Provider Preferences and Time Allocation in a Clinic Setting*

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Abstract

We adapt models from the queuing literature to formulate a provider's optimization problem as a function of time spent with each patient and ensuring all patients are seen. We then examine the trade-off between patients seen and time spent with patients by exploiting exogenous temporary reductions in staff levels of public health clinics wherein clinic staff are temporarily removed to administer Flu vaccines in local schools. We find that staff reductions influence clinic behaviors along two margins: 1) on the extensive margin, clinics see fewer patients and prioritize scheduled visits over walk-ins; and 2) on the intensive margin, clinics first work to minimize administrative aspects of the visit but may ultimately reduce time with patients on high volume days. In the context of our queuing model, the results suggest that clinicians in a public health setting prioritize time with patients over number of patients seen.

Keywords: health care production, nurse staffing, quality of care

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1 Introduction

Demand for health care services is inherently stochastic, and in systems with stochastic demand, firms by definition will carry excess capacity on some days. Reducing the excess capacity on a median day will then increase the number of days when demand exceeds clinic capacity and where providers, facing a binding time constraint, must choose between spending less time on average with each patient or having some patients go untreated. Patients going unseen has obvious externalities, particularly if they are in the clinic for communicable illness; however, a reduction in time spent with each patient may also negatively affect the quality of care.[1] Ultimately, the optimal amount of median day 'excess capacity' in health care staffing hinges on how clinicians trade off time with patients and the number of patients seen. For example, if providers are reluctant to reduce the time spent with patients, and leaving patients untreated has a high social cost, then carrying excess capacity can have significant benefits in a stochastic demand environment (Hughes and McGuire, 2003).

In this paper, we examine the relationship between capacity and provider behaviors by estimating the effects of exogenous temporary reductions in clinician staffing on the number and length of visits to public health clinics. We incorporate insights from queueing models such as DeVany (1976) and Anand et al. (2011) to construct an expository theoretical model of providers' responses to decreased clinic capacity. For our purposes, the queuing model posits a provider's utility as a function of the number of patients seen and the amount of time spent with each patient, relative to some threshold 'sufficient' visit length. We derive comparative statics showing that the optimal amount of time that providers spend with patients is a function of the relative importance of visit length versus number of patients seen and the stochastic arrival rate of patients, among other parameters.

Our empirical analysis then aims to quantify a provider's trade-off between patients seen versus time with each patient, where an exogenous reduction in clinic staff serves as a shock to a given provider's arrival rate. Our data were provided by the Knox County Health Department (KCHD) in Tennessee and are comprised of time records for each patient visit in six public health clinics over

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

eighteen months. The exogenous variation in staffing (capacity) comes from the administration of FluMist vaccines to public school students, which we refer to as "FluMist days."

Our initial analysis finds that, when capacity is reduced, there were fewer patients seen and patients' total visit time significantly decreased by at least 6% (or about 5 minutes). This primarily occurred through a reduction in check-in and check-out times, with a small (and insignificant) reduction in time with providers. Exogenous staff reductions also lead nurses to prioritize scheduled visits over walk-in patients, which suggests a reduction in access to care among walk-in patients. In the context of our queuing model, our results suggest that nurses prioritize time with patients over number of patients seen. Additional analysis allowing for differential effects along the support of daily visit volumes shows that these results are reflective of actual provider preferences rather than any excess capacity built into each clinic. While we interpret the inelasticity of time spent with patients as indicative of provider preferences, we acknowledge that our findings may be partially driven by the structural constraints of the provider-patient interaction. In other words, providers may truly be unable, rather than unwilling, to shorten visit lengths to clear the queue. In either case, the empirical and policy implications of our results for reducing clinic capacity are the same.

Our study offers three distinct contributions to the literature. First, investigating staffing shortages in public health clinics is novel.[2] Most prior relevant work 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); however, over 20 million people in the United States 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 clearing the queue of patients relative to clinicians in emergency departments.

[2]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).

All else equal, exogenous staff reductions necessarily increase nurse workload. In a hospital setting, increased workload has been found to be correlated with an increase in mortality rates (Kuntz et al., 2015; Kc and Terwiesch, 2009), as well as an increase in nurses' intention to leave their jobs (Shields and Ward, 2001; Holmås, 2002) and absenteeism (Green et al., 2013). Theoretically, the link between nurse staffing and quality of care may derive from changes in time spent observing patients or in patient/family education (Mark et al., 2013). With inadequate staffing, these efforts could be compromised. Kalisch et al. (2009) also reported that the largest contribution to missed nursing care (errors of omission in providing care) was 'labor resources'. Thus, one would expect higher staffing levels to be related with better quality of care. That said, empirical evidence on the relationship between nurse staffing levels and quality of care remains mixed.[3]

Second, most prior work on exogenous staffing changes focuses on increases rather that reductions. There have been a growing number of studies that exploit regulation changes in required staffing/patient ratios as exogenous shocks to staffing levels and investigate the effects of the regulation change. Results are mixed. 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, while Evans and Kim (2006), Matsudaira (2014), and Cook et al. (2012) found no change in quality of care. In addition, previous studies that prompted such regulation change have been criticized for problems including omitted variable bias and endogeneity of staffing levels (Evans and Kim, 2006).[4] To our knowledge, this is the first study to investigate the effects of exogenously *decreased* staffing levels on time spent with patients.

Finally, whereas prior work has examined *permanent* regulation-induced changes in staffing levels in acute or long-term care settings, we study temporary exogenous decreases in a clinic setting. Previous studies have linked 'lower than target' nurse staffing levels and higher patient turnover with higher mortality rate on a daily basis (Needleman et al., 2011; Schilling et al., 2010). Our results indicate that effects of staff reductions were strongest on days with the largest patient volume, therefore suggesting differential effects of capacity constraints over short periods of time

[3]See Backhaus et al. (2014), Bostick et al. (2006), and Kane et al. (2007) for a more detailed review from the medical literature.

[4]Variation across hospitals that could not all be captured might contribute to quality of care, or patients admitted during the weekend tend to have more severe conditions than those admitted during the week.

such that estimates derived from a permanent capacity change may not inform as to effects of more temporary changes.

The rest of the paper proceeds as follows: Section 2 motivates our empirical analysis with a standard queuing model. Section 3 reviews our data. Sections 4 and 5 present our empirical analysis and results, respectively, and Section 6 concludes with a brief discussion.

2 Motivation

To motivate our empirical analysis, we incorporate elements from the literature on queuing models to formulate a hypothetical loss function for a provider in a public health setting (DeVany, 1976; Anand et al., 2011). Individuals (patients) are assumed to arrive following a Poisson process, with mean arrival rate, denoted λ, over a unit of time normalized to one. Service time is also assumed to be distributed exponentially, with a mean service time denoted by μ.

While in the queuing literature, the arrival rate and service time are used to formulate optimal pricing rules and equilibrium wait times, we rely on three implications of these models to illustrate the relevant aspects of the provider's optimization problem. First, since demand is stochastic, there is inherently excess capacity built into the system. Second, given an expected arrival rate of patients, reduced capacity at the clinic level can be modeled as a positive shock to the arrival rate of a given provider's queue. Distinct from a standard queuing model, the goal of the agents in our context is not to maximize profits but instead to ensure that a patient's needs for care are met.[5] Third, the queuing literature holds that if customers face wait times greater than some number, they will 'balk' or leave the queue. In our setting, we cannot observe the untreated patients, but we offer some evidence of patients leaving the queue by examining the share of scheduled versus walk-in visits on FluMist days.

Providers minimize a loss function in each period (day) with respect to the average time spent with each patient (μ). We assume the function is additively separable in two arguments: 1) disutility from spending less time on average with patients than some fixed ideal amount of time, denoted by τ; and 2) disutility from leaving patients unseen, whether that occurs because of balks or because they have to turn patients away. Assuming that the mean service time is less than one,

[5] Prices are pre-determined by KCHD, and most patients visiting the public health clinics face a nominal price of zero.

the number of unseen patients can be expressed as $(\lambda - 1/\mu)$, and the provider's loss function can be written as

$$U(\mu|\tau, \lambda) = f(\tau - \mu) + g(\lambda - \frac{1}{\mu}). \tag{1}$$

By definition, both $f(\cdot)$ and $g(\cdot)$ are assumed to be decreasing and convex. We impose a convenient functional form to derive a comparative static and evaluate how shocks to the provider's arrival rate, λ, affect the provider's optimal choice of time spent with patients. Assuming that $f(\cdot)$ and $g(\cdot)$ are exponential functions,

$$U(\mu|\tau, \lambda) = -e^{\alpha(\tau-\mu)} - e^{\beta(\lambda - \frac{1}{\mu})}, \tag{2}$$

where α captures the disutility from spending less time than ideal with patients, and β captures the disutility from leaving patients unseen. Taking the derivative with respect to μ yields the first order condition for the optimal amount of time spent with a patient, μ^*:

$$\alpha e^{\alpha(\tau-\mu)} - \frac{\beta}{\mu^2} e^{\beta(\lambda - \frac{1}{\mu})} = 0. \tag{3}$$

Note that when $\lambda \leq \frac{1}{\tau}$, it follows that $\mu^* = \tau$ since the provider's time constraint is not binding. In other words, when the arrival rate of patients is sufficiently low, providers can spend the time they need with each patient without incurring disutility from turning patients away or having patients balk from the queue. When $\lambda > \frac{1}{\tau}$, however, providers choose μ^* such that equation 3 holds.

We are centrally interested in how μ^* changes in response to an exogenous change in λ, which is captured in our empirical analysis by the reduction in clinic staffing to administer FluMist vaccines. Using the implicit function theorem, we derive the following comparative static:

$$\frac{d\mu^*}{d\lambda} = \frac{\frac{\beta^2}{\mu^2} e^{(\beta\lambda - \beta/\mu)}}{\frac{\beta(2\mu-\beta)}{\mu^4} e^{(\beta\lambda-\beta/\mu)} - \alpha^2 e^{(\alpha\tau - \alpha\mu)}}, \tag{4}$$

such that the effect of a change in the arrival rate on the optimal amount of time spent with each patient is a function of preference parameters α and β, the current value of $(\tau - \mu)$, and the initial value of the arrival rate, λ.

From equations 2 and 3, we can take two key insights. First, the convex disutility of shortening visits equates to diminishing marginal returns with respect to average visit length. Providers are more willing to sacrifice time with patients when their average visit time is close to ideal than when it is considerably smaller. Second, conditional on a fixed μ, greater arrival rates will result in larger adjustments to μ^*; however, this is somewhat misleading. As λ increases, we expect that providers will reduce μ^*, which will mute the effects of the increased arrival rate. In Figure 1, we therefore solve for μ^* for values of λ from 2 to 5 in 0.05 increments, and then present the first differences in μ^* as a numerical comparative static that takes into account changes in μ^* as λ increases. The observation that the numerical change in μ^* decreases as λ increases implies that increasing marginal disutility of $(\tau - \mu)$ dominates.

FIGURE 1 HERE

Figure 1 depicts how the comparative static of the optimal amount of time spent with patients changes under different conditions and different relative valuations of α and β. The figure offers two primary insights. First, we see $d\mu^*/d\lambda$ is negative and larger in magnitude when providers place more importance on seeing all patients relative to spending the "ideal" amount of time with each patient. Second, exactly how providers will change μ^* in response to a FluMist induced change in λ will depend on the circumstances of the clinic in that day - including the arrival rate of patients.

Our queue-based model therefore implies that the effect of an exogenous shock to the arrival rate in a provider's queue will have different effects, depending on the preferences of the provider and the volume of patients in the clinic that day. On relatively light days (i.e., when $\lambda < 1/\tau$), the clinic will have some amount of excess capacity. Since providers' time constraints are not binding, there is no need to adjust the time they spend with each patient. On days when the clinic is closer to capacity, we expect a positive shock to the arrival rate to result in some decrease in μ^*. Finally, when the clinic is seeing very high numbers of patients, a change in λ is likely to have very little effect on μ^* as providers may be unwilling to sacrifice additional time with each patient. We examine these predictions empirically in Sections 4 and 5.

3 Data

Data were provided by the Knox County Health Department (KCHD) in Tennessee and are comprised of time records for each patient visit in six public health clinics over 16 months and two flu seasons. 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, the age range of the patient, and the unique provider/nurse ID for each visit. We also observed detailed time stamps for different stages of each visit, including: 1) Check-in time, the time between signing in and being taken to a treatment room; 2) Ready Nurse time, the time spent in the treatment room awaiting a nurse; 3) Nurse time, the time spent from the start of the consultation to the conclusion of any treatment; and 4) Ready Check-Out time, the time between the conclusion of treatment and when the patient leaves.

KCHD provides many services to the community, including health education, awareness, vaccinations, and clinical services. Clinical services in the KCHD health clinics, the focus of this paper, are provided almost exclusively by registered nurses (RNs) rather than physicians. In addition, KCHD administers FluMist vaccines to public school children in Knox County, typically in October, November, or December.

Several features of the FluMist vaccinations are useful in establishing FluMist as an exogenous cause of temporary reductions in clinic capacity. First, on FluMist days, RNs were pulled from clinic duty to administer FluMist in schools, but were not replaced by nurses from other clinics or temporary staff. Second, FluMist vaccines were administered at one school per day, meaning that only one clinic was short-staffed on a given FluMist day. The clinic from which nurses were drawn was selected by the KCHD based on proximity to a given school and the time since that particular clinic had last administered FluMist, and all scheduling decisions were made by the KCHD central office without consulting the clinic. When a clinic was selected for a FluMist day, the staff who remained were told to keep all scheduled appointments and accept as many walk-in patients as feasible. In other words, the particular clinic that had RNs out at schools was told to treat the day like a normal day - but with fewer clinicians.[6] Typically, clinics were notified of a FluMist day

[6] It is also worth noting that there were no compensating actions taken in any way by the central office. 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 not understood. The central office wanted to know what (if any) compensating actions should be taken.

only days in advance. Thus, FluMist-induced staffing shortages are exogenous to the scheduled daily activity of a given clinic, and the number of their scheduled patients was not influenced by the staff shortage.[7] On a FluMist day, nurses on FluMist duty were away the whole morning and would return to work in the clinics in the afternoon.

Summary statistics are provided in Table 1. In total, our data consist of 44,936 visits to six public health clinics from September 2014 through January 2016. Approximately 36 percent of the visits were scheduled and 64 percent were walk-ins. In addition, about 37 percent of the patients were younger than 20 years old and 42 percent were from 20 to 40 years old. The rest of the visits were for patients (21 percent) over age 40. Approximately 6% of our observed visits occurred on a FluMist day.

Table 1 here

We see from Table 1 that total visits to the clinic were higher on FluMist days, reflective of the seasonality in clinic visits. For example, approximately 60% of FluMist days occur in November or December, which are also months with higher clinic visits overall. Our regression analysis in Sections 4 and 5 controls for this with a set of indicator variables for year, month, and day of week. Table 1 also reveals an increase in the share of scheduled visits relative to walk-in visits on FluMist days, which suggests providers may prioritize certain types of visits over others. Finally, we see from Table 1 that time spent with nurses is the dominant aspect of most visits. On FluMist days, nurse time and ready check-out times were comparable to non-FluMist days, while check-in times and ready nurse times were shorter.

4 Methods

Motivated by our queuing model in Section 2, our goal is to quantify the trade-off between number of patients seen versus time spent with each patient; however, several factors make a direct structural estimation of the provider's optimization problem infeasible. First, we do not observe "balks from the queue" in our data. We instead only observe patients who ultimately receive treatment at the clinic. Second, while the stochastic nature of demand for public health services

[7] This is supported empirically in our data, where we see no reduction in the number of scheduled visits between FluMist days and non-FluMist days, as summarized in Table 1.

(approximately 2/3 of visits are walk-ins) means there is excess capacity on median days, we do not directly observe when constraints become binding. What we define in Section 2 as the "ideal" visit length, τ, will vary by provider, patient, and reason for the visit.

Nevertheless, we can use the exogenous shock to arrival rates provided by FluMist days to gain some insight into how willing providers are to trade visit length with number of visits. We need the exogenous variation from FluMist days because the number of patients seen in the clinic may otherwise be endogenous. If the clinic is operating near or above capacity, the volume of patients seen may not reflect the volume of patients who sought treatment, as we cannot observe balks from the queue. Additionally, providers may compensate somewhat on high volume days to minimize their loss function as discussed in Section 2. The FluMist days represent a true exogenous shock and therefore are necessary for identifying tradeoffs between seeing patients versus spending less time with each patient.

For our empirical model, we adopt a linear, additively-separable functional form,

$$y_{it} = \alpha + \beta_h FluNurse + \beta_t FluDay + g\left(k_i, \theta_i, \theta_t\right) + \varepsilon_{it}. \tag{5}$$

We denote daily output for a given provider as y_{it}, measured as log numbers of scheduled visits, log number and share of walk-ins, and log mean time spent with patients. The variable $FluNurse$ is an indicator set to one for a particular nurse if he or she was on FluMist duty on that day. Similarly, we form a $FluDay$ indicator set to one for all visits in a day when any nurse from that clinic administered FluMist. Therefore, if provider i is on FluMist duty on a given day, both the FluNurse and FluDay indicators are set to 1. Meanwhile, if some other provider (not i) from provider i's clinic is on FluMist duty, then FluDay will equal 1 but FluNurse will be 0. In the context of our queuing model, the indicator for FluDay therefore captures an increase in the arrival rate of patients to each provider who remains in the clinic on a FluMist day. The term $g\left(k_i, \theta_i\right)$ is comprised of a rich set of fixed effects to proxy for clinic and provider characteristics, including indicators for the provider, clinic, day of the week, month, and year. Coefficients are estimated using a fixed effects "within-estimator" and robust standard errors.

In addition to this provider-level specification, we also conduct analysis at the visit level to better understand how shocks to the arrival rate affect the nature of a given patient visit. We adopt a similar specification as in equation 5, with three main differences: 1) we include a larger set of covariates, including fixed effects for patient age (in 10-year bands), clinic, provider, reason for visit, day of the week, month, and year; 2) we only consider the FluDay indicator, since this indicator overlaps with the FluNurse indicator at the visit level; and 3) 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. Since patients do not visit clinics with sufficient frequency over time, we estimate our visit-level model using ordinary least squares.

Finally, to evaluate how the effect of FluMist days varies by the volume in the clinic on a given day, we estimate two additional models. First, we estimate an unconditional quantile regression with provider-level 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). Second, we model how the effect of FluMist on time with patients and other visit times change as we restrict the sample to increasingly high-volume days.

5 Results

Table 2 presents our provider-level estimates, with columns (1) and (2) based on the full sample and column (3) based only on nurses who were not removed from the clinic on a given day.

Table 2 here

The estimates in column (1) of Table 2 provide an initial reasonableness check for our provider-level analysis, as these estimates reflect changes to behaviors specifically for nurses who are removed from the clinic to administer the FluMist vaccines. Since FluMist nurses typically spend a little less than half of their day out of the clinic, our estimates that total time spent with patients and total patients seen decreases by around 45% for FluMist nurses are in-line with *a priori* expectations. We also find that FluMist nurses reduce their share of scheduled patients relative to walk-in patients. This is consistent with a backlog of walk-in patients on FluMist days, where nurses staying in the clinic prioritize scheduled patients over walk-in patients and where, upon their return to the clinic, nurses out for FluMist administration work to alleviate the queue of walk-in patients.

The estimates in column (2) of Table 2 reflect the estimated effect of FluMist days on non-FluMist nurses (i.e., the nurses that remained in the clinic for the entire day). The magnitudes of these estimates are small and insignificant, suggesting that the remaining nurses do not fully compensate for the reductions in output from nurses temporarily removed from the clinic. Similar results emerge from column (3), which presents analogous estimates as column (2) but for the sample limited only to non-FluMist nurses. Here, we find a small but significant increase in total visits (at the 90% confidence level) and a significant decrease in the share of walk-in visits (at the 95% level) among non-FluMist nurses, with the latter result again suggesting a prioritization of scheduled visits over walk-in visits.

Results in columns (2) and (3) of Table 2 are consistent with providers placing more value on spending the appropriate amount of time with each patient relative to seeing as many patients as possible. If instead RNs sufficiently valued the number of patients seen, our estimates should reflect a compensating adjustment among nurses remaining in the clinic on FluMist days. For example, the average clinic has around 6 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 FluDay in column (2) of Table 2 suggest that the remaining nurses collectively increase patient time that day by about 0.24 average-person days (5.9 percent increase, presumably of a normal day's activity $\times 4 \approx 0.24$ additional person days), see an additional 17.6 percent of a person-day's equivalent of patients, and see an additional 27 percent of a person-day equivalent scheduled patients and four percent of a person-day equivalent walk-in patients. Given that on a FluDay, the clinic loses 0.9 person-days of capacity, the magnitudes of these increases would not compensate for the reduction from RNs removed from the clinic. In other words, the sign of the coefficients on the FluDay indicator are consistent with some form of compensating behavior, but the estimates are statistically insignificant and the magnitudes are insufficient to fully compensate for the reductions in output from nurses temporarily removed from the clinic.

For our visit-level specification, Table 3 presents the estimated effects of FluMist on total visit time, time spent in different components of the visit, and visit type. These results again indicate that providers value spending time with each patient over clearing all patients from the queue. Specifically, while we find a reduction in time spent in the waiting room, these estimates are imprecisely estimated. We also find a larger 8-10% reduction in the length of time spent in the check out process, and we estimate a slight reduction of 3% (significant only at the 90% level) in the length of time with a nurse; however, the effect on time with nurses appears to be driven by the nurses who are removed from the clinic, as the estimate reduces in magnitude and is insignificant when focusing only on the non-FluMist nurses.

Table 3 here

Overall, patients' total visit time on a FluMist day decreased by around 7%, regardless of whether they were seen by a nurse who administered FluMist on that day, but this reduction is driven by a streamlining of other areas of the process, including waiting room minutes and check-out times, with no significant reduction in nurse minutes among non-FluMist nurses. Given that a FluDay represents, on average, a 16% reduction in production capability, the compensations we see are relatively small.

5.1 Role of Excess Capacity

While the conditional mean results in Tables 2 and 3 support the notion that providers prioritize time with each patient over queue management, they are confounded by the unknown amount of excess capacity in a given clinic on a given day. For example, an alternative explanation for our initial empirical findings could be that the presence of excess capacity allows clinics to absorb a temporary staff reduction without affecting actual patient care. We examine the role of excess capacity with a series of additional regressions allowing for differential effects over the support of daily visit volume. The goal of this analysis is to focus on days in which capacity constraints are more likely binding, in which case our regression estimates may better estimate actual provider preferences for patients seen versus time with each patient.

At the provider level, we first consider an unconditional quantile regression model with provider-level fixed effects and (log) total visits as our outcome measure (Firpo et al., 2009; Borgen, 2016). In this case, our fixed effects specification intuitively controls for time-invariant work characteristics of a given provider (i.e., nurse), and our quantile regressions investigate the different effects of increases in the mean arrival rate (for a given provider) driven by higher visit volumes. We also include as covariates a set of dummy variables for day of the week, year, month, and clinic. Estimates and 95% confidence intervals are presented in Figure 2.

Figure 2 here

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 a sufficiently low volume of total visits in which a given nurse may otherwise have some downtime in a given day. As total patient volume increases, we see a consistent reduction in patient volume among FluMist nurses by about 50%. Meanwhile, for the nurses remaining in the clinic, we see no significant change in patient volume even on high volume days, although the magnitude of our estimates is larger on high volume days. Collectively, these results suggests that non-FluMist nurses do not sufficiently compensate for a staff reduction on high volume days, suggesting that providers prioritize time with patients over number of patients seen.

Next, we consider visit-level outcomes, where we focus on average nurse minutes and all other components of the visit. 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 nurse minutes, and the bottom panel presents results for log minutes of all other components of the visit. Each line is constructed from a separate visit-level regression using ordinary least squares, analogous to that of Table 3, but where the estimation sample is limited only to those days with at least v visits in a day.

Figure 3 here

The results support a relationship between clinic capacity and visit length and are consistent with our regression analysis in Table 3. Specifically, as the number of visits per day increases, we initially see 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 75^{th} percentile of visit volume. Starting at 15 visits per day, providers' time constraints begin to bind to where increased arrival rates from FluMist days reduces an RN's time spent with patients. For days with total visit volume between 20 and 33 visits, RNs spend slightly over 5% less time with each patient, and even at the point where the estimated effect is largest (visit volume of 30), providers only reduce the time spent with patients by approximately 7% (or just over 2 minutes). However, consistent with the queuing model, RNs do not further reduce time with patients on days where they are already sufficiently constrained (days with over 35 visits). This again suggests that providers strongly value time with patients over number of patients seen.

5.2 Falsification Checks

While we contend that our comprehensive set of fixed effects has eliminated likely sources of omitted variable bias, we also conduct placebo tests to verify that our results are not driven by sampling error. To that end, we randomly draw 50 sets of placebo 'FluMist' days and compare our estimated coefficients to the distribution of estimated coefficients from the placebo 'FluMist' days.

Figure 4 contains the results. Effects of the true $FluDay$ on total visit time and check-out time are greater than all placebo estimates (Figure 4a and Figure 4d).[8] Figure 4b and Figure 4c show that 5% and 3% of placebo coefficients have lower estimates than the true estimate for ready nurse time and nurse time, respectively. Given the placebo test results, our analysis on 'FluMist' days does not seem to be driven by sampling error.

FIGURE 4 HERE

6 Discussion

In this paper, we exploit an exogenous source of variation in arrival rates to providers' queues in the form of temporary staff reductions induced by FluMist days. Our results indicate that capacity reductions influence clinic behaviors along two margins: 1) on the extensive margin, clinics see fewer patients and prioritize scheduled visits over walk-ins; and 2) on the intensive margin, clinics first work to minimize administrative aspects of the visit but may ultimately reduce time with patients on high volume days. Overall, our findings indicate that providers value giving the patients they see the necessary time over clearing the queue.

In several aspects, we emphasize that these results represent a lower bound on the effect of staffing reductions. First, much of the care provided in the setting we study is fairly transactional (e.g., immunizations, disease screening, pregnancy tests, etc.). Most patients are referred to other providers if they have more nuanced or specialized needs. Because the nature of these visits is relatively simple within the health care context, there is less discussion/education to truncate than

[8]Since the estimates are negative, the true estimates are expected to be to the left end of the distributions.

there may be in a family physician or hospital setting. Because providers face different constraints in different contexts, our results stand in contrast to Sharma et al. (2008), who examine provider behavior in emergency rooms. While 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, while we do find evidence of shortened visits, these are only 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. While the context of our study contributes to our empirical identification, it also means that these results do not necessarily hold across all care-provision settings.

In a highly cost-conscious environment where health care costs are top-of-mind, our results may offer some guidance as to the potential effects of staffing reductions in a public clinic setting. As in any environment with stochastic demand, we observe some excess capacity in clinics, but a reduction in this excess capacity is not without cost. First, the finding that providers reduce the proportion of walk-in visits and only slightly reduce their time spent with patients, even on high volume days, implies that more patients are 'balking' from the queue or going untreated. Given that public health clinics immunize against communicable disease and treat sexually transmitted infections, patients leaving the queue may generate substantial negative externalities.

Second, while a 5%-7% decrease in time with nurses may seem small, these magnitudes are not trivial. Yarnall et al. (2003) collected data on the time necessary to counsel patients on preventative care, which coupled with our estimates suggests that the reduction in time spent with patients is sufficient to otherwise have counseled patients on STD prevention or contraception. More generally, 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). Although our data are insufficient to examine formal quality indicators, our estimates in the context of the broader literature on time with patients suggests that reduced staffing levels may also negatively impact quality of patient care, insofar as capacity constraints are already sufficiently binding.

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Tables and Figures

Table 1: Summary Statistics for Clinic Visits[a]

	Overall	FluMist Days	Non-FluMist Days
Total Visits	21.83	26.86	21.57
	(12.16)	(9.85)	(12.21)
Scheduled Visits	7.84	10.06	7.73
	(8.32)	(9.55)	(8.24)
Walk-in Visits	13.98	16.80	13.84
	(11.52)	(11.74)	(11.49)
Components of Visit Length			
Total Visit Time	77.04	66.35	77.61
	(57.55)	(43.22)	(58.15)
Check-in Time	11.31	10.23	11.37
	(13.62)	(10.03)	(13.79)
Ready-nurse Time	10.90	9.76	10.97
	(18.42)	(13.54)	(18.69)
Nurse Time	30.32	30.09	30.33
	(28.47)	(24.71)	(28.70)
Ready-check-out Time	14.40	14.35	14.40
	(28.41)	(28.90)	(28.38)

[a]Standard deviations in parenthesis.

Table 2: Results for Provider-level Analysis[a]

	All Providers		Non-FluMist Nurses[b]
	FluNurse	FluDay	FluDay
Log Nurse Minutes	-0.433***	0.059	0.071
	(0.062)	(0.040)	(0.046)
Log Total Visits	-0.444***	0.044	0.058*
	(0.049)	(0.030)	(0.034)
Log Walk-in Visits	-0.347***	0.009	0.005
	(0.070)	(0.036)	(0.037)
Log Scheduled Visits	-0.339***	0.068	0.086
	(0.070)	(0.049)	(0.057)
Log Walk-in Share	0.112**	-0.059	-0.089**
	(0.050)	(0.036)	(0.038)

[a]Results from a "within-estimator" with provider-level fixed effects. Columns (1) and (2) reflect estimates for the coefficients on FluNurse and FluDay, respectively, based on the full sample. Column (3) presents estimates for the coefficient on FluDay when limiting the sample only to non-FluMist nurses. Different outcomes are presented in each row. Additional covariates excluded from the table include indicator variables for the clinic, day of the week, month of the year, and year. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[b]Estimates based on nurses who were in the clinic all day (i.e., excluding nurses who left the office to administer FluMist).

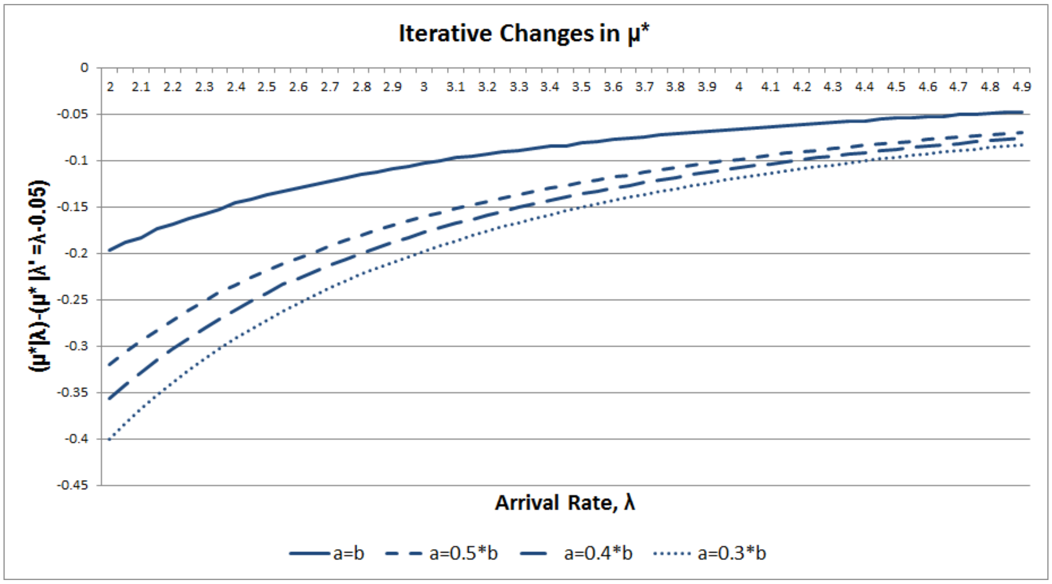
Table 3: Results for Visit-level Analysis[a]

	All Visits	Non-FluMist Nurses[b]
Log Total Minutes	-0.073***	-0.079***
	(0.018)	(0.020)
Log Check-in Minutes	-0.022	-0.019
	(0.048)	(0.061)
Log Waiting Room Minutes	-0.066*	-0.074
	(0.038)	(0.043)
Log Nurse Minutes	-0.032*	-0.021
	(0.017)	(0.021)
Log Check-out Minutes	-0.106***	-0.082**
	(0.034)	(0.039)
Walk-in Visit	-0.104***	-0.109***
	(0.030)	(0.034)

[a]Results for the estimate on the FluDay coefficient based on ordinary least squares regressions with standard errors in parentheses, clustered at the provider level. Column (1) reflects estimates from the full sample of all clinic visits, while column (2) presents results limited to non-FluMist nurses. Different outcomes are presented in each row. Additional covariates excluded from the table include indicator variables for the clinic, provider, reason for visit, age range of patient, day of the week, month of the year, and year. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[b]Estimates based on patients seen by nurses who were in the clinic all day (i.e., excluding nurses who left the office to administer FluMist).

Figure 1: First differences in μ^* as λ increases by 0.05



α normalized to 1

Figure 2: Quantile Regression Estimates on Log Total Visits by Total Visit Volume

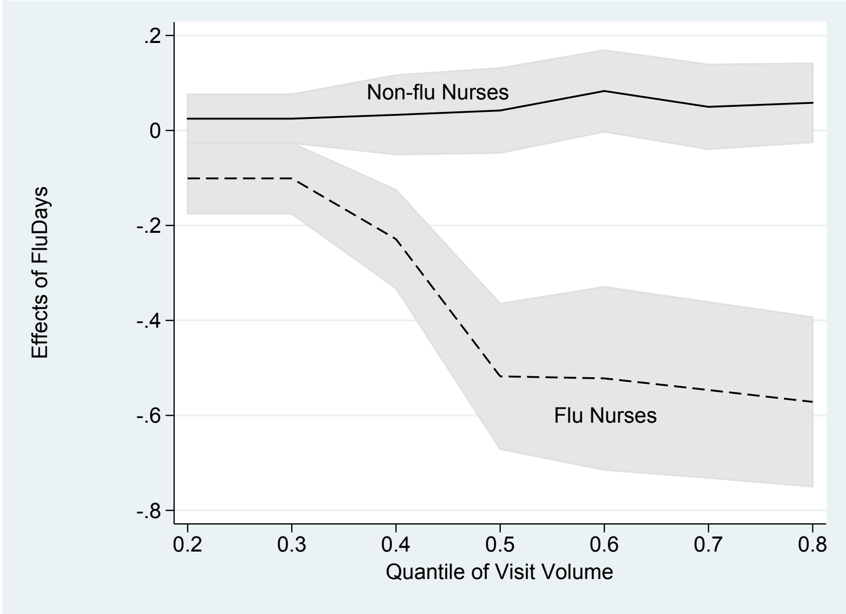


Figure 3: Effects of FluMist on Length of Visit by Visit Volume

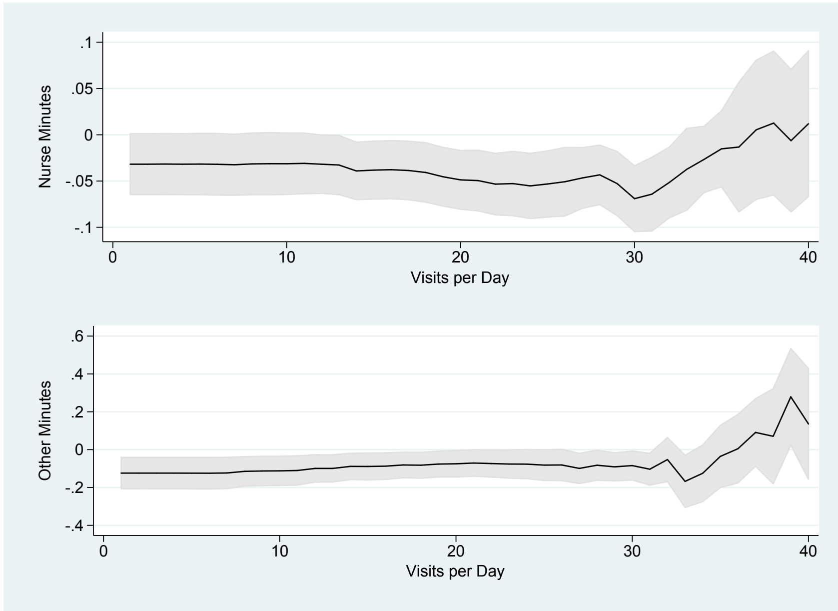
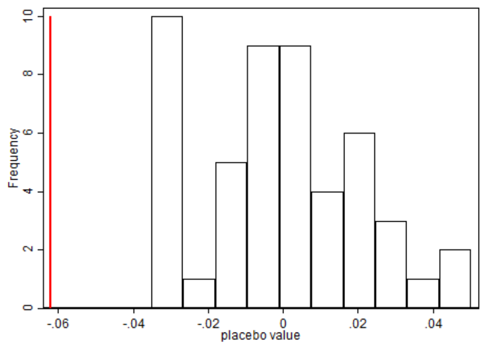
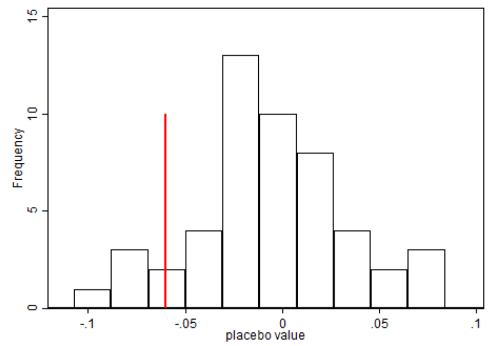


Figure 4: Placebo Tests

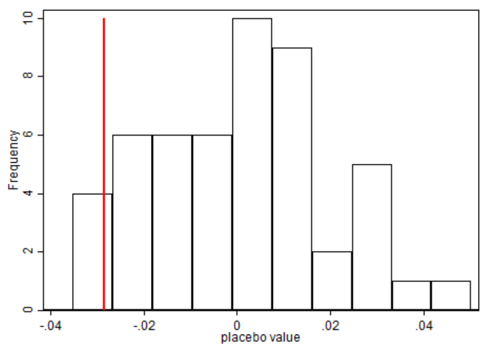
(a) Total Time



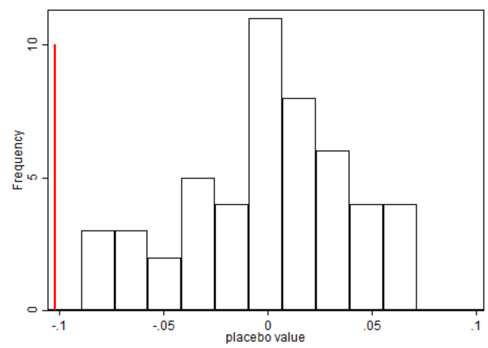
(b) Ready Nurse Time



(c) Nurse Time



(d) Check-out Time



NOTE: Each figure illustrates a distribution of β_t estimates from Equation 5 for the given outcome, where the distribution is generated by randomly sampling about 6% of the dates from the dataset. Solid lines represent the β_t estimate for $FluDay$, which can be found in column 1 of Table 3.