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Essays in Health Economics

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To the Graduate Council:

I am submitting herewith a dissertation written by Yinan Liu entitled "Essays in Health Economics." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

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Essays in Health Economics

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Abstract

In chapter one, I investigate the direct and indirect effects of employment decisions on body weight. I formulate a dynamic model in which an individual makes decisions in three stages in each period. He first chooses an occupation and realizes his wage. Then he decides how to allocate money and time. As a result of his choices, his body weight updates in the last stage. Using data from PSID and U.S. Census Bureau, I estimate a joint system of equations and use a flexible error structure to account for selection on unobservables. I find that employment decisions have insignificant effects on body weight because individuals choose to compensate for changes in the workplace by adjusting their off-work food and exercise behavior. 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 chapter two, 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 nurses? trade-off between patients treated and time spent with each patient, which we treat as a proxy for a quality v. 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.

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Chapter 1

The Direct and Indirect Effects of Employment Behavior on Body Weight

1.1 Introduction

Over the past four decades, Americans have grown substantially heavier. The obesity rate among U.S. adults has almost tripled since 1980 and reached 39.8% in 2015-2016. The extreme obesity rate increased substantially from 0.9% in 1960-1962 to 8.1% in 2013-2014.[1] This problem extends beyond the U.S.. The World Health Organization has referred to this phenomenon as 'an escalating global epidemic of overweight and obesity'.[2] Obesity not only poses serious health risks to individuals (including several chronic diseases and lower life expectancy) and worsens labor market results, but also incurs great financial costs to society.[3] Concurrent with changes in the obesity rates, the distribution of occupations and individuals' daily activities in the workplace have changed. The share of jobs in manufacturing has

[1] National Health Examination Survey and National Health and Nutrition Examination Surveys.
[2] http://www.who.int/nutrition/topics/obesity/en/
[3] [12, 47, 80, 61, 6, 44]

dropped from 25% to less than 10% in the past five decades and jobs in professional and business services, leisure and hospitality have increased considerably.[4] On average, jobs have become less physically demanding.[5]

Ultimately, body weight is the result of choices on calorie intake and calorie expenditure. However, there may be a number of channels through which an individual's job may affect one's body weight. The nature of one's job directly affects one's calorie expenditure in the workplace, and thus, affects one's body weight. One's occupation also determines the constraints one faces when allocating money and time for off-work decisions regarding food and exercise, which also affect body weight. For example, an individual with a sedentary but stressful job may choose to eat at a restaurant and spend some time exercising instead of preparing a meal at home.

Job requirements are the result of a choice. Individuals choose their occupation based on preferences and constraints. For example, an individual may choose a more physical job and choose to engage in calorie burning behavior because he likes physical activity. Thus, it is important to control for selection into occupation and the unobserved individual heterogeneity when I investigate how one's occupation affects body weight.

Several previous studies have investigated the effects of occupation on body weight often with conflicting evidence.[6] [55] find job-related exercise reduces male workers' body weight significantly. It has been shown that having a more physical job (e.g. a blue-collar job) is associated with worse health outcomes [63, 39, 70, 85, 79]. Contrary to what one would expect, given the physical nature of the job, blue-collar work early in life is associated with increased probabilities of obesity in later life [54, 73]. Also, longer working hours have been linked with increased body weight [24, 1]. While evidence suggests that what people do

[4] U.S. Bureau of Labor Statistics

[5] [21] show that occupation-related energy expenditure has decreased more than 100 calories per day for both men and women in the past five decades.

[6] Researchers have suggested a wide range of economic reasons to explain the rise in obesity. Results are mixed and inconsistent. These causes include: lowered price of food [56, 33, 25, 4], participation in government's food subsidy programs [52, 82], lower education [26, 22], macroeconomic conditions [81, 18, 29] and lower income for women, but not for men [84, 14]. See [13] for a comprehensive review.

at work is related to their body weight, that evidence is mixed and often omits key channels. It is still not clear what the transmission mechanism of the effect of employment behavior on body weight is and I try to address it in this paper.

This paper estimates the direct and indirect effects of individuals' employment choices on body weight. Direct effects are defined as effects directly attributable to the requirements of the job. I refer to indirect effects as those resulting from the employment choices on off-work choices regarding food and exercise. To that end, I formulate a dynamic model in which, in each period, a forward-looking individual chooses an occupation and decides how to allocate money and time to maximize his expected present discounted utility. At the end of each period, his body weight updates as a result of his decisions and enters the next period. The primary data source is the geo-coded Panel Study of Income Dynamics (PSID). With this dataset, for over a decade, I not only observe the same individuals' occupations, wages, body weight, spending on food eaten at home, food eaten away from home, exercise, and other very detailed lifestyle data; I also know where individuals are located and I use their community characteristics and local job market characteristics as exclusion restrictions when estimating the model.

Unlike previous studies, I find insignificant direct and indirect effects of job requirements on body weight. My estimation shows that individuals compensate for changes in the workplace by changing their food and exercise choices. For example, when stress at work increases, individuals work fewer hours, eat at home less and exercise less and that is why I see an insignificant indirect effect of stress on body weight. The social and physical requirements of occupations have the opposite effects on food and exercise to stress, and the composite indirect effect on body weight is also insignificant. The finding that individuals compensate for at-work physical activities has policy implications.[7] Specifically, the results indicate that interventions to make individuals lose weight in the workplace may be undone by

[7] Consistent with my finding, [50] do not find significant causal effects of workplace wellness programs on health behaviors.

compensating behaviors outside the workplace. It is very likely that the caloric expenditure changes in the workplace can be offset by people's off-work behavior changes.

This study contributes to the literature in three ways. First, I extend the literature on the effects of employment decisions on body weight by modeling the individual's demand for exercise and food jointly with their occupational choice [24, 38, 79]. This offers possible channels through which employment choice affects body weight. Second, occupational choice is endogenized with respect to body weight. As outlined above, body weight is permitted to affect occupational choice in the model. In addition, selection bias might arise if individuals prefer certain types of tasks and preferences are correlated with body weight. For example, if an individual prefers physical activity, he might choose a more physically demanding job and also choose to exercise. Therefore, he is more likely to have a lower body weight. Studies have shown that selection into occupation is important [37, 79]. My empirical specification includes using exclusion restrictions and a flexible structure of the error term that allows for correlation in one's initial body weight, one's propensity to take on jobs with certain requirements, one's propensity to choose certain life styles and one's propensity to gain weight [71]. Third, differences in body weight are likely to result from repeated small decisions, which the dynamics of the model enables me to capture. Because body weight affects the marginal utility of exercise and food intake, changes in job requirements that affect contemporaneous body weight could have compounding effects in future periods.

The paper is organized as follows. Section 1.2 discusses the theoretical model and section 1.3 introduces the data. Section 1.4 describes the empirical specification. Section 1.5 discusses the results. Section 2.7 concludes the study.

1.2 Model

The theoretical model in this section motivates the empirical estimation specified in section 1.4. It shows the timing of the agent's decisions and describes how the individual's employment behavior affects his allocation of time and money. This section also formalizes the direct and indirect effects of employment behavior on body weight. The model also details the sources of identification discussed in the empirical specification.

1.2.1 Key Features of the Model

In each period t, this individual derives utility from his body weight, the requirements of his job, leisure, consumption of a non-food aggregate and consumption of food. His body weight is determined both by caloric expenditure at work and lifestyle behaviors (food consumption, exercise and home production) that may be influenced by the demands of his job. This model allows one's employment decision in time t to influence not only his contemporaneous utility but also his expected future utility via body weight. The timing of an individual's decision is described as follows:

1. At the beginning of each period the individual observes his body weight, his age, his level of education, the size and composition of his household.

2. With this information, the individual chooses an occupation with full knowledge of how stressful, socially and physically demanding the job is and realizes his wage.

3. Conditional on his chosen occupation and realized wage, the individual chooses how many hours to work and allocates his money and time between food eaten at home, food eaten away from home, hours of home production, exercise, leisure and an inedible aggregate good.[8]

4. The individual's body weight updates as a result of the requirements of his job, hours of work and money and time allocation and is observed at the beginning of the next period.

[8] I also estimated an alternative specification with hours of work moved to the first stage. Results were not quantitatively or qualitatively different.

1.2.2 Optimization Problem

The forward-looking individual chooses an occupation and decides how to allocate money and time to maximize his expected present discounted lifetime utility. At the beginning of each period, the individual realizes his preferences for requirements in the workplace (ν_t^P,ν_t^S,ν_t^{St}). He chooses an occupation, defined by continuous measures of physical, social and stress demands:

$$\mathbf{J_t} = \{P_t, S_t, St_t\}, \quad s.t. \quad P_t, S_t, St_t \in [0,1] \tag{1.1}$$

and realizes his wage (ω_t).

In the second stage of each period, the individual learns his budget constraints (determined by wage). He then allocates his time between the number of hours to work (H_t), home production (HP_t), exercise (Ex_t), sedentary leisure (L_t). He jointly allocates his disposable income to food consumed at home (F_t^H), food consumed away from home (F_t^R), and a non-food aggregate good (C_t). The individual derives utility (or disutility) from consumption of the aggregate good (C_t), leisure (L_t), body weight (B_t), food consumed at home (F_t^H) and food consumed away from home (F_t^R). His utility also depends on a vector of exogenous preference shifters ($\mathbf{X_t}$) and a vector of shocks, denoted by ν_t. The individual's expected present discounted lifetime utility can be expressed as:

$$E\left[\sum_{t=1}^{T} \beta^t U(C_t, L_t, F_t^H, F_t^R, \mathbf{J_t}, B_t; \mathbf{X_t}, \nu_t)\right] \tag{1.2}$$

where E is the expectation operator, β is the discount factor, and $U_t(\cdot)$ is the utility function.[9]

The individual's body mass in the next period (B_{t+1}) depends on his body mass in the current period (B_t), caloric intake (I_t) and expenditure (O_t), a vector of individual characteristics that can influence the conversion of calories into body mass ($\mathbf{X_t}$) and shocks

[9] In this section the individual subscript i is dropped for notational simplicity.

to the body weight ν_t^B. The body mass function is:

$$B_{t+1} = B(B_t, I_t, O_t, \mathbf{X_t}, \nu_t^B) \tag{1.3}$$

Caloric intake, I_t is a function of amount of food consumed at home (F_t^H) and food consumed away from home (F_t^R) that includes food from full-service restaurants and fast food restaurants. Caloric intake is assumed to be increasing in both categories, but I assume that food consumed at home is healthier or less energy dense [59]. Caloric expenditure, O_t is a function of the individual's current body weight (B_t), energy expended in the workplace ($\mathbf{J_t}$), the number of hours he works (H_t), his exercise (Ex_t) and home production (HP_t).

$$I_t = I(F_t^H, F_t^R) \tag{1.4}$$

$$O_t = O(B_t, \mathbf{J_t}, H_t, Ex_t, HP_t) \tag{1.5}$$

The individual allocates his disposable income on food and the non-food aggregate good (F_t^H, F_t^R, C_t). The individual's budget constraint is a function of his wages (ω_t), hours worked (H_t), unearned spousal income (Y_t^s) and a vector of food prices (defined below).

$$\omega_t H_t + Y_t^s = p_t^H F_t^H + p_t^R F_t^R + P_t^C C_t^C \tag{1.6}$$

where p_t^H, p_t^R and P_t^C are the prices for food eaten at home, food eaten away from home and the aggregate good, respectively.

The individual's weekly time constraint is:

$$\Omega = H_t + HP_t + L_t + Ex_t \tag{1.7}$$

where Ω is the total number of hours available in a week. Figure 1.1 shows the timing of the individual's decisions in each stage in period t.

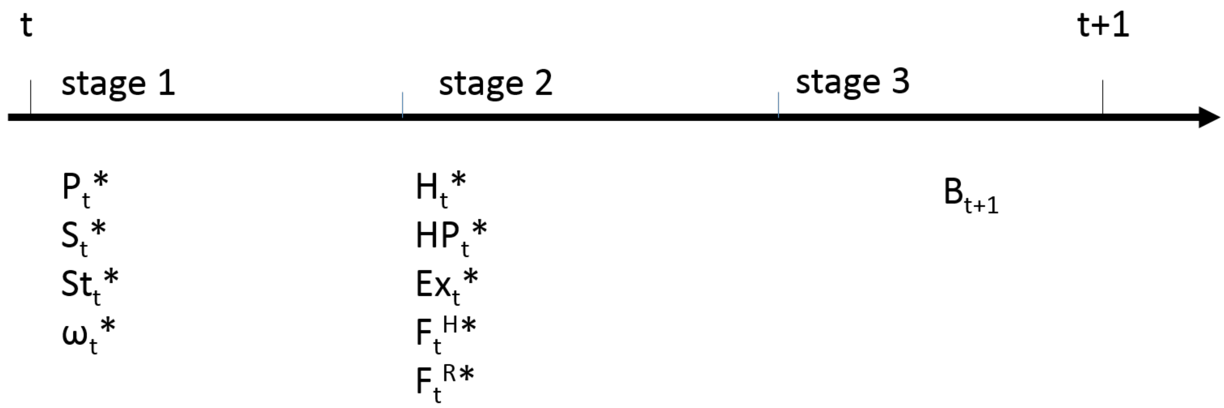


Figure 1.1: Timing of the Individual's Decisions

1.2.3 Solution

An "occupation" is modeled as a bundle of job requirements and a wage. The demand for job requirements (P_t, S_t, St_t) is a function of body weight (B_t), observable characteristics of the individual that include age, sex, education, size and composition of his family ($\mathbf{X_t}$), community characteristics $\mathbf{X_t^c}$ such as the number of grocery stores, fast food restaurants, bars and fitness centers in the individual's ZIP code and the characteristics of jobs available ($\mathbf{M_t}$) in the individual's local labor market defined at the MSA level. Specifically, $\mathbf{M_t}$ includes the mean level of job requirements (physical, social and stress) and mean wage of all the jobs at the MSA level. In the meantime, he receives a wage (ω_t), drawn from a distribution that is also a function of the above factors. See appendix A for a detailed explanation on how the model is solved.

$$P_t^* = P(B_t, \mathbf{X_t}, \mathbf{X_t^c}, \mathbf{M_t}) \tag{1.8}$$

$$S_t^* = S(B_t, \mathbf{X_t}, \mathbf{X_t^c}, \mathbf{M_t}) \tag{1.9}$$

$$St_t^* = St(B_t, \mathbf{X_t}, \mathbf{X_t^c}, \mathbf{M_t}) \tag{1.10}$$

$$\omega_t^* = \omega(B_t, \mathbf{X_t}, \mathbf{X_t^c}, \mathbf{M_t}) \tag{1.11}$$

Once the individual chooses an occupation and realizes his wage, he allocates his budget and time simultaneously. He chooses how many hours to work (H_t), how much time he spends on home production (HP_t) and exercise (Ex_t). He allocates his budget on food consumed at home (F_t^H) and food consumed away from home (F_t^R). Conditional on his chosen occupation and realized wage, his joint demand for hours to work, home production time, exercise, food consumed at home and away from home is not affected by the characteristics of jobs available in the local labor market ($\mathbf{M_t}$), and is a function of his body weight, his individual characteristics and community characteristics.

$$H_t^* = H(B_t, \mathbf{X_t}, \mathbf{X_t^c} \mid P_t^*, S_t^*, St_t^*, \omega_t^*) \tag{1.12}$$

$$HP_t^* = G^H(B_t, \mathbf{X_t}, \mathbf{X_t^c} \mid P_t^*, S_t^*, St_t^*, \omega_t^*) \tag{1.13}$$

$$Ex_t^* = G^X(B_t, \mathbf{X_t}, \mathbf{X_t^c} \mid P_t^*, S_t^*, St_t^*, \omega_t^*) \tag{1.14}$$

$$F_t^{H*} = F^H(B_t, \mathbf{X_t}, \mathbf{X_t^c} \mid P_t^*, S_t^*, St_t^*, \omega_t^*) \tag{1.15}$$

$$F_t^{R*} = F^R(B_t, \mathbf{X_t}, \mathbf{X_t^c} \mid P_t^*, S_t^*, St_t^*, \omega_t^*) \tag{1.16}$$

Substituting equations (1.4) and (1.5) into equation (1.3), the body mass equation can be rewritten as the following:

$$B_{t+1} = B(B_t, \mathbf{X_t}, P_t^*, S_t^*, St_t^*, \omega_t^*, H_t^*, HP_t^*, Ex_t^*, F_t^{H*}, F_t^{R*}) \tag{1.17}$$

Equations (1.8)-(1.17) will be used in the empirical specification.

1.3 Data

1.3.1 Description of Key Variables

The individual-level data used in this study is from the restricted version of the Panel Study of Income Dynamics (PSID). PSID has been following a national representative sample of 5,000 families since 1968.[10] Detailed information on education, family composition, employment, income, expenditures, health and other individual characteristics has been collected at each wave, including how individuals spend their time and money. Beginning in 2001, individuals were asked about their health choices, including food and exercise. Individuals are asked about exercise, how many hours they work and the number of hours per peek they spend on home production. Respondents are asked about how much they spend on food eaten at home and food eaten away from home. In addition, I have repeated data on the same individuals for over a decade. The combination of the long-panel and information on both work, food, exercise and health markers make the geo-coded PSID uniquely and well suited for my research question. There are 4,102 individuals in my sample and six waves of data are used in the analysis (1999, 2001, 2003, 2005, 2007 and 2009) for a total of 24,612 observations. The restricted use data also allows me to use zip codes of the individuals to match with data that contains their community characteristics and local job market characteristics. Community characteristics data (the number of grocery stores, the number of bars, the number of fitness centers and the number of fast food restaurants) is from U.S. Census Bureau's ZipCode Business Patterns and Local job market characteristics data (average levels of the three job requirements and the mean wage) is from Bureau of Labor Statistics' Occupational Employment Statistics. Table 1.1 and 1.2 describe the key variables mentioned in the previous section. Table 1.1 describes the ten dependent variables in the three stages and Table 1.2 describes the individual characteristics, community characteristics and local market characteristics.[11]

1.3.2 Job Requirements

The Occupational Information Network (O*NET) contains a large number of detailed descriptors on occupations, including information on knowledge, work activities, abilities,

[10] https://psidonline.isr.umich.edu/default.aspx

[11] Wage, hours of work, home production, food at home, food out and BMI are all divided by ten to facilitate estimation. Exercise is a dummy variable where 1 indicates yes and 0 indicates no exercise.

Table 1.1: Descriptive Statistics of Outcome Variables

Variable	Mean	Standard Deviation
Stress	0.397	0.287
Social	0.298	0.244
Physical	0.073	0.082
Wage	1.839	2.204
Hours of work	3.562	2.051
Exercise	0.593	0.491
Home production	0.891	0.903
Food at home	1.569	0.569
Food out	0.886	0.576
BMI	2.805	0.551

Note: Some variables are scaled down to facilitate estimation.

Table 1.2: Descriptive Statistics of Exogenous Variables and Individual Characteristics

Vriable	Mean	Standard Deviation
Individual Characteristics X_t		
Age	48.622	13.969
Education	12.438	3.818
Female	0.227	0.419
Married	0.614	0.487
Number of kids	0.857	1.175
Age of youngest kid	3.512	5.234
Housework_wife	7.693	12.154
Lagged wife income	1.386	2.134
Community Characteristics $\mathbf{X_t^c}$		
# of Bars	3.554	5.437
# of Grocery stores	5.719	6.282
# of Fast food restaurants	1.704	1.568
# of Fitness centers	2.183	2.541
# of Full-service restaurants	1.545	1.686
Local Job Market $\mathbf{M_t}$		
Stress	0.349	0.189
Social	0.271	0.147
Physical	0.075	0.041
Wage	1.669	0.928
Sample Size (person-year observations)	24612	

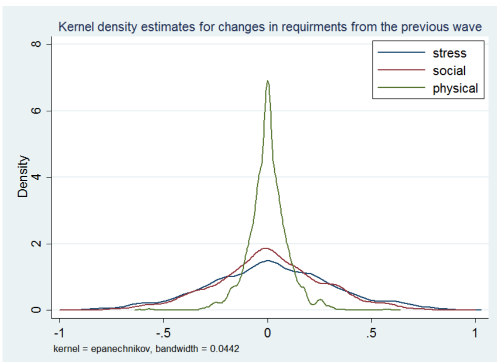
Note: Education measures how many years of education one has finished.

requirements, skills and environmental conditions. I use principle component analysis (PCA) to convert these aspects into a tractable amount of job requirements, which include the physical, social and stress levels of an occupation (P_t, S_t, St_t). I re-scale these requirements to lie between 0 and 1. Tables 1.1 and 1.2 show summary statistics of individuals' job requirements and local job markets' average job requirements (defined in section 1.4).

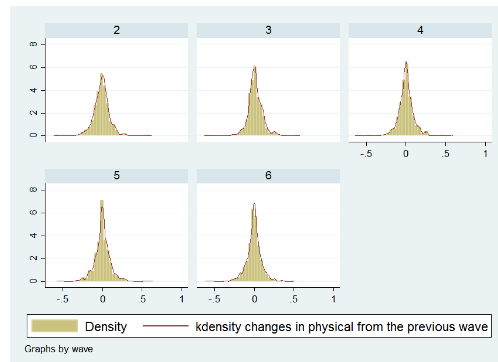
The components with the most weight of the physical requirement index are 'indoors no AC', 'outdoors no cover', 'outdoors under cover', 'exposed to extreme temperature', 'exposed to extreme light', 'confined space work' and 'exposed whole body vibration'. Top occupations with this index include oil derrick operators, mobile heavy equipment operators, structural steel workers, insulation workers and millwrights. Factors that contribute the most to the social requirement index are 'leadership', 'instructing', 'negotiation', 'persuasion' and 'social perceptiveness'. Top occupations with the social requirement are clergy, CEO's, arbitrators, counseling psychologists, and psychiatrists. For the stress requirement, most important contributing factors include 'responsibility for others' health and safety', 'responsibility for outcomes and results' and 'consequence of error'. Top occupations with the stress index are ship caption, offshore rig drill operators, EMT/paramedic, surgeons and pharmacists.

In order to answer my primary research question, there must be sufficient variation in job requirements year over year. Figure 1.2 depicts how job requirements change over time in my data. Figure 1.2a shows that changes in social and stress have a similar distribution, while physical does not change as much over time. Figures 1.2b, 1.2c and 1.2d show changes of each requirement by wave. Changes are mostly stable over time. My data shows that, on average, 50% of the sample changes their occupation in each wave.[12]

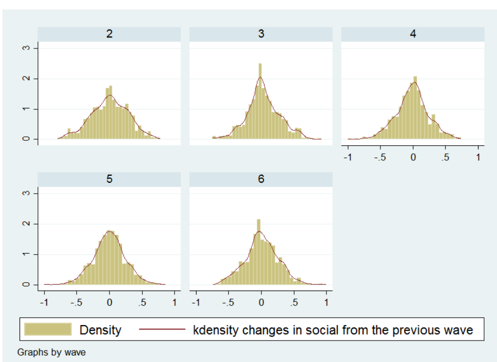
[12] According to Bureau of Labor Economics, the median of employee tenure was 4.2 years (https://www.bls.gov/news.release/tenure.nr0.htm). My data is bi-annual and it shows that about half of the individuals change their occupation every other year. That means on average, they change their occupation every 4 years. I admit that the frequency of changing an occupation is not the same as employee tenure, but they are highly correlated and this provides a reasonable check on my data.



(a) All Waves



(b) How Physical Changes by Wave



(c) How Social Changes by Wave

(d) How Stress Changes by Wave

NOTE: Changes are calculated by subtracting requirements of the previous wave from the current wave.

Figure 1.2: Changes of Job Requirements Over Time

1.4 Empirical Model

The goal of the analysis is to investigate the direct and indirect causal effects of occupational choice on body mass. The solution to the model in the previous section provides the basis for the empirical specifications. In the first stage, the individual chooses an occupation and realizes his wage (equations (1.8)-(1.11)). In the next stage, the individual makes simultaneous decisions on how many hours to work, the amount of home production, exercise, food eaten at home and food eaten away from home (equations (1.12)-(1.16)). Note that conditional on a chosen occupation and realized wages, his second stage decisions are not affected by the characteristics of jobs available in his local job market ($\mathbf{M_t}$). In the last stage, his body mass evolves as shown in equation (1.17). Conditional on all the choices he has made in the previous stages, his body mass does not depend on the characteristics of jobs available in the local job market ($\mathbf{M_t}$) or the individual's community characteristics ($\mathbf{X^c_t}$); rather those factors only affect BMI by affecting the individuals's demand for the outcome variables of interest.

Identification

Empirically, identification of the joint decisions requires exogenous variables which are correlated with the joint decision outcomes, but uncorrelated with the error in the body mass equation after controlling for the unobserved heterogeneity. Note that the individual's occupation choice in the first stage is a function of characteristics of jobs available in the local job market defined at the MSA level (defined as a vector of average job requirements). However, conditional on his chosen occupation and realized wage, his second-stage choices are no longer a function of characteristics of the local job market. Nor is his body weight in the last stage. Furthermore, conditional on all his first and second stage decisions, his body weight is not affected by characteristics of the local community (the number of fast food restaurants, bars, fitness centers and grocery stores). Thus, the average physical, social and stress levels of the local job market $\mathbf{M_t}$ and characteristics of the local community $\mathbf{X_t^c}$ jointly serve as identification for the model. Furthermore, the nonlinearity of the exercise equation (exercise is a binary variable) and the timing of body mass (body mass in the last period $t-1$ enters estimation in the current period t) help ensure the vector of parameters that solve the system of equations is unique.

Discrete Factor Random Effects

If there are unobserved individual characteristics that affect one's occupation choice and are also correlated with body weight, estimates that do not address this correlation will lead to bias. For example, if an individual has a strong preference for social activity, he might choose a more socially intensive job and may be more likely to eat out with friends or join other social events after work and maybe has less time for exercise. On the other hand, if an individual strongly dislikes social activity, he might choose an occupation that is less socially intensive, decide to eat at home and maybe use his time to exercise more after work. To address the issue of selection on the basis of unobservables, a flexible random effects discrete factor estimation approach that allows for correlation in the unobservables that affect each expression including initial body weight (see discussion below), the propensity to choose jobs with certain requirements, the propensity to make certain life styles (e.g., choice of food and exercise) and the propensity to gain weight.

The discrete factor estimation approach [48, 71] treats the unobserved heterogeneity components as a discrete distribution and approximate these components as a joint step-wise function. The relaxed distributional assumptions about the error terms are an advantage of this approach. There are two types of unobserved heterogeneity components. The first is an unobserved permanent heterogeneity component. An individual's ability or type may be an example. The second component is a time-varying one that may include a shock to one's emotional well-being that affects the joint outcomes observed in a given period. The error terms in each equation are decomposed as follows:

$$\epsilon_{ijt} = \mu_j + \nu_{jt} + \varepsilon_{ijt} \tag{1.18}$$

where ϵ_{jit} is the error term for equation j, μ_j and ν_{jt} capture the permanent and time-varying unobserved heterogeneity, respectively and ε_{jit} is the remaining idiosyncratic component of the error term. Conditional on the unobserved heterogeneity factors, the likelihood function value is calculated by taking expectations over the distribution of the first two components.

Initial Conditions and Likelihood Function

Due to the dynamic nature of the model, body weight B_1 and education E_1 in the first period affect the individual's all subsequent decisions. However, they cannot be modeled within the dynamic structure because I do not observe data in the previous period. Thus, I estimate the initial conditions with reduced form equations and allow for correlation in the unobservables between initial body weight and the individual's choices. An individuals parents' education levels serve as the exclusion restrictions for the initial conditions. Empirically, these two equations are jointly estimated with the system of equations discussed previously.

The unconditional likelihood function for individual i is

$$
\begin{aligned}
L_i(\Theta, \psi, \pi) = \sum_{k=1}^{K} \pi_k \Bigg\{ & \frac{1}{\sigma_{B_1}} \phi(B_{i1} \mid \mathbf{X_{iB}}, \mu_{1k}; \theta_{B_1}) \\
& \frac{1}{\sigma_{E_1}} \phi(E_{i1} \mid \mathbf{X_{iE}}, \mu_{2k}; \theta_{E_1}) \times \\
\prod_{t=2}^{6} \sum_{l=1}^{L} \psi_l \Big[& \frac{1}{\sigma_P} \phi(P_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, \mathbf{M_{it}}, \mu_{3k}, \nu_{3l}; \theta_p) \\
& \frac{1}{\sigma_S} \phi(S_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, \mathbf{M_{it}}, \mu_{4k}, \nu_{4l}; \theta_s) \\
& \frac{1}{\sigma_{St}} \phi(St_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, \mathbf{M_{it}}, \mu_{5k}, \nu_{5l}; \theta_z) \\
& \frac{1}{\sigma_\omega} \phi(\omega_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, \mathbf{M_{it}}, \mu_{6k}, \nu_{6l}; \theta_\omega) \\
& \frac{1}{\sigma_H} \phi(H_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, P_{it}, S_{it}, Z_{it}, \omega_{it}, \mu_{7k}, \nu_{7l}; \theta_h) \\
& \frac{1}{\sigma_{Hp}} \phi(Hp_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, P_{it}, S_{it}, Z_{it}, \omega_{it}, \mu_{8k}, \nu_{8l}; \theta_{hp}) \\
& \frac{1}{\sigma_{F^H}} \phi(F^H_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, P_{it}, S_{it}, Z_{it}, \omega_{it}, \mu_{9k}, \nu_{9l}; \theta_{f^h}) \\
& \frac{1}{\sigma_{F^R}} \phi(F^R_{it} \mid B_{it-1}, \mathbf{X_{it}}, \mathbf{X^c_{it}}, P_{it}, S_{it}, Z_{it}, \omega_{it}, \mu_{10k}, \nu_{10l}; \theta_{f^r}) \\
& Pr(Ex_{it} = 1 \mid \mu_{11k}, \nu_{11l})^{Ex_{it}} [1 - Pr(Ex_{it} = 1 \mid \mu_{11k}, \nu_{11l})]^{1-Ex_{it}} \\
& \frac{1}{\sigma_B} \phi(B_{it} \mid B_{it-1}, \mathbf{X_{it}}, P_{it}, S_{it}, Z_{it}, \omega_{it}, H_{it}, Hp_{it}, F^H_{it}, F^R_{it}, Ex_{it}, \mu_{12k}, \nu_{12l}; \theta_b) \Big] \Bigg\}
\end{aligned}
\tag{1.19}
$$

where Θ and θ are the vector of variables to be estimated in the model and in each equation, respectively. L is the number of time-varying mass points and K is the number of permanent mass points. ψ_l and π_k are the probabilities that ν_{jt} and μ_j take on the respective values.

1.5 Results

1.5.1 Coefficient Estimates

Coefficients from the jointly estimated twelve equations are reported in Table 1.3-1.6. The likelihood ratio test shows that the exogenous variables (community characteristics and local job market characteristics) are jointly significant. As shown in Table 1.3, in the first stage, body mass positively contributes to a more social occupation, but not the to the physical or stress requirements of an occupation or wage. Age does not affect one's wage or how one chooses occupation, but education, gender, marital status and age of the youngest kid all have some effects on one's employment choice.

Next, Table 1.4 shows estimation results of the second-stage variables. Recall that the individual chooses how to allocate time and money in this stage. Because job requirements affect body weight indirectly through these choices, I look at the effects of each job requirement on these as a group. Here I interpret the effects of social as an example. Estimation for hours of work shows that having a more social occupation increases the number of hours one would work, but the effect is smaller for individuals with higher body mass. Home production is not significantly affected by social. Having a more social occupation significantly increases the probability one would exercise, but the effect is smaller for individuals with higher body mass. When it comes to food, social has a positive and significant effect on food eaten at home, and the effect gets smaller for individuals with higher body mass. However, social does not affect food eaten away from home significantly. Physical has a similar effect on these exercise and food choices with social and stress affects most of these choices on the opposite direction.

Lastly, Table 1.5 reports results for the BMI equation. One variable to note is lagged BMI. It shows that body mass is highly autoregressive. Education is negatively associated with BMI, which is consistent with the literature. As one would expect, exercise is also negatively associated with body mass. Spending more on food out significantly increases

Table 1.3: Stage One Regression Results

	Outcome			
Variable	Physical	Social	Stress	Wage
MSA_Stress	-0.1851**	-0.0663	-0.4153**	-1.6650***
	(0.08)	(0.14)	(0.19)	(0.48)
MSA_Social	0.0769	0.1861*	0.2337	-0.3627
	(0.06)	(0.11)	(0.13)	(0.59)
MSA_Physical	0.5582***	-0.3238	1.3004***	2.7583***
	(0.17)	(0.31)	(0.42)	(0.96)
MSA_Wage	-0.0042*	-0.0053	-0.0212***	0.3569***
	(0.00)	(0.00)	(0.01)	(0.03)
Age	-0.0001	-0.0001	-0.0002	-0.0006
	(0.00)	(0.00)	(0.00)	(0.00)
Education	-0.0060***	0.0120***	-0.0089***	0.0785***
	(0.00)	(0.00)	(0.00)	(0.00)
Lagged BMI	0.0007	0.0062***	0.0016	-0.0029
	(0.00)	(0.00)	(0.00)	(0.01)
Married	-0.0087***	0.0132***	0.0069	0.1627***
	(0.00)	(0.00)	(0.00)	(0.02)
Female	-0.0195***	0.0154***	-0.0646***	-0.1273***
	(0.00)	(0.00)	(0.00)	(0.02)
Number of kids	-0.0003	0.0003	-0.0053***	-0.0070
	(0.00)	(0.00)	(0.00)	(0.01)
Age of youngest kid	0.0003***	-0.0008***	0.0010***	0.0034**
	(0.00)	(0.00)	(0.00)	(0.00)
Housework_wife	-0.0001	0.0001	0.0006***	0.0029***
	(0.00)	(0.00)	(0.00)	(0.00)
Lagged wife income	-0.0001	0.0014**	0.0003	0.0129***
	(0.00)	(0.00)	(0.00)	(0.00)
Bars	0.0002	0.0000	0.0002	-0.0052***
	(0.00)	(0.00)	(0.00)	(0.00)
Grocery stores	0.0003***	-0.0005**	-0.0002	-0.0060***
	(0.00)	(0.00)	(0.00)	(0.00)
Fast food	0.0003	-0.0003	-0.0013	0.0169***
	(0.00)	(0.00)	(0.00)	(0.01)
Fitness centers	-0.0017***	0.0027***	-0.0016**	0.0261***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.1122***	-0.1959***	0.2247***	-0.6166***
	(0.01)	(0.01)	(0.02)	(0.07)

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table 1.4: Stage Two Regression Results

	Outcome				
Variable	Hours of work	Home production	Exercise	Food at home	Food out
Stress	0.0691	0.0897	-2.6352***	0.0462	0.1052
	(0.37)	(0.28)	(0.65)	(0.16)	(0.17)
Social	1.8534***	-0.3428	2.6609***	0.3901**	-0.0364
	(0.36)	(0.27)	(0.80)	(0.17)	(0.17)
Physical	1.3412	-1.1516	4.2454***	0.5141	0.4904
	(0.91)	(0.70)	(0.99)	(0.38)	(0.41)
Wage	0.0113	-0.0001	0.2168***	-0.0051	0.0346***
	(0.03)	(0.01)	(0.06)	(0.01)	(0.01)
Age	-0.0107**	-0.0079**	-0.0420***	0.0032	-0.0055**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Education	0.0118***	-0.0024	0.1141***	0.0095***	0.0214***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Lagged BMI	-0.1193	-0.1569***	-0.0163	-0.1371***	-0.0913**
	(0.08)	(0.06)	(0.17)	(0.04)	(0.04)
Married	0.0948***	-0.2756***	-0.1260**	0.2505***	-0.0082
	(0.03)	(0.02)	(0.06)	(0.01)	(0.01)
Female	-0.2987***	0.3363***	-0.4549***	-0.1146***	-0.1737***
	(0.03)	(0.02)	(0.06)	(0.01)	(0.01)
Number of kids	-0.0207**	0.0660***	-0.0249	0.0701***	-0.0116***
	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)
Age of youngest kid	0.0027	0.0020*	-0.0039	0.0102***	0.0032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Housework_wife	0.0036***	0.0096***	0.0050***	0.0050***	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lagged wife income	-0.0160***	0.0319***	0.0449***	0.0196***	0.0406***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Bars	0.0011	00013	0.0040	0.0001	-0.0026***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Grocery stores	-0.0019	0.0018*	-0.0162***	0.0018**	-0.0018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fast food	-0.0086	-0.0027	-0.0159	-0.0021	0.0085***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Fitness centers	0.0092*	-0.0007	0.0154*	0.0092***	0.0111***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Age*Stress	-0.0730	-0.0128	0.19651*	-0.0724***	-0.0563**
	(0.05)	(0.04)	(0.10)	(0.02)	(0.02)
Age*Social	-0.0290	0.0697*	-0.1251	-0.0212	0.0424*
	(0.05)	(0.04)	(0.11)	(0.02)	(0.02)
Age*Physical	-0.1023	0.1043	-0.4362*	0.0120	-0.0913
	(0.13)	(0.10)	(0.23)	(0.06)	(0.06)
BMI*Age	0.0360**	0.0263**	0.0018	0.0245***	0.0238***
	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)
BMI*Stress	0.2776***	-0.0216	0.5468***	0.1327***	0.0788
	(0.10)	(0.08)	(0.19)	(0.05)	(0.05)
BMI*Social	-0.2982***	-0.0330	-0.7024***	-0.0843*	0.0172
	(0.10)	(0.07)	(0.21)	(0.05)	(0.05)
BMI*Physical	-0.2788	0.3153*	-1.0482***	-0.2905***	-0.1216
	(0.26)	(0.21)	(0.38)	(0.11)	(0.11)
BMI*Wage	-0.0224**	-0.0031	-0.0509**	0.0113***	0.0046
	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)
Working	1.8988***	-0.2052***	0.3773***	0.1340***	0.0453**
	(0.05)	(0.03)	(0.09)	(0.02)	(0.02)
Constant	0.3700	1.2317***	0.9716*	0.9244***	0.7295***
	(0.25)	(0.18)	(0.51)	(0.12)	(0.12)

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table 1.5: Stage Three (BMI) Regression Results

Individual characteristics		Previous-stage decisions		Interactions w decisions	
Constant	0.5364*** (0.08)	Stress	0.1414 (0.10)	Age*Stress	-0.0216* (0.01)
Age	-0.0036*** (0.00)	Social	0.0878 (0.10)	Age*Social	0.0082 (0.01)
Age of youngest kid	-0.0005 (0.00)	Physical	-0.1914 (0.23)	Age*Physical	0.0120 (0.03)
Lagged BMI	0.8370*** (0.03)	Wage	-0.0004 (0.00)	BMI*Stress	-0.0380 (0.03)
Lagged wife income	-0.0001 (0.00)	Hours of work	-0.0011 (0.01)	BMI*Social	0.0196 (0.03)
Married	0.0385* (0.02)	Home production	-0.0087 (0.01)	BMI*Physical	0.0416 (0.06)
Number of kids	-0.0080 (0.01)	Exercise	-0.0175*** (0.01)	Hours*Stress	0.1303 (0.10)
Female	0.0389*** (0.01)	Food at home	-0.0032 (0.01)	Hours*Social	-0.3059*** (0.11)
Education	-0.0109*** (0.00)	Food out	0.0156* (0.01)	Hours*Physical	-0.0783 (0.24)
Housework_wife	-0.0001 (0.00)			Wage*Hours	-0.0003 (0.00)
Working	-0.0500** (0.02)			Age*Hours	0.0179 (0.02)
BMI*Numkid	0.0311 (0.03)			BMI*Foodhome	-0.0001 (0.01)
BMI*Age	0.0086* (0.00)			BMI*Foodout	-0.0016 (0.01)
BMI*AgeYKid	0.0026 (0.01)			BMI*Hours	0.0041 (0.03)
BMI*Education	0.0308*** (0.01)			BMI*Exercise	0.0022 (0.00)
BMI*Married	-0.0967 (0.08)			BMI*Homeprod	0.0102 (0.04)

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table 1.6: Initial Condition Regression Results

Variable	Outcome: Initial BMI	Outcome: Initial Education
Dad_BS	-0.1120***	1.4428***
	(0.03)	(0.13)
Dad_HS	-0.0642***	0.6301***
	(0.02)	(0.08)
Mom_BS	-0.0284	0.6081***
	(0.03)	(0.15)
Mom_HS	-0.0535**	0.8270***
	(0.02)	(0.08)
Age	-0.0004	0.0301***
	(0.00)	(0.00)
Diet	0.0126	
	(0.02)	
Fruit	-0.0180	
	(0.02)	
Grain	-0.0366*	
	(0.02)	
Health	0.0045	
	(0.02)	
Low fat	0.0952***	
	(0.02)	
Pyramid	-0.0182	
	(0.02)	
Weight	-0.0907***	
	(0.02)	
Constant	2.9780***	4.5012***
	(0.06)	(0.30)

Note: Standard errors in parentheses.
* indicates significance level at 10%,
** at 5% and *** at 1%, respectively.

one's body mass, which confirms that eating out, on average, makes one consume more calories. There is no overall effect of either hours of work or social, but there is a negative cross-over effect of the two on BMI.

1.5.2 Marginal Effects

Table 1.7 presents the marginal effects of job requirements (physical, social and stress) on body weight when I increase job requirements by one unit. As previously defined, directs effects are effects from direct caloric expenditure in the workplace and indirect effects are effects through off-work channels regarding one's food and exercise choices. Total effects are direct and indirect effects combined. Direct effects of physical and social on body weight are both negative, but insignificant. Stress has an insignificant positive effect on body weight.[13] The magnitude of this effect implies a 2-3 pounds of weight increase in two years for an adult from increasing stress by one standard deviation. On the other hand, calculated indirect marginal effects are all statistically insignificant. Total effects of job requirements on body weight are, therefore, insignificant as well.

A closer look at the second and third stage results offers an explanation to the result. As shown in Table 1.5, exercise, hours of work, home production and food at home have a negative effect on body weight and food out has a positive effect on body weight. Table 1.7 shows marginal effects of job requirements on these second-stage choices. For example, more stress leads to less food at home, food out and exercise, more home production and fewer hours of work. The composite effect of all the behavioral change does not influence body weight significantly. Similarly for physical and social, they affect one's second-stage choices in such a way that the net combined effects are not significant. Job requirements do not affect body weight because individuals compensate for changes in the work place with changes in their food and exercise behavior off-work.

[13] https://www.cell.com/cell-metabolism/fulltext/S1550-4131(18)30190-6 explains how stress alone could lead to weight gain without any behavioral change.

Table 1.7: Marginal Effects of Job Requirements on Body Weight and Second-stage Dependent Variables

	Job requirement		
Variable	Physical	Social	Stress
Effects on BMI			
Total effects	-0.0915	-0.1947	0.2947
	(0.26)	(0.38)	(0.47)
Direct effects	-0.1659	-0.0845	0.5672
	(0.23)	(0.35)	(0.43)
Indirect effects	-0.0034	0.0022	-0.0133
	(0.01)	(0.02)	(0.03)
Effects on Second-stage Choices			
Hours of work	0.1155	0.6204***	-0.3395*
	(0.10)	(0.14)	(0.18)
Food at home	0.0933**	0.1264*	-0.2105***
	(0.04)	(0.06)	(0.08)
Food out	0.0210	0.0316	-0.1213
	(0.04)	(0.06)	(0.08)
Exercise	0.0474**	0.1112***	-0.1919***
	(0.02)	(0.03)	(0.07)
Home production	-0.1022	0.0229	0.0276
	(0.07)	(0.10)	(0.12)

Note: Standard errors in parentheses.
* indicates significance level at 10%,
** at 5% and *** at 1%, respectively.

1.5.3 Robustness Checks

To address possible simultaneous bias, a robustness check is carried out by adding lagged choice variables (lagged food at home, lagged food out and lagged exercise) as state variables. Regression results and marginal effects are presented in tables B.1 to B.5. The estimation results are very similar. I also get very similar marginal effects except for the effects of job requirements on food at home where there are a few flipped signs. It shows that my estimation is robust.

1.6 Discussion

This paper investigates an empirical question: how do job requirements affect body weight? I show job requirements can affect one's body weight directly and indirectly. Direct effects are the effects of caloric expenditure in the work place. Indirect effects are effects on body weight through off-work channels. I formulate a dynamic model in which an individual chooses his occupation and realizes his wage, and subsequently allocates time and money to maximize lifetime utility and his body weight updates as a result. I estimate the solution of the model with data from PSID and other sources. My empirical identification includes the use of exclusion restrictions and a flexible error structure.

Unlike previous studies, I do not find significant effects of job requirements on body weight. I show that individuals compensate for changes in the workplace by adjusting their off-work food and exercise behaviors. For example, when the physical requirement of work increases, individuals work more hours, eat at home more and exercise more and that is why I see an insignificant indirect effect of physical on body weight. My results have important policy implications. My results indicate that interventions in the workplace to make individuals lose weight may be undone by compensating behaviors outside the workplace. It is very likely that the caloric expenditure changes in the workplace can be offset by people's off-work behavior changes.

My findings raise some interesting questions for future work. It is a documented fact that the U.S. population has been getting heavier over the years. I show that workplace is not to blame for this. Then what is causing it? What makes people choose to behave in such ways that they are gain weight over time? I show that people may choose to compensate for changes in the workplace, then how can I design policy interventions to nudge people not to change their off-work behavior? Another thing is in my data. I only observe people's weekly spending on food at home and food away from home. As shown in [46], spending on food is not the equivalence of calorie intake, even though it is a good proxy. It would be interesting to better understand how job requirements affect individuals' choice on calorie intake in future work as well.

Chapter 2

Capacity Constraints and Provider Preferences: Evidence from Public Health Clinics

2.1 Introduction

The public labor force is a large component of the economies of most developed countries. Over 15 percent of the labor force is employed in the public sector in the U.S., and payroll expenses account for approximately half of all state government expenditures [75, 45]. Many of these workers are engaged in the production of labor-intensive services. For example, according to the Bureau of Labor Statistics, six of the ten most common occupations for government workers include: clerks, postal service workers, repair workers, highway workers, corrections officers, and (most importantly for this paper) registered nurses.

Most service providers, in both the public and private sector, face inherently stochastic demand but cannot store inventory. Suppliers therefore tend to carry excess capacity on a median day [31]; however, the presence of excess capacity is heavily influenced not only by stochastic fluctuations in demand but also variations funding. Such variation in capacity constraints due to funding is a particularly salient issue for public services, where debates over funding levels and threats of budget cuts are regular occurrences with important consequences. For example, DeAngelo and Hansen [28] show that when budget cuts forced layoffs of State Troopers in Oregon, traffic fatalities increased. Other work examining law enforcement show that capacity constraints do affect the provision of public services, providing evidence that greater funding for law enforcement decreases crime [35, 15, 69].

Given that capacity constraints affect outcomes related the provision of public services, how do employees respond when capacity constraints bind and prices cannot adjust?[1] Understanding how providers of public services reallocate their time when demand exceeds capacity (or vice versa) is critical for understanding how changes in funding for the provision of public services will affect outcomes of interest. In a for-profit setting, we expect that employees will respond in some way consistent with the profit maximization of the firm, or respond to the incentives in place to alleviate principal agent problems. However, there is a large body of work showing that employees in non-profit and public settings fundamentally differ from workers who select into for-profit employment, making the response of public sector employees *ex ante* less clear [78, 58, 5, 65, 77, 30, 10].

In this paper, we provide evidence on how service workers in the public sector respond to capacity constraints, focusing specifically in the context of public health clinics. We examine how nurses in public health clinics respond to unexpectedly tight time constraints created by exogenous temporary reductions in staff. When demand spikes and capacity is constrained, how much time with the average patient are providers willing to trade-off to see as many patients as possible? While the specific answer within this context can inform about the amount of median excess capacity built into the provision of public clinical services, more broadly this paper examines how providers of public services make quality v. quantity tradeoffs under binding time constraints. For example, if providers are reluctant to reduce the time spent with patients, and leaving patients untreated has a high social cost, then

[1] Prior work has examined the effects of congestion (i.e., capacity constraints) under different levels of demand in the transportation industry, and when prices are efficient allocation mechanisms [11, 27, 9, 67].

ensuring median day excess capacity in the public provision of clinical services can yield significant welfare gains [49]. While 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.[2]

We identify the causal effects of reductions in capacity 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 sixteen months. In addition to providing certain types of health care in the clinic, KCHD is also responsible for administering FluMist vaccines in public schools. On days when KCHD is administering FluMist, two nurses would be 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. Indeed, we were asked to examine these data by KCHD because the effects of FluMist administration on clinical production were unknown. KCHD wanted to know if their current practices in conducting FluMist had any adverse effects on their clinical mission. We therefore contend that 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. We expand on these institutional details and provide empirical evidence on the exogeneity of FluMist days in Section 2.2.

[2]See, for example, [89], [87], [72], and [68], among others.

Our empirical analysis exploits these reductions in clinic staff, along with unexpectedly high-demand days, to quantify a provider's trade-off between patients seen versus time with each patient. Our analysis proceeds as follows. First, we quantify the effects of reductions in clinic staff on provider behaviors and specific components of the clinic visit. 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 provider-days further confirms that nurses removed for FluMist administration see significantly fewer patients, thereby reducing overall clinic capacity. We also find that providers in affected clinics (who are not administering FluMist) decrease their share of walk-in patients, indicating they are prioritizing those patients with scheduled appointments. At the visit level, when clinic capacity is reduced, average total visit time significantly decreases by 7% (or about 5 minutes). This primarily occurred through a reduction in check-in and check-out times, with small (and insignificant) reductions in time with nurses.

Next, we consider the underlying mechanisms that may drive our estimated effects. To guide our analysis, we construct an expository theoretical model of providers' responses to staff reductions, where we posit that a provider's utility is 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. In the context of our theoretical model, the null effects on provider time with patients are reflective of providers' preference for time spent with each patient over the number of patients seen. We then conduct additional analyses to test whether our results are plausibly driven by provider preferences or simply a reflection of existing excess clinic capacity. For example, we estimate unconditional quantile regressions allowing for differential effects along the support of daily visit volumes. Even on the busiest days (upwards of the 75th percentile of visit volume) when capacity constraints are likely binding, nurses never reduce their time with each patient by more than 5%. We interpret the inelasticity of time spent with patients as indicative of provider preferences; however, we acknowledge that our findings may be partially driven by the structural constraints of the provider-patient interaction.[3]

Focusing on a specific institution and context allows for a strong identification strategy and thus aids our causal analysis. This ultimately improves the internal validity of our analysis, but potentially at the expense of generalizability. Nonetheless, we contend that our results are at least partially generalizable to other public provided services, particularly those where demand is stochastic. For example, during the government shut down in the winter of 2018-2019, Transportation Security Administration (TSA) employees called out sick, and public reports suggested significantly longer queues for airline passengers. TSA officials therefore appear to have made the choice to maintain (or at least approximate) pre-existing screening standards rather than more quickly clear the queue of passengers. Additional areas where employees engaged in the provision of services to the public may exhibit similar responses include postal service, guidance counselors in public schools, public defenders, and rehabilitation facilities. While some of these entities are more leanly funded than others, the effects of budget cuts or increases to any of these services depends on how providers manage tradeoffs between quality of service and customers served. Our analysis and conceptual framework may offer insights into future studies in these other important areas.

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.[4] 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 [41, 43,

[3]In other words, providers may truly be unable, rather than unwilling, to shorten visit lengths to clear the waiting room. In either case, the empirical and policy implications of our results for reducing clinic capacity are the same.

[4]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 [42], a decline in the positive experiences and increased workload stress in an educational service setting [92], and less than optimal sales and profitability in stores [64].

53, 49, 86] or providers' acceptance of patients and time spent with each patient in emergency departments [16, 17]. Recent work from [40] 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 [32] discusses how incentives and competition can inefficiently distort worker effort and performance in the public sector.[5]

Second, most prior work on exogenous capacity changes in health care settings focuses on increased capacity rather than reduced capacity. For example, there have been a 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, with mixed findings.[6] In addition, previous studies that prompted such regulation change have been criticized for problems including omitted variable bias and endogeneity of staffing levels [34].[7] 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. For example, previous studies have linked 'lower than target' nurse staffing levels and higher patient turnover with higher mortality rate on a daily basis [74, 83]. Our results indicate that effects of staff reductions were strongest on days with the largest patient volume, which suggests that

[5]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 [51]. 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.

[6][20], [8], [76], [88], [2], and [60] found quality of care increased in at least one dimension, while [34], [66], and [23] found no change in quality of care.

[7]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.

estimates derived from a permanent capacity change may mask larger effects on critical days.

2.2 Data and Institutional Details

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 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. On FluMist days, two RNs are pulled from a subset of the five main clinics to administer FluMist in schools, subsequently reducing capacity in the nurse's clinic during that time. On a FluMist day, nurses on FluMist duty were away the whole morning and would return to work in the clinics in the afternoon.

In total, our data consist of 42,514 visits to five public health clinics from September 2014 through January 2016. Approximately 6% of our observed visits occurred on a FluMist day. Overall summary statistics are provided in Table 2.1, where we present statistics for all clinic visits in the first column and statistics by FluMist/Non-FluMist days in columns 2 and 3, respectively. Statistics at the clinic level are summarized in the top panel of Table 2.1, with statistics on individual components of each visit in panel 2 and general patient/visit characteristics in panel 3.

As shown in panel 1, clinics saw around 25 patients on average per day, where approximately 33% of visits were scheduled and 67% were walk-ins. From panel 2 of Table 2.1, clinic visits last around 73 minutes on average, with shorter visit lengths of 66 minutes on FluMist days. Time spent with nurses is the most time consuming aspect of a visit, with average nurse times of around 30 minutes. Nurse time and ready check-out times were comparable on FluMist days relative to non-FluMist days, while check-in times and ready nurse times were shorter. Finally, panel 3 of Table 2.1 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. These statistics suggest that the age distribution across patients is similar between FluMist and non-FluMist days, as is the underlying reason for the patient visit. We also see that FluMist days are not isolated to specific days of the week or disproportionately concentrated among a single clinic.

2.2.1 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. When a clinic was selected for a FluMist day, the staff who remained were instructed to maintain their scheduling patterns and staffing levels. In other words, clinics that had RNs out at schools were told to treat the day like a normal day – but with fewer clinicians.[10]

[10]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

Table 2.1: Summary Statistics for Clinic Visits[8]

	Overall	FluMist Days	Non-FluMist Days
Total Clinic Days (N=1,713 with 101 FluMist observations)			
Total Visits	24.82	26.86	24.69
	(11.03)	(9.85)	(11.09)
Scheduled Visits	8.07	10.06	7.96
	(8.96)	(9.55)	(8.91)
Walk-in Visits	16.74	16.80	16.74
	(10.68)	(11.74)	(10.62)
Components of Visit Length (N=42,514 with 2,713 FluMist observations)			
Total Visit Time	72.61	66.35	72.98
	(49.99)	(43.22)	(50.34)
Check-in Time	11.25	10.23	11.31
	(14.04)	(10.03)	(14.24)
Ready-nurse Time	10.65	9.76	10.71
	(17.83)	(13.54)	(18.08)
Nurse Time	30.61	30.09	30.64
	(28.70)	(24.71)	(28.95)
Ready-check-out Time	14.45	14.35	14.45
	(28.62)	(28.90)	(28.61)
Visit/Patient Characteristics (%) (N=42,514 with 2,713 FluMist observations)			
Age Range			
0-10 yrs	18.32	20.32	18.19
11-20 yrs	20.72	17.18	20.96
21-30 yrs	26.53	26.40	26.54
31-40 yrs	15.70	15.86	15.69
41-50 yrs	7.96	7.89	7.97
51-60 yrs	5.45	6.23	5.39
61-70 yrs	3.45	3.87	3.43
71-80 yrs	1.44	1.55	1.44
81+	0.42	0.70	0.40
Reason for Visit[9]			
Immunization	33.48	37.82	33.19
STD Screen/Treat	16.79	22.12	16.42
Depo-Provera	5.95	4.83	6.03
Back-to-School Immunization	5.04	n/a	5.35
Travel Immunization	4.84	4.57	4.86
Day of Visit			
Monday	21.45	22.74	21.36
Tuesday	21.70	18.43	21.92
Wednesday	18.41	12.75	18.79
Thursday	19.30	22.67	19.07
Friday	19.15	23.41	18.86
Clinic Visited			
CDC	24.07	32.10	23.52
KCTE	9.96	7.96	10.10
KCWE	18.19	16.48	18.31
KCWH	22.35	16.00	22.78
TIC	25.43	27.46	25.29

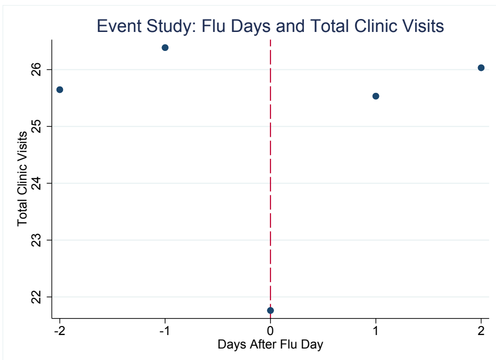
days with respect to quality of care or production of public health were not understood. The central office wanted to know what (if any) compensating actions should be taken.

While the institutional details of FluMist administration suggest that staffing reductions were indeed exogenous, it is of course possible that clinics anticipated the FluMist days and adjusted accordingly. We therefore consider a series of event studies that examine 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: 1) to illustrate the reduction in capacity from FluMist administration; and 2) to examine whether clinics anticipated the staffing reductions in some way and adjusted their behaviors leading up to FluMist days. Results are summarized in Figure 2.1, where we present statistics for clinic visits (total, scheduled, and walk-in) and total minutes spent in each stage of a visit, including nurse-patient time, check-in time and check-out time for each day within two business days of a FluMist day.

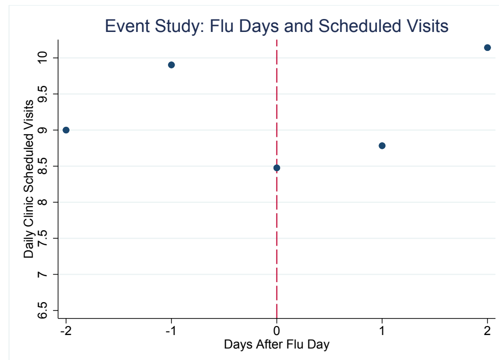
Figure 2.1a depicts total daily visit volume at the clinic level for +/- 2 business days surrounding a FluMist Day. For each of the two days before and after a FluMist day, the clinic sees an average of 25.8 patients. But on FluMist days, the clinic sees an average of 21.8 patients, which represents more than a 15% decrease in total patient volume. Figures 2.1b and 2.1c plot 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 indicates that FluMist days do indeed reduce clinic capacity.[11]

We also examine how FluMist days differ from adjacent days in terms of total time patients spend with their providers and in administrative components of the visit such as

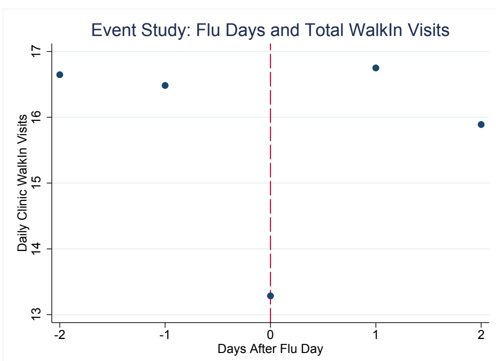
[11]This comparison differs somewhat from the overall summary statistics in Table 2.1, where we see more scheduled visits on an average FluMist day and a comparable number of walk-in visits relative to an average non-FluMist day; however, the comparison group of days in this event study is only for days immediately surrounding FluMist days rather than all non-FluMist days over the sample period. The numbers reflected in Figure 2.1 therefore offer a more apples-to-apples comparison between FluMist and non-FluMist days.



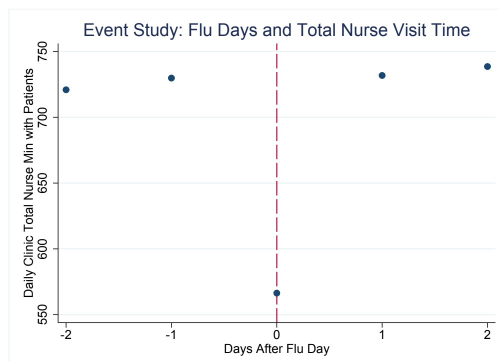
(a)



(b)



(c)



(d)

Note: 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 Flu Mist.

Figure 2.1: Event Study: Daily Clinic Total Activity around Flu Mist Days

check-in and check-out times. Figure 2.1d shows that on FluMist days, patients collectively spend a total of 570 minutes with nurses throughout the day compared to 725 minutes 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 on those days.

In summary, these figures provide descriptive evidence that FluMist days reduce total clinic capacity. To the extent that providers are able to 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, and three-fourths of the drop in patients seen is due to decreases in walk-in patients. Nonetheless, these preliminary takeaways are purely descriptive and based on simple clinic means. In subsequent sections, we turn to regression methods to examine how nurses respond to reduced capacity and tighter time constraints when controlling for a rich set of patient, clinic, visit, and provider characteristics.

2.3 Initial Evidence on the Effects of Capacity Reductions

We first provide initial evidence of the average effect of FluMist days on various activities at both the provider and visit level, respectively. This analysis provides another reasonableness check that FluMist administration does indeed reduce clinic activity among those nurses directly impacted. We then further show the effects of FluMist days on nurses that remain in the clinic (i.e., nurses that were exposed to a reduction in capacity but where not removed from the clinic for FluMist administration). Details of these analyses and findings are discussed throughout the remainder of this section.

2.3.1 Provider-level Analysis

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

$$y_{it} = \alpha + \beta_n FluNurse + \beta_d FluDay + \mu_i + \nu_c + \eta_d + \gamma_m + \delta_y + \varepsilon_{it}. \tag{2.1}$$

We denote daily output for a given clinician (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 he or she was on FluMist duty on that day. Similarly, we form a $FluDay$ indicator that takes a value of one if any nurse from that clinic administered FluMist on that day. Therefore, if provider i from clinic c is on FluMist duty on a given day, both the FluNurse and FluDay indicators are set to 1. Meanwhile, if some other provider ($\neg i \in c$) from i's clinic is on FluMist duty, then FluDay will equal 1 but FluNurse will be 0. From the provider's perspective, the indicator for FluDay therefore implies an increase in the expected number of patients to be seen by each each provider 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 of year (γ_m), and year (δ_y).[12] Standard errors are clustered at the nurse level.

Table 2.2 presents our provider-level estimates of the average effects of FluMist-induced staff reductions on nurses' daily production. Column (1) presents the estimated effect from being called out of the clinic to administer FluMist on a given day. These estimates are based on the full sample. Column (2) presents estimates on the effect of a FluMist day among nurses who were not removed from the clinic on that day. The estimates in column (1) of Table 2.2 therefore provide a reasonableness check for our provider-level analysis, as these estimates reflect changes to behaviors specifically for nurses who are removed from the

[12] Among other things, the inclusion of nurse fixed effects captures any potential selection at the clinic level with regard to which nurses are ultimately pulled from the clinic to administer the FluMist vaccine.

Table 2.2: Results for Provider-level Analysis[a]

	FluNurse	FluDay[b]
Log Nurse Minutes	-0.439***	0.063
	(0.061)	(0.046)
Log Total Visits	-0.446***	0.061*
	(0.049)	(0.033)
Log Walk-in Visits	-0.346***	-0.001
	(0.070)	(0.037)
Log Scheduled Visits	-0.343***	0.095*
	(0.071)	(0.053)
Walk-in Share	0.113**	-0.089**
	(0.050)	(0.038)

[a]Results from a "within-estimator" with provider-level fixed effects. Column (1) reflects estimates for the coefficient on FluNurse based on the full sample. Column (2) 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. Standard errors in parenthesis clustered at the nurse level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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 being scheduled 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, where nurses staying in the clinic prioritize scheduled patients over walk-in patients, and 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 2.2 reflect the estimated effect of FluMist days on non-FluMist nurses (i.e., the nurses that remained in the clinic for the entire day). Here, we find a statistically significant but small 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.

These results are consistent with providers placing more value on spending a certain amount of time with each patient relative to seeing as many patients as possible. 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 2.2 suggest that the remaining nurses collectively increase patient time that day by about 0.25 average-person days (6.3 percent increase, presumably of a normal day's activity $\times 4 \approx 0.25$ additional person days), see an additional 24 percent of a person-day's equivalent of patients, and see an additional 38 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 RNs removed from the clinic. Note also that while the nurses who remain in the clinic may see slightly more patients, they do not appear to be sacrificing average time with patients to do so. In summary, the sign of the coefficients on the FluDay indicator are 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 temporarily removed from the clinic.[13]

2.3.2 Visit-level Analysis

We also examine the effects of capacity reductions on the average time spent in each stage of a visit. We adopt a similar specification as in equation 2.1, with three main differences: 1) 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; 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

[13] If capacity constraints are at all binding (even for just a portion of the time), some compensating behavior is to be expected. The job of these providers is to manage demands on the clinic as a whole rather than demand for their specific personal services.

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. We specify the visit-level model as:

$$y_{vt} = \alpha + \beta FluDay + \mu_i + \nu_c + \eta_d + \gamma_m + \delta_y + \rho_v + a_v + \varepsilon_{vt}, \tag{2.2}$$

where arguments are defined as in equation 2.1 but with fixed effects for the reason for the visit (ρ_v) and age range of the patient (a_v).

Table 2.3 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 again indicate that providers value spending time with each patient over clearing all patients from the waiting room. 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 temporarily removed from the clinic for FluMist administration. Also, note that on FluMist days, visits are more than 10% less likely to be walk-in patients, implying that scheduled patients get priority when time constraints bind. Overall, patients' total visit time on a FluMist day decreased by at least 7%, regardless of whether they were seen by a nurse who administered FluMist on that day, 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 16% reduction in production capability, the compensations we see are far from complete.

Table 2.3: Results for Visit-level Analysis[a]

	All Visits	Non-FluMist Nurses[b]
Log Total Minutes	-0.071***	-0.077***
	(0.018)	(0.020)
Log Check-in Minutes	-0.019	-0.016
	(0.048)	(0.060)
Log Waiting Room Minutes	-0.058	-0.066
	(0.037)	(0.042)
Log Nurse Minutes	-0.028*	-0.016
	(0.016)	(0.021)
Log Check-out Minutes	-0.105***	-0.081**
	(0.034)	(0.039)
Walk-in Visit	-0.105***	-0.110***
	(0.030)	(0.035)

[a]Results for the estimate on the FluDay coefficient based on ordinary least squares regressions. 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. Standard errors in parenthesis clustered at the nurse level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[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).

2.4 Theoretical Framework

While the initial analysis in Section 2.3 shows some evidence of nurse behaviors when short-staffed, several features of the clinical context and the FluMist vaccine administration enable greater insight on the underlying mechanisms driving these results. In particular, what (if anything) do these results say about a provider's preferences and willingness to trade off time with patients versus patients seen? To that end, we borrow elements from [31] and [3], among others, to motivate further empirical analysis with a hypothetical loss function for a provider engaged in the production of public services.

This conceptual framework is a natural fit for our research question as it accommodates two key stylized facts of services where labor is the primary input and quality of the service provided is a function of time with the customer. First, since demand is stochastic, clinics have some excess capacity on a median day. Second, given an expected arrival rate of patients to the clinic as a whole, a reduction in the number of providers is equivalent to a proportional increase in the arrival rate of patients to a remaining provider. 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.[14]

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. 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. Assuming that the mean service time is less than one, the number of unseen patients can be expressed as $(\lambda - 1/\mu)$, and the provider's loss function can be written as

$$U(\mu|\tau, \lambda) = f(\tau - \mu) + g(\lambda - \frac{1}{\mu}). \tag{2.3}$$

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,

$$U(\mu|\tau, \lambda) = -e^{\alpha(\tau-\mu)} - e^{\beta(\lambda-\frac{1}{\mu})}, \tag{2.4}$$

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

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

μ yields the first order condition for the optimal amount of time spent with a patient, μ^*:

$$\alpha e^{\alpha(\tau-\mu)} - \frac{\beta}{\mu^2} e^{\beta(\lambda - \frac{1}{\mu})} = 0. \tag{2.5}$$

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 leave voluntarily because of wait times. When $\lambda > \frac{1}{\tau}$, however, providers choose μ^* such that equation 2.5 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:

$$\frac{d\mu^*}{d\lambda} = \frac{\frac{\beta^2}{\mu^2} e^{(\beta\lambda - \beta/\mu)}}{\frac{\beta(2\mu-\beta)}{\mu^4} e^{(\beta\lambda-\beta/\mu)} - \alpha^2 e^{(\alpha\tau - \alpha\mu)}}, \tag{2.6}$$

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.

This framework provides 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 2.2, 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

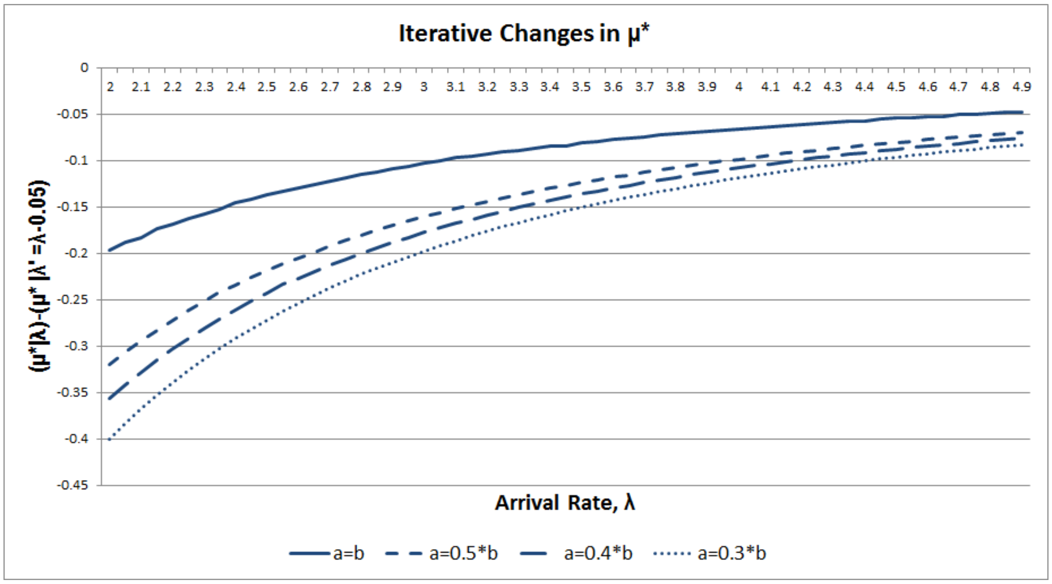


Figure 2.2: First differences in μ^* as λ increases by 0.05

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 2.2 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 two key takeaways here are: 1) $d\mu^*/d\lambda$ 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; and 2) 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.

This expository model therefore shows that exogenous reductions in capacity (i.e., an increase in the arrival rate of patients for remaining providers) can 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.

2.5 Provider Responses to Decreased Capacity

Our initial results in Section 2.3 showed relatively little evidence of sufficient compensating behavior on behalf of the non-FluMist nurses. Our expository model suggests that this result could be driven by at least two factors: 1) there could be sufficient excess capacity already in the clinic such that clinics can absorb a temporary staff reduction without affecting actual patient care; or 2) nurses may exhibit a preference for time with patients over the number of patients seen. While several factors make a direct structural estimation of the provider's optimization problem infeasible, we attempt to distinguish between these two explanations throughout this section.[15]

Our 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. While we do not directly observe when constraints are binding, we attempt to identify such instances by exploiting variation in daily total visits to the clinic as well as exogenous short staffing. This approach arguably separates the role of nurse preferences from the role of built-in clinic capacity.

We pursue this approach with 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 [36, 7]. 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 FluMist days as the mean arrival rates also increases. We also include as covariates a set of dummy variables for day of the week, year, month, and

[15] One barrier in particular is that we do not observe people leaving the clinic. We instead only observe patients who ultimately received treatment at the clinic; although we do observe whether the visit was previously scheduled or was an unscheduled "walk-in" visit.

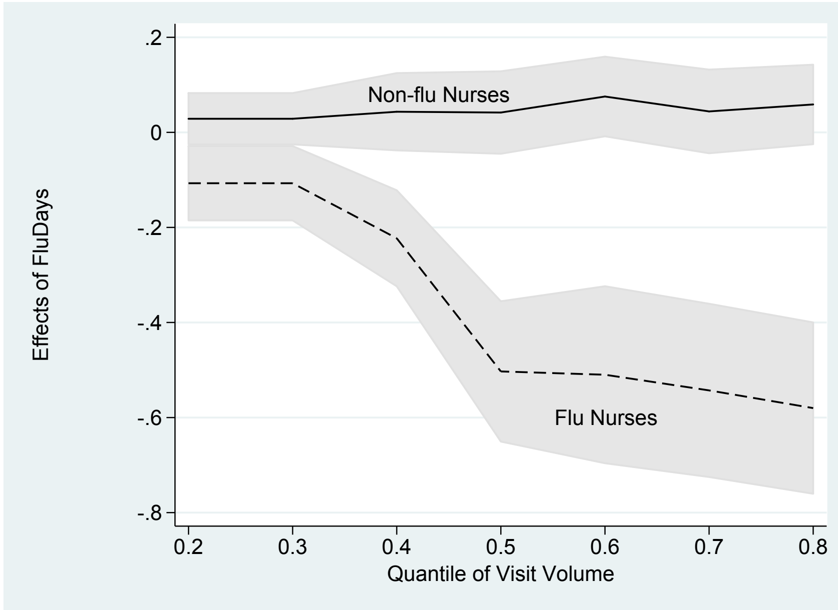


Figure 2.3: Quantile Regression Estimates on Log Total Visits by Total Visit Volume

clinic, as in our initial estimates of equation (1). Estimates and 95% confidence intervals are presented in Figure 2.3.

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 otherwise have some downtime. On these low demand days, being gone from the clinic for half the day does not substantially affect total visit volume, and administering FluMist vaccines essentially absorbs some of that downtime. As total patient volume increases, we see that being absent 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. While 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 large enough to offset the lost capacity from the FluMist nurses, and these estimates are never statistically significant for the nurses remaining in the clinic. Collectively, these

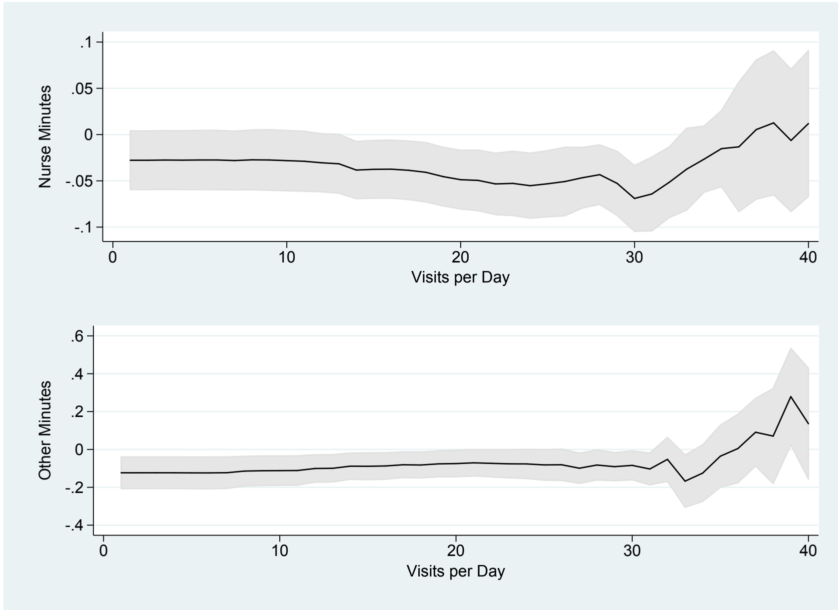


Figure 2.4: Effects of FluMist on Length of Visit by Visit Volume

results show that non-FluMist nurses do not fully compensate in the number of patients seen when staff is reduced on high volume days, suggesting that nurses prioritize time with individual patients over number of patients seen.

Second, we consider visit-level outcomes, where 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. Similar to our quantile regressions at the provider-level, this analysis focuses on days in which capacity constraints are more likely binding and offers additional insight on a provider's underlying preference for patients treated versus time with each patient. The differential effects of FluMist days by patient volume are presented graphically in Figure 2.4. The top panel presents the estimated effect and 95% confidence interval of FluMist on log number of minutes the nurse spends with a given patient, 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 equation (2), but where the estimation sample is limited only to those days with at least v visits in a day.

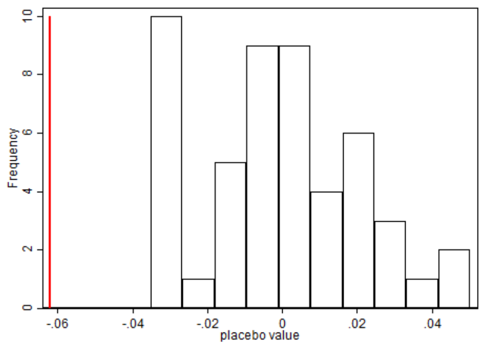
The results support a relationship between clinic capacity and visit length. While they are broadly consistent with the regression analysis in Table 2.3, they further inform that providers prioritize spending time with patients when capacity constraints bind. Specifically, as the number of visits per 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 32 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 our theoretical framework in Section 2.4, 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.

2.6 Robustness

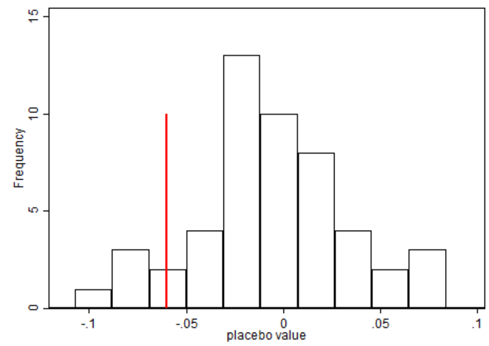
While we contend that the administration of the FluMist vaccine was exogenous to any given clinic, it remains possible that other time-varying factors may be driving the selection of FluMist days from the KCHD central office. To examine this potential issue, we conducted placebo tests to verify that our results are driven by FluMist adminstration. To do so, we randomly draw 50 sets of placebo 'FluMist' days and compare our estimated coefficients in Section 2.3 to the distribution of estimated coefficients from the placebo 'FluMist' days.

Figure 2.5 presents the results. Effects of the true $FluDay$ on total visit time and check-out time are greater than all placebo estimates (Figure 2.5a and Figure 2.5d).[16] Looking at ready nurse time and nurse time, respectively, Figures 2.5b and 2.5c similarly show that

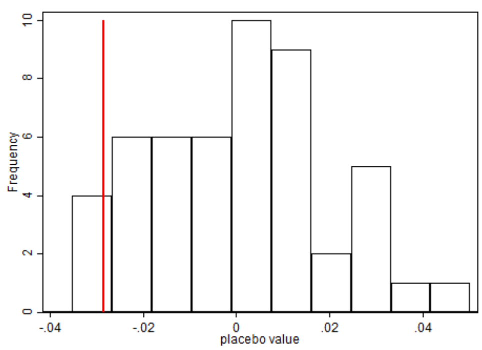
[16] Since the estimates are negative, the true estimates are expected to be to the left end of the distributions.



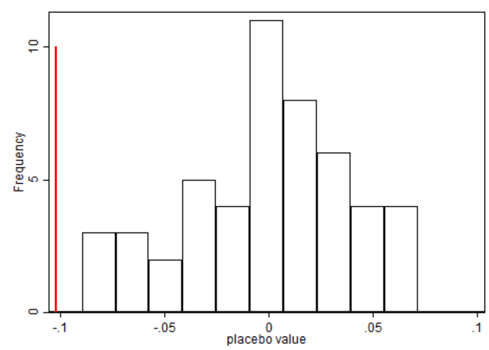
(a) Total Time



(b) Ready Nurse Time



(c) Nurse Time



(d) Check-out Time

Note: Each figure illustrates a distribution of β_t estimates from Equation 2.1 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 2.3.

Figure 2.5: Placebo Tests

over 95% of placebo coefficients have larger estimates than the true estimate. We conclude from these results that our estimates specifically from 'FluMist' days 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.

2.7 Discussion

In this paper, we exploit an exogenous source of variation in the capacity of public health clinics 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 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 other areas of service provision. First, the service 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 there may be in a family physician or hospital setting. For example, our results stand in contrast to [86], 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, 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 due to other factors such as provider fatigue from increased workload, absenteeism, or intention to quit.

Our results may offer some guidance as to 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 without cost. 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 staffing reduction. We also find that providers prioritize scheduled visits over walk-in visits. The implication from these findings is that some customers go unseen. Second, while the reduction in time with customers is relatively small, the magnitude of reduction could be meaningful in certain settings.

Given our specific setting of public health clinics, each of these responses could carry important costs. For example, given that public health clinics immunize against communicable disease and treat sexually transmitted infections, untreated patients may generate substantial negative externalities. In addition, while 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' [62, 89, 90, 57, 87, 19, 3, 72, 68]. For example, findings from Yarnall et al. [91] 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 if we are to understand the full effects of local, state, and federal budget decisions.

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Appendices

A Solving the Model

Section 1.2 discusses how the individual makes decisions in each period to maximize his lifetime utility. Recall that in the first stage, he chooses an occupation and realizes his wage. Then he chooses how to allocate time and money in the second stage. His body weight updates in the beginning of the next period as a result. In this appendix, we show how to solve the model. First, given the timing of the individual's decisions, we rewrite equation 1.2, or the individual's utility function in the following way:

$$U(\mathbf{J_t}, EV(C_t, L_t, F_t^H, F_t^R); \mathbf{X_t}, B_t, \nu_t) \tag{A.1}$$

Equation A.1 is different from equation 1.2 in the $EV()$ term, which shows the timing of the individual's choices. In the first stage, the individual chooses his occupation with knowledge of the expected value of utility from his second stage choices (food, consumption and leisure). Thus, when we take the first order condition of the utility function with respect to job requirements, we get the following:

$$\mathbf{J_t^*} = \mathbf{J}(B_t, \mathbf{X_t}) \tag{A.2}$$

In the theoretical model, wage is considered a function of job requirements and so the solution for wage is as follows:

$$\omega_t^* = \omega(B_t, \mathbf{X_t}) \tag{A.3}$$

In the empirical specification, wage and job requirements are jointly determined in the first stage.[17]

In the second stage,conditional on his chosen occupation and realized wage, the individual maximizes the $EV()$ term in equation A.1 subject to his time and money

[17]With exclusion restrictions $\mathbf{M_t}$ and $\mathbf{X_c}$ added to the first order condition, we get the solutions in equations 1.8 to 1.11.

constraints (equations 1.6 and 1.7). Substituting C_t and L_t with the constrains and rewriting the utility function, now we have:

$$V(H_t, HP_t, Ex_t, F_t^H, F_t^R; \mathbf{X_t}, B_t, \mathbf{J_t^*}, \omega_t^*) \tag{A.4}$$

This is what the individual maximizes in the second stage. Now we take the first order condition of this equation with respect to H_t, HP_t, Ex_t, F_t^H and F_t^R, we get:[18]

$$H_t^* = H(B_t, \mathbf{X_t}, \mathbf{J_t^*}, \omega_t^*) \tag{A.5}$$

$$HP_t^* = G^H(B_t, \mathbf{X_t}, \mathbf{J_t^*}, \omega_t^*) \tag{A.6}$$

$$Ex_t^* = G^X(B_t, \mathbf{X_t}, \mathbf{J_t^*}, \omega_t^*) \tag{A.7}$$

$$F_t^{H*} = F^H(B_t, \mathbf{X_t}, \mathbf{J_t^*}, \omega_t^*) \tag{A.8}$$

$$F_t^{R*} = F^R(B_t, \mathbf{X_t}, \mathbf{J_t^*}, \omega_t^*) \tag{A.9}$$

Lastly, the solution for BMI (equation 1.17) has already been discussed in section 1.2.

[18]Similarly, with exclusion restrictions $\mathbf{X_c}$ in this stage added to the first order condition, we get the solutions in equations 1.12 to 1.16.

B Tables for Robustness Checks

Tables B.1 - B.5 mentioned in section 2.6 are in this appendix.

Table B.1: Robustness Check: Stage One Regression Results

	Outcome			
Variable	Physical	Social	Stress	Wage
MSA_Stress	-0.0559 (0.09)	-0.1216 (0.19)	-0.1803 (0.21)	-1.3893*** (0.53)
MSA_Social	0.0240 (0.07)	0.1109 (0.16)	-0.0427 (0.17)	-0.2411 (0.64)
MSA_Physical	0.2030 (0.19)	0.2377 (0.44)	1.0471** (0.48)	2.1815** (1.06)
MSA_Wage	0.0060** (0.00)	-0.0005 (0.00)	-0.0101 (0.01)	0.2854*** (0.03)
Age	-0.0002*** (0.00)	-0.0001 (0.00)	-0.0005*** (0.00)	-0.0006 (0.00)
Education	-0.0009*** (0.00)	0.0112*** (0.00)	0.0003 (0.00)	0.0521*** (0.00)
Lagged BMI	0.0031*** (0.00)	0.0031 (0.00)	0.0016 (0.00)	-0.0053 (0.01)
Married	-0.0039** (0.00)	0.0102*** (0.00)	0.0113** (0.00)	0.1031*** (0.02)
Female	-0.0093*** (0.00)	0.0156*** (0.00)	-0.0449*** (0.00)	-0.1085*** (0.02)
Number of kids	-0.0005 (0.00)	0.0028** (0.00)	-0.0050*** (0.00)	-0.0098 (0.01)
Age of youngest kid	0.0001 (0.00)	-0.0005* (0.00)	0.0006** (0.00)	0.0017 (0.00)
Housework_wife	-0.0001** (0.00)	0.0004*** (0.00)	0.0007*** (0.00)	0.0019** (0.00)
Lagged wife income	-0.0003 (0.00)	0.0027*** (0.00)	0.0004 (0.00)	0.0042 (0.00)
Bars	0.0001 (0.00)	0.0004 (0.00)	0.0002 (0.00)	-0.0041*** (0.00)
Grocery stores	0.0001 (0.00)	-0.0009** (0.00)	-0.0008** (0.00)	-0.0044 (0.00)
Fast food	0.0002 (0.00)	-0.0010 (0.00)	-0.0016 (0.00)	0.0137** (0.01)
Fitness centers	-0.0011*** (0.00)	0.0014*** (0.00)	-0.0013* (0.00)	0.0177*** (0.00)
Lagged food out	-0.0009 (0.00)	0.0208*** (0.00)	0.0191*** (0.00)	0.1393*** (0.01)
Lagged food at home	-0.0010* (0.00)	0.0079*** (0.00)	0.0233*** (0.00)	0.1425*** (0.01)
Lagged exercise	0.0026** (0.00)	0.0072*** (0.00)	0.0060* (0.00)	0.0748*** (0.01)
Constant	0.0461*** (0.01)	-0.2113*** (0.02)	0.0671*** (0.02)	-0.5949*** (0.07)

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table B.2: Robustness Check: Stage Two Regression Results

	Outcome				
Variable	Hours of work	Home production	Exercise	Food at home	Food out
Stress	0.4237 (0.36)	0.0730 (0.32)	-2.3207*** (0.71)	0.0319 (0.14)	0.1564 (0.15)
Social	1.6351*** (0.35)	-0.2371 (0.28)	2.1429** (0.85)	0.3729** (0.15)	0.0473 (0.15)
Physical	1.0157 (0.91)	-1.4135 (0.89)	5.2727*** (0.99)	0.5500* (0.34)	0.1363 (0.34)
Wage	0.0199 (0.03)	-0.0016 (0.02)	0.1531*** (0.06)	-0.0093 (0.01)	0.0191* (0.01)
Age	-0.0044 (0.00)	-0.0072** (0.00)	-0.0315** (0.01)	0.0026 (0.00)	-0.0014 (0.00)
Education	-0.0020 (0.00)	-0.0022 (0.00)	0.0848*** (0.01)	0.0042** (0.00)	0.0096*** (0.00)
Lagged BMI	-0.0332 (0.08)	-0.1485** (0.06)	-0.0379 (0.17)	-0.0691** (0.03)	-0.0186 (0.03)
Married	0.0901*** (0.03)	-0.2783*** (0.02)	-0.0835** (0.06)	0.1515*** (0.01)	-0.0128 (0.01)
Female	-0.2183*** (0.03)	0.3595*** (0.02)	-0.3347*** (0.06)	-0.0429*** (0.01)	-0.0754*** (0.01)
Number of kids	-0.00214** (0.00)	0.0626*** (0.01)	-0.0229 (0.01)	0.0451*** (0.00)	-0.0049 (0.00)
Age of youngest kid	0.0045*** (0.00)	0.0012 (0.00)	-0.0053 (0.00)	0.0056*** (0.00)	0.0024*** (0.00)
Housework_wife	0.0026*** (0.00)	0.0093*** (0.00)	0.0038* (0.00)	0.0035*** (0.00)	0.0001 (0.00)
Lagged wife income	-0.0149*** (0.01)	0.0286*** (0.00)	0.0254** (0.01)	0.0113*** (0.00)	0.0216*** (0.00)
Bars	0.0018 (0.00)	0.0009 (0.00)	0.0020 (0.00)	-0.0001 (0.00)	-0.0018*** (0.00)
Grocery stores	-0.0033* (0.00)	0.0023** (0.00)	-0.0129*** (0.00)	0.0009 (0.00)	-0.0007 (0.00)
Fast food	-0.0056 (0.01)	-0.0021 (0.00)	-0.0172 (0.01)	-0.0006 (0.00)	0.0056* (0.00)
Fitness centers	0.0075* (0.00)	-0.0011 (0.00)	0.0145* (0.01)	0.0049** (0.00)	0.0048*** (0.00)
Age*Stress	-0.0919* (0.05)	-0.0037 (0.04)	0.2043* (0.10)	-0.0336 (0.02)	-0.0276 (0.02)
Age*Social	-0.0299 (0.05)	0.0622* (0.03)	-0.1124 (0.11)	-0.0431* (0.02)	0.0011 (0.02)
Age*Physical	-0.1522 (0.12)	0.0881 (0.11)	-0.5392** (0.24)	-0.0271 (0.05)	-0.0613 (0.05)
BMI*Age	0.0145 (0.01)	0.0264** (0.01)	-0.0034 (0.03)	0.0124* (0.01)	0.0072 (0.01)
BMI*Stress	0.2229** (0.10)	-0.0539 (0.08)	0.4239** (0.19)	0.0566 (0.04)	0.0070 (0.04)
BMI*Social	-0.3567*** (0.10)	-0.0032 (0.07)	-0.5248** (0.21)	-0.0523 (0.04)	0.0156 (0.04)
BMI*Physical	-0.2607 (0.25)	0.3589* (0.22)	-0.8895** (0.39)	-0.1506 (0.09)	0.0183 (0.10)
BMI*Wage	-0.0063 (0.01)	-0.0031 (0.01)	-0.0371* (0.02)	0.0076* (0.00)	0.0018 (0.00)
Working	1.7248*** (0.04)	-0.1983*** (0.03)	0.1983** (0.09)	0.0697*** (0.02)	0.0057 (0.02)
Lagged food out	0.0753*** (0.02)	0.0096 (0.01)	0.0693* (0.03)	0.0521*** (0.01)	0.5120*** (0.01)
Lagged food at home	0.0514*** (0.02)	0.0539*** (0.01)	0.0509 (0.03)	0.4245*** (0.01)	0.0309*** (0.01)
Lagged exercise	-0.0176 (0.02)	0.1519*** (0.01)	1.4271*** (0.03)	0.0167** (0.01)	0.0097 (0.01)
Constant	0.0656 (0.24)	1.0244*** (0.18)	-0.1534 (0.53)	0.4209*** (0.10)	0.2195** (0.10)

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table B.3: Robustness Check: Stage Three (BMI) Regression Results

Individual characteristics		Previous-stage decisions		Interactions w decisions	
Constant	0.5318*** (0.07)	Stress	0.1460 (0.10)	Age*Stress	-0.0226* (0.01)
Age	-0.0036*** (0.00)	Social	0.0541 (0.10)	Age*Social	0.0093 (0.01)
Age of youngest kid	-0.0005 (0.00)	Physical	-0.1359 (0.23)	Age*Physical	0.0189 (0.03)
Lagged BMI	0.8363*** (0.03)	Wage	-0.0008 (0.00)	BMI*Stress	-0.0375 (0.02)
Lagged wife income	-0.0001 (0.00)	Hours of work	-0.0019 (0.01)	BMI*Social	0.0191 (0.02)
Married	0.0403* (0.02)	Home production	-0.0084 (0.01)	BMI*Physical	0.0419 (0.06)
Number of kids	-0.0077 (0.01)	Exercise	-0.0203*** (0.01)	Hours*Stress	0.1227 (0.10)
Female	0.0390*** (0.01)	Food at home	-0.0013 (0.01)	Hours*Social	-0.3059*** (0.11)
Education	-0.0110*** (0.00)	Food out	0.0181** (0.01)	Hours*Physical	-0.0974 (0.24)
Housework_wife	-0.0001 (0.00)			Wage*Hours	-0.0003 (0.00)
Working	-0.0515** (0.03)			Age*Hours	0.0182 (0.01)
BMI*Numkid	0.0304 (0.03)			BMI*Foodhome	-0.0001 (0.01)
BMI*Age	0.0087** (0.00)			BMI*Foodout	-0.0014 (0.01)
BMI*AgeYKid	0.0026 (0.01)			BMI*Hours	0.0050 (0.03)
BMI*Education	0.0311*** (0.01)			BMI*Exercise	0.0024 (0.00)
BMI*Married	-0.0985 (0.08)			BMI*Homeprod	0.0088 (0.04)
Lagged Food out	-0.0054 (0.01)				
Lagged Food home	-0.0060 (0.01)				
Lagged exercise	0.0089 (0.01)				

Note: Standard errors in parentheses.
* indicates significance level at 10%, ** at 5% and *** at 1%, respectively.

Table B.4: Robustness Check: Initial Condition Regression Results

	Outcome	
Variable	Initial BMI	Initial Education
Dad_BS	-0.1090***	1.1218***
	(0.03)	(0.11)
Dad_HS	-0.0326	0.3896***
	(0.02)	(0.09)
Mom_BS	-0.0127	0.4682***
	(0.03)	(0.12)
Mom_HS	-0.0391*	0.6373***
	(0.02)	(0.08)
Age	0.0004	0.0252***
	(0.00)	(0.00)
Diet	0.0040	
	(0.02)	
Fruit	-0.0170	
	(0.02)	
Grain	-0.0224	
	(0.02)	
Health	0.0154	
	(0.02)	
Low fat	0.0789***	
	(0.02)	
Pyramid	-0.0209	
	(0.02)	
Weight	-0.0789***	
	(0.02)	
Constant	2.7763***	4.3441***
	(0.05)	(0.34)

Note: Standard errors in parentheses.
* indicates significance level at 10%,
** at 5% and *** at 1%, respectively.

Table B.5: Robustness Check: Marginal Effects of Job Requirements on Body Weight and Second-stage Dependent Variables

	Job requirement		
Variable	Physical	Social	Stress
Effects on BMI			
Total effects	-0.1028	-0.5102	0.4077
	(0.26)	(0.38)	(0.47)
Direct effects	-0.1265	-0.1542	0.5673
	(0.21)	(0.33)	(0.42)
Indirect effects	-0.0007	-0.0014	-0.0002
	(0.00)	(0.02)	(0.01)
Effects on Second-stage Choices			
Hours of work	0.0649	0.6001***	-0.2129
	(0.10)	(0.13)	(0.17)
Food at home	0.0572	0.0718	-0.0890
	(0.04)	(0.06)	(0.07)
Food out	-0.0178	0.0001	0.0033
	(0.04)	(0.06)	(0.07)
Exercise	0.0577**	0.1082**	-0.1471**
	(0.02)	(0.04)	(0.07)
Home production	-0.1387	0.0157	0.0653
	(0.08)	(0.10)	(0.14)

Note: Standard errors in parentheses.
* indicates significance level at 10%,
** at 5% and *** at 1%, respectively.

Vita

Yinan Liu was born in a small city in China. She left her hometown and went to college in Beijing where she majored in international economics at University of International Relation. After getting her bachelor degree, Yinan went to University of Delaware for a master's degree in agricultural and resource economics. There, she served as a research assistant for her academic advisor, Dr. John Bernard. Motivated and encouraged by her advisor, she was determined to get a doctoral degree in economics and so she joined the economics department at the University of Tennessee. Her primary research was in health economics. She and her advisor, Dr. Matthew Harris worked together on a couple of papers in this field. During her time at UTK, she also worked as a research assistant at the Howard Baker Center for Public Policy. After graduating in 2019, Yinan Liu started her career in the private sector.