses that remain in the clinic (i.e., nurses working under reduced capacity but who were not administering vaccines).

TABLE 2 Results for Provider-level analysis

All nurses, $N = 8,239$	**Log nurse minutes**	**Log total visits**	**Log walk-in visits**	**Log scheduled visits**	**Log walk-in share**
FluMist day	.078*	.077***	.034	.081*	−.063*
	(0.042)	(0.029)	(0.035)	(0.046)	(0.035)
FluMist nurse	−.465***	−.463***	−.363***	−0.347***	0.111**
	(0.062)	(0.050)	(0.068)	(0.066)	(0.047)
FluMist + FluNurse	−.387***	−.386***	−.329***	−.266***	.048*
	(0.060)	(0.044)	(0.055)	(0.062)	(0.027)
Non-FluMist nurses, $N = 5,143$					
FluMist day	0.068	.080**	0.014	0.091	−.095**
	(0.052)	(0.033)	(0.040)	(0.056)	(0.038)

Note. Results from a "within estimator" with nurse-level fixed effects. Different outcomes are presented along the columns, and all outcomes reflect daily totals for a given nurse (e.g., log nurse minutes is the log of the total minutes spent with patients by a nurse on a given day). Panel 1 presents results for the full sample, and panel 2 presents results when restricting to nurses that were in the clinic for the entire day. Additional covariates excluded from the table include indicator variables for the clinic, day of the week, month of the year, and year. Standard errors in parenthesis clustered at the nurse level. $^*p < .10$. $^{**}p < .05$. $^{***}p < .01$.

3.1 | Nurse-level analysis

For the nurse-level analysis, we construct a panel of nurse/days and estimate the following fixed effects model:

$$y_{it} = \alpha + \beta_n FluNurse + \beta_d FluDay + \mu_i + \nu_c + \eta_d + \gamma_m + \delta_y + \varepsilon_{it}. \tag{1}$$

We denote daily total output for a nurse i at time t by y_{it}, measured as log numbers of scheduled visits, log number and share of walk-ins, and log time spent with patients. The variable *FluNurse* is an indicator set to one for a particular nurse if that nurse was on FluMist duty that day. Similarly, $FluDay$ is an indicator taking a value of one if any nurse from that clinic administered FluMist that day. Therefore, if nurse i from clinic c is on FluMist duty on a given day, both the FluNurse and FluDay indicators are set to 1. Meanwhile, if another nurse ($\neg i \in c$) from i's clinic is on FluMist duty, $FluDay = 1$ and $FluNurse = 0$. From the nurse's perspective, $FluDay = 1$ implies an expected increase in the number of patients seen by each nurse who remains in the clinic on a FluMist day. We estimate this model using a fixed effects "within estimator" at the nurse level, also including fixed effects for each clinic (ν_c), day of week (η_d), month (γ_m), and year (δ_y).[9] Standard errors are clustered at the nurse level.

Table 2 presents our nurse-level estimates of the average effects of FluMist-induced staff reductions on nurses' daily production. Panel 1 presents the estimated effect from being called out of the clinic to administer FluMist on a given day. Specifically, "FluMist day" denotes the estimate for β_d in Equation (1), and "FluMist nurse" denotes the estimate for β_n. To calculate the composite effect for nurses who administer FluMist, we calculate ($\beta_d + \beta_n$). These composite estimates and their standard errors are reported in the third row. These estimates are based on the full sample. Panel 2 presents estimates of the effect of a FluMist day among nurses who were not removed from the clinic on that day. Because there are no FluMist nurses in this analysis, the regression underlying panel 2 excludes the "FluNurse" indicator.[10]

The estimates in Table 2 offer three important findings. First, the estimates for "FluMist nurse" in panel 1 reflect output changes specifically for nurses who are removed from the clinic to administer vaccines. Since FluMist nurses typically spend approximately half of their day out of the clinic, estimates indicating that total time spent with patients and total number patients seen decreases by 39% for FluMist nurses are in-line with a priori expectations. Second, being tapped for FluMist increases the nurse's share of walk-in patients relative to scheduled patients. This is consistent with a backlog of walk-in patients on FluMist days. If scheduled patients are prioritized over walk-in patients, then when FluMist nurses return to the clinic, they will likely face a longer queue of walk-in patients. Third, when focusing on nurses that remained in the clinic for the entire day in panel 2, we find a small and statistically significant increase in total visits and a significant

[9]Among other things, the inclusion of nurse fixed effects captures any potential selection at the clinic level regarding which nurses are ultimately pulled from the clinic to administer vaccines. It is important to account for such selection because clinics are allowed input into which nurses are removed to administer FluMist. As discussed in the supporting information, clinics appear to select the relatively more productive nurses to administer FluMist vaccines in schools; however, there is also evidence that the differences between FluMist and non-FluMist nurses are time-invariant. Also, because 35% of nurses are observed working in more than one clinic during our sample, both the clinic-level and nurse-level fixed effects are important.

[10]Results are qualitatively unchanged if we focus specifically on flu season months. The estimates from this restriction are excluded for brevity but available upon request.

TABLE 3 Results for visit-level analysis

	Log minutes					
All visits, $N = 37,748$	**Total**	**Check-in**	**Waiting room**	**Nurse**	**Check-out**	**Walk-in**
FluMist day	−.067***	−.020	−.046	−.017	−.062*	−.102***
	(0.019)	(0.057)	(0.042)	(0.020)	(0.037)	(0.031)
FluMist nurse	0.017	−0.011	0.033	−0.051	−.106*	0.023
	(0.034)	(0.081)	(0.066)	(0.036)	(0.054)	(0.033)
FluMist + FluNurse	−0.049	−0.031	−0.013	−.068**	−.168***	−.079***
	(0.033)	(0.055)	(0.058)	(0.026)	(0.046)	(0.029)
Visits to non-FluMist nurses, $N = 37,120$						
FluMist day	−.067***	−0.020	−0.047	−0.017	−.063*	−.101***
	(0.019)	(0.057)	(0.042)	(0.020)	(0.037)	(0.031)

Note. Results for the estimate on the FluDay coefficient based on ordinary least squares regressions. Panel 1 reflects estimates from the full sample of clinic visits, whereas panel 2 presents results limited to non-FluMist nurses. Different outcomes are presented along the columns. Additional covariates excluded from the table include indicator variables for the clinic, nurse, reason for visit, patient age range, week day, month, and year. Standard errors in parenthesis are clustered at the nurse level. *$p < .10$. **$p < .05$. ***$p < .01$

decrease (at the 5% level) in the share of walk-in visits, with the latter result again suggestive of prioritizing scheduled visits over walk-ins.

These results are consistent with prioritizing a certain amount of time with each patient relative to seeing as many patients as possible. For example, the average clinic has six nurses staffed in a given day. Typically, two nurses are removed for the morning to administer FluMist, leaving four nurses remaining in the clinic. The estimates for "FluMist day" in panel 2 of Table 2 suggest that the remaining nurses collectively increase patient time that day by about 0.27 average-person days,[11] see an additional 32 percent of a person–day's equivalent of patients, and an additional 36 percent of a person–day equivalent scheduled patients. Given that on a FluMist day, the clinic loses nearly a full person–day of capacity (and activity), the magnitudes of these increases do not compensate for the reduction from nurses removed from the clinic. The sign of the coefficients on the FluDay indicator are therefore consistent with some form of compensating behavior, but the estimates are often statistically insignificant, and the magnitudes are insufficient to fully compensate for the reductions in output from nurses on FluMist duty.

3.2 | Visit-level analysis

In order to examine the effects of FluMist at the patient level, we also estimate the effects of capacity reductions on the average (per patient) time spent in each stage of a visit. We adopt a similar specification as in Equation (1), with two differences: (a) We include a larger set of fixed effects, including patient age (in 10-year bands), clinic, provider, reason for visit, day of the week, month, and year, and (b) our visit-level outcome measures include total visit time, check-in minutes, waiting room time, nurse minutes, and check-out minutes (all in logs), as well as an indicator for whether the visit is a walk-in. Because we do not have sufficient repeat observations per patient, we estimate the visit-level model using ordinary least squares. We specify the visit-level model as

$$y_{vt} = \alpha + \beta_n FluNurse + \beta_d FluDay + \mu_i + \nu_c + \eta_d + \gamma_m + \delta_y + \rho_v + a_v + \varepsilon_{vt}, \tag{2}$$

where arguments are defined as in Equation (1) but with fixed effects for the visit reason (ρ_v) and patient age range (a_v).

Table 3 presents the estimated effects of FluMist on total visit time, time spent in different components of the visit, and the probability a visit is a walk-in. These results are again consistent with prioritization of time with each patient over clearing the waiting room. Specifically, although we find FluDays to reduce time spent in the waiting room, these estimates are imprecisely estimated. We find a 6–10% reduction in the length of time of the check-out process, as well as a small and statistically insignificant reduction of 2–5% in the length of time with a nurse; however, the effect on time with nurses appears to be driven by the nurses who are administering FluMist. Also, note that on FluMist days, visits are more than 10% less likely to be walk-ins, implying that scheduled patients get priority when time constraints bind.

[11] A 6.8% increase (presumably of a normal day's activity) ×4 ≈ 0.27 additional person days.

It is possible that on FluMist days, affected clinics refer patients to other clinics so as to offset the reduction in walk-in visits. We investigate this with a simple adjustment to Equation (2), where we replace the "FluDay" and "FluNurse" indicators with two new variables: (a) a dummy for whether *any* clinic was selected for FluMist administration on that day and (b) a dummy for whether the selected clinic is a different clinic from that which the patient is currently visiting. The coefficient on this latter variable can offer some evidence as to whether clinics attempt to offset the reduction in walk-in visits by referring to other clinics. Re-estimating Equation (2) with these adjustments, we estimate that walk-in visits to non-FluMist clinics (but on days where another clinic was selected for FluMist administration) increase by about 3% (p=0.02). Because, on average, three clinics are selected for FluMist administration on any given FluMist day, the magnitude of this estimate is insufficient to fully offset the reduction in walk-in patients but is nonetheless suggestive of some offsetting behaviors among clinics selected for FluMist administration. Note that this offsetting behavior need not be driven specifically by the clinic and could instead reflect the choice of walk-in patients to voluntarily leave one clinic (without formally initiating the visit) and visit an alternative clinic on the same day.

Overall, patients' total visit time on a FluMist day decreased by nearly 7%, but this reduction is driven by streamlining administrative areas of the process, in particular check-out times, with no significant reduction in nurse minutes among non-FluMist nurses. Given that a FluDay represents, on average, a 17% reduction in production capability, the compensations we see are far from complete. However, the decreased check-out time does represent an improvement in operational efficiency. KCHD relayed that the check-out process is mostly financial. In cases where patients do have private insurance (e.g., for travel immunizations), the clinic may seek payment. In cases where the individual has Medicaid or the visit is covered with public funds, the treatment/tests still need to be documented for reimbursement when appropriate. Although these results indicate that providers found ways to streamline the process, the evidence from the decrease in walk-ins implies that any increases in efficiency are not sufficient to completely offset the effects of reduced capacity.

Although we contend that the administration of the FluMist vaccine was exogenous to any given clinic, it remains possible that other time-varying factors may be driving the selection of FluMist days from the KCHD central office. To examine this potential issue, we conducted placebo tests to verify that our results are driven by FluMist adminstration. Details of these tests are presented in supporting information, where we present evidence that our results do not appear to be driven simply by random variation in visits over time but are instead reflective of some true underlying changes in nurse behaviors on FluMist days.

4 | PROVIDER RESPONSES TO DECREASED CAPACITY

Our initial results in Section 3 showed relatively little evidence of sufficient compensating behavior by non-FluMist nurses. This result could be driven by at least two factors: (a) there could be sufficient excess capacity in the clinic such that clinics can absorb a temporary staff reduction without affecting patient care or (b) providers may prioritize time with patients over the number of patients seen.[12] We attempt to distinguish between these two explanations throughout this section.[13] The goal is to isolate situations in which capacity constraints are more likely binding and examine the effect of a reduction in capacity on such days. Although we do not directly observe when constraints are binding, we can partially identify such instances by exploiting variation in daily total visits to the clinic in conjunction with exogenous short staffing.

We implement two additional models. First, at the provider level, we estimate an unconditional quantile regression with provider fixed effects to examine how the effect of FluMist on total number of patients seen varies over the distribution of patient volume (Firpo et al., 2009; Borgen, 2016). In this case, our fixed effects specification intuitively controls for time-invariant work characteristics of a given provider, and our quantile regressions investigate the different effects of FluMist days as patient volume increases. We also include as covariates a set of dummy variables for day of the week, year, month, and clinic, consistent with Equation (1). Estimates and 95% confidence intervals are presented in Figure 2.

For nurses removed from the clinic (the dashed line and respective confidence interval), we see no reduction in total patient volume for very low-volume days. This is consistent with the notion that on sufficiently low-demand days, a given provider may have some downtime. On these low-demand days, being gone from the clinic for half the day does not

[12]We refer to "providers" (instead specifically to nurses or clinics) due to the ambiguity in assigning a decision maker for patient visits and visit times. For example, nurses may be constrained in their individual responses due to institutional control at the clinic level or simply due to technology constraints imposed at the clinic level.
[13]One key barrier is we do not observe people leaving the clinic and instead only observe patients who ultimately received treatment at the clinic; however, we do observe whether the visit was previously scheduled or was an unscheduled "walk-in" visit.

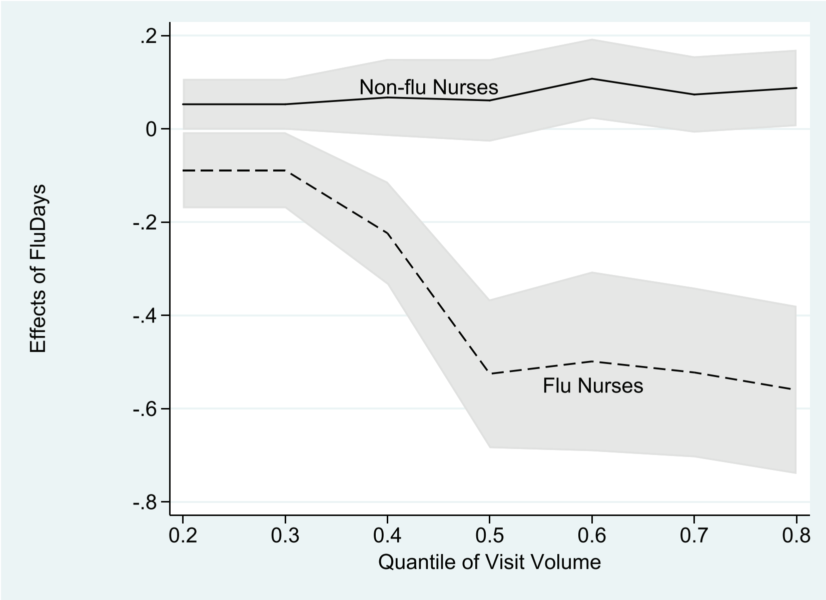

FIGURE 2 Quantile regression estimates on log total visits by total visit volume

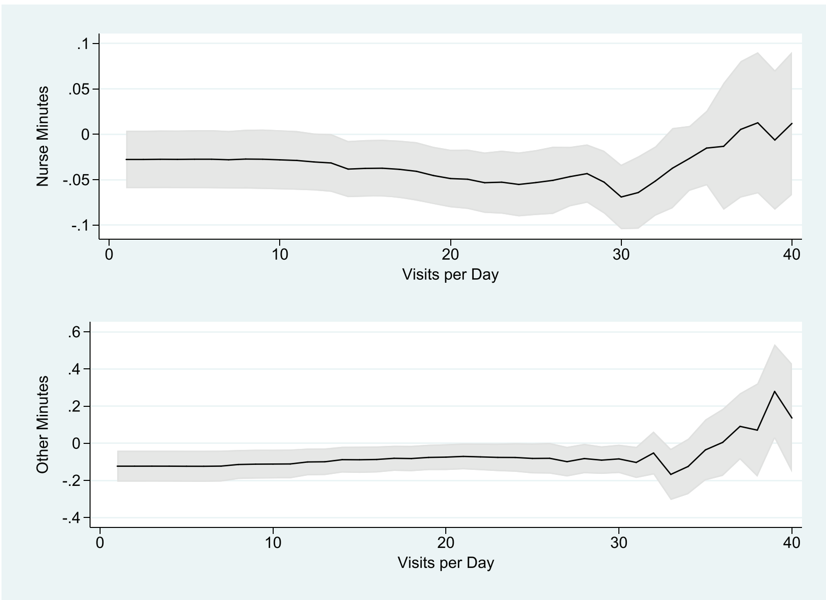

FIGURE 3 Effects of FluMist on length of visit by visit volume [Colour figure can be viewed at wileyonlinelibrary.com]

substantially affect total visit volume, and administering FluMist vaccines essentially absorbs some of that downtime. As total patient volume increases, being absent from the clinic for half the day has a larger negative effect on the number of patients seen. In other words, on days that are busier than the median day, providers who are removed from the clinic see fewer than half the patients they otherwise would have. Of perhaps greater importance, among the nurses remaining in the clinic during FluMist days, we see no significant change in patient volume even on high-volume days. Although the magnitude of our estimates for the effect of FluMist on daily patient volume is larger on high-volume days, the estimated effects are not sufficient to offset the lost capacity from FluMist nurses, and these estimates are generally not statistically significant for the nurses remaining in the clinic. Collectively, these results show that non-FluMist nurses do not fully compensate in the number of patients seen when staff is reduced on high-volume days. This suggests that providers prioritize time with individual patients over seeing all patients.

Second, we consider visit-level outcomes, modeling how FluMist yields differential effects on time with patients and other visit times when restricting the sample to increasingly high-volume days. Similar to the provider-level quantile regressions, this analysis focuses on days when capacity constraints are more likely binding and offers additional insight on the trade-off between patients treated versus time with each patient. The differential effects of FluMist days by patient volume are presented graphically in Figure 3. The top panel presents the estimated effect and 95% confidence interval of FluMist on log number of minutes the nurse spends with each patient, and the bottom panel presents results for log minutes of all other visit components. Each line is constructed from a separate visit-level regression using ordinary least squares, analogous to that of Equation (2), but where the estimation sample is restricted to days with at least ν visits that day.

These results are consistent with the regression analysis in Table 3 and further suggest that providers prioritize spending time with patients when capacity constraints bind. Specifically, as the number of visits per day increases, we observe a small effect from a staffing reduction on nurse minutes, but a substantial effect on other minutes (over 10% reduction). This effect on other minutes persists up to over 30 visits per day, or the 75th percentile of visit volume. Beginning at 15 visits per day, providers' time constraints begin to bind, and increased patients-per-provider from FluMist days reduces average time spent with patients. For days with total visit volume between approximately 20 and 30 visits, nurses spend around 5% less time with each patient. Even where the estimated effect is largest ($\nu = 30$), providers only reduce the time spent with patients by approximately 7% (just over 2 min), and nurses do not further reduce time with patients on days where they are already sufficiently constrained ($\nu > 35$).

5 | DISCUSSION

In this paper, we exploit an exogenous source of variation in the capacity of public health clinics: temporary staff reductions induced by FluMist days. Our results indicate that capacity reductions influence clinic behaviors along two margins: (a) on the extensive margin, providers see fewer patients and prioritize scheduled visits over walk-ins and (b) on the intensive margin, providers first work to reduce administrative aspects of the visit but may ultimately reduce time with patients on high-volume days. Overall, these results indicate that providers value spending sufficient time with patients over seeing as many patients as possible.

In several aspects, we emphasize that these results represent a lower bound on the effect of capacity reductions, particularly when generalized to provision of other services. First, the service provided in this setting is fairly transactional (e.g., immunizations, disease screening, pregnancy tests, etc.). Patients are referred to other providers if they have more nuanced or specialized needs. Because the nature of these visits is relatively simple by health care standards, there is less discussion/education to truncate than in a family physician or hospital setting. Our results stand in contrast to Sharma et al. (2008), who examine provider behavior in emergency rooms. Although emergency rooms are less able to delay care than public health clinics, they may be better able to adjust to increased demand by hastening discharges. Second, our estimates only reflect the short-run effects from temporary staff reductions. The nature of our exogenous variation does not capture longer term compounding effects on the quality of care, such as provider fatigue from increased workload, absenteeism, or intention to quit.

Our results may offer some guidance on the potential effects of staffing reductions in the provision of public services. Such reductions, even in the presence of some median day excess capacity, are not costless. We identify two responses to capacity reductions in particular. First, we find that providers maintain some minimum amount of time with customers such that remaining service providers do not fully compensate for the reduced capacity. Also, providers prioritize scheduled visits over walk-in visits, meaning some customers go unseen. Second, whereas the reduction in time with customers is relatively small, the magnitude could be meaningful in certain settings.

Given our specific setting of public health clinics, each of these responses could carry important costs. For example, our data show that, relative to scheduled visits, walk-in patients are much more likely to visit the clinic for STD screening, STD treatment, or tuberculosis screening. Although our data cannot quantify the effects of any such missed screenings or treatments, there is reason to suspect that prioritizing scheduled patients over walk-in patients may generate substantial negative externalities. In addition, whereas a 5–7% decrease in time with nurses may seem small, length of patients' time spent with providers has been shown to be a key determinant of "quality of care" (Linzer et al., 2000; Whittington and McLaughlin, 2000; Wilson and Kaplan, 2000; Landau et al., 2007; Tai-Seale et al., 2007; Chen et al., 2009; Anand et al., 2011; Munyisia et al., 2011; McCloskey et al., 2014). Findings from Yarnall et al. (2003) suggest that a 5% reduction in time with patients would be sufficient to have otherwise counseled patients on STD prevention or contraception. Quantifying these responses in other contexts is a key piece of information in understanding the full effects of local, state, and federal budget decisions.

Although this study makes several contributions, there are some limitations that offer potential for future work. Most notably, these data do not have direct measures for "quality of care." Such a measure would enable researchers to trace out the effects of providers' time allocation and make inferences about welfare implications. Although useful, these data are not sufficient to capture the full welfare effects of short staffing on FluMist days. Second, we are unable to observe patients' decisions to not join the queue at health clinics. Patient responses on that margin also have important welfare implications for expanding/contracting clinic capacity. Finally, most of the patients seen in this context have relatively simple needs. In other health care contexts, changes in the way patients are triaged by severity of need would be an important response to capacity constraints. However, that analysis is beyond the scope of our data. All of these limitations of this paper provide areas for future work on the effects of changes in capacity for the provision of public health services.

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SUPPORTING INFORMATION

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How to cite this article: Harris MC, Liu Y, McCarthy I. Capacity constraints and time allocation in public health clinics. *Health Economics*. 2020;29:324–336. https://doi.org/10.1002/hec.3984