HEALTH ANALYTICS FOR DECISION MAKING IN HEALTHCARE SPATIAL ACCESS

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HEALTH ANALYTICS FOR DECISION MAKING IN HEALTHCARE SPATIAL ACCESS

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LIST OF SYMBOLS AND ABBREVIATIONS

ACA	Affordable Care Act
ACS	American Community Survey
CA	California
CDC	Centers for Disease Control and Prevention
CHIP	Children's Health Insurance Program
CMS	Centers for Medicare and Medicaid Services
CPT	Current Procedural Terminology
FPL	Federal Poverty Level
FTE	Full-time Equivalent
GA	Georgia
HRSA	Health Resources and Services Administration
LA	Louisiana
MAX	Medicaid Analytic eXtract
MH	Mental Health
MHP	Mental Health Provider

MIP	Mixed Integer Programming
MN	Minnesota
MS	Mississippi
NIH	National Institute of Health
NC	North Carolina
NP	Nurse Practitioner
NPI	National Provider Identifier
NPPES	National Plan and Provider Enumeration System
NY	New York
OECD	Organization for Economic Co-operation and Development
OT	Other Therapy
PA	Physician Assistant
PCP	Primary Care Provider
PCPG	Primary Care Provider Group
RUCA	Rural-Urban Commuting Area
TN	Tennessee
US	United States

SUMMARY

Appropriate access to healthcare services is important for preventing the spread of disease, reducing hospitalizations and emergency department use, and increasing quality of life. However, within the United States healthcare system, there exist many disparities in access to care. In this thesis, we aim to quantify and assess disparities in healthcare access, for informed decision making towards improving access. Compared to existing methods, our approach allows for local-level estimates, is data-rich, and is statistically rigorous.

In Chapter 2 of this thesis, we focus on access to pediatric primary care services in seven states. We design an optimization model to match primary care need with supply while taking into consideration system constraints such as health insurance acceptance and maximum travel distance. Output of this model enables computation of census tract-level average distance children must travel to reach their primary care providers and average congestion children face to schedule visits with their providers. We perform statistical inference, both between and within states, to determine whether there are significant disparities in travel distance and congestion.

In Chapter 3, we focus on primary care for non-elderly adults in Georgia and how it may be impacted by the Affordable Care Act (ACA). Specifically, we project the supply and need to primary care services starting from year 2013 through year 2025 under two scenarios: ACA implementation without Medicaid expansion and ACA implementation with expansion. Similar to Chapter 2, we use an optimization model to obtain census tract-level estimates of availability and accessibility and test whether they significantly change by year 2025 due to ACA implementation or additional Medicaid expansion. We

additionally evaluate the impact of two other policies intended to improve access: increasing the number of residency positions in Georgia and implementing a parity program so that more providers accept Medicaid insurance.

In Chapter 4, we begin analysis of psychosocial services for Medicaid-insured children. Using Medicaid claims data for 34 states, we identify which providers are likely to treat Medicaid-insured children and their practice settings. We estimate per-provider and per-state psychosocial service caseloads and compare across states, urbanicity/rurality, and provider specialties.

Finally, in Chapter 5, we develop a modeling framework for one potential intervention to increase access to psychosocial services: collaboration between mental health providers and primary care providers. Our framework mimics providers' making individual decisions on who they partner based on their unique preferences. We create this framework by extending congestion games into a setting in which players have their own private cost function for each resource and resources have their own capacities and preferences over the players. We construct a polynomial-time algorithm to find a Nash equilibrium for singleton games with non-decreasing cost functions under this setting and demonstrate our model for services to Medicaid-insured children in New York.

CHAPTER 1. INTRODUCTION

Healthcare access has been on the national policy agenda since the 1967 Report of the National Advisory Commission on Health Manpower [1]. An Institute of Medicine (IOM) report states that disparities in access to care are "among this nation's most serious healthcare problems" [2]. Appropriate access can increase life expectancy and quality of life by diagnosing and treating health conditions early and by preventing the spread of disease. As of 2015, about 10% of Americans under 65 years of age have no health insurance and nearly 25% of Americans do not have a regular primary care provider [3].

Access can be characterized by multiple dimensions, namely availability, accessibility, accommodation, affordability, and acceptability. All are necessary to eliminate health disparities [4]. In this thesis, we focus on the first two dimensions: *availability*, defined as the opportunity patients have to choose among different providers of healthcare services, varying in the service quality and patient accommodation, and *accessibility*, defined as the time and/or distance barriers that patients experience in reaching their providers [5]. Spatial access, referring to availability and accessibility together [6-8], is critical to promote preventive care and wellness, and to reduce severe health outcomes. Lack of spatial access to healthcare can lead to higher costs, higher emergency outbreaks, and inconsistency in health treatments and outcomes [9-10]. Spatial access is particularly relevant when addressing healthcare disparities for the Medicaid-insured population because of the reduced network of providers accepting Medicaid-insured patients due to low reimbursement rates and the burden of the required paperwork [11-16].

Several methods to measure spatial access exist including population-to-provider ratios, distance to nearest provider, gravity models, and two-step floating catchment area models [7, 12]. However, these methods do not consider providers' maximum capacities and artificially limit where a patient can travel to receive care. They also cannot incorporate population groups' differing insurance and mobility, characteristics that affect which providers a patient can potentially visit, when computing overall congestion. Instead, we use optimization modeling, as described in [13-14] to assign patients to providers. With this model, we can minimize overall travel distance while using constraints to limit the number of patients assigned to a provider and to incorporate patients' travel distance and provider preferences.

In the remaining chapters of this thesis, we describe the access model framework, apply it to different healthcare services, and identify systematic disparities in access across geographies or due to factors influencing access. In Chapter 2, we focus on pediatric primary care with comparisons made within and among seven states. In Chapter 3, we evaluate the impact of the Affordable Care Act (ACA) on access to adult primary care in Georgia between years 2013 and 2025 by projecting the supply and need of adult primary care visits under three scenarios: no ACA implementation, implementation without Medicaid expansion, and implementation with expansion. In Chapter 4, we provide a thorough analysis on the supply of psychosocial services available to Medicaid-insured children. Finally, in Chapter 5 we explore how integration of psychosocial services with primary care may affect access by introducing a congestion game-based modeling approach.

CHAPTER 2. QUANTIFYING DISPARITIES IN ACCESSIBILITY AND AVAILABILITY OF PEDIATRIC PRIMARY CARE ACROSS MULTIPLE STATES

2.1 Introduction

Access to preventive health care is a major determinant of health among children [17]. Along with social and environmental factors, appropriate access to primary care for children can result in fewer missed days of school, lower emergency room utilization to treat ambulatory sensitive conditions, and better lifelong health [18-19].

Despite these benefits, children enrolled in either state Medicaid programs or state Children's Health Insurance Programs (CHIP) have historically received less primary care than children not eligible for public insurance [11, 20]. Reducing disparities and increasing access to individual-centered and family-centered care, including primary care for children, were identified as priorities for all federally funded insurance programs, including Medicaid and CHIP in the federal National Quality Strategy [21].

Existing research has focused on identifying factors associated with systematic disparities including demographics, socio-economics, healthcare infrastructure and/or environmental factors [13, 22-23]; geographic variations using GIS-supported provider data and population demographics [12, 24-29]; and national summaries using individual-level survey data [30-32]. While these existing studies provide the foundation for understanding disparities in healthcare access, managing access through targeted interventions and policies requires a leap from current research [33].

The aim of this chapter is to understand differences in spatial access to pediatric primary across and within states. Similar to [4], for the purposes of this chapter, we define availability as providers' patient volume or time available for healthcare delivery that patients would experience when seeking care and accessibility as the distance barriers that patients would experience in reaching their providers.

Outcomes include quantification of systematic disparities of accessibility and availability measured at the census tract level accompanied by a systematic geographic analysis within- and between-states in order to suggest interventions and to identify communities in need for improvement of pediatric primary care access. The states piloted in this analysis include southeastern states (Georgia, Louisiana, Mississippi, North Carolina and Tennessee) and comparative states (California and Minnesota). The seven selected states vary significantly in implementation of Medicaid/CHIP programs, as well as in population size, population distribution, and demographics.

Specific research questions include:

• Are there systematic disparities in spatial access to pediatric primary care between- and within-states?

• Are there systematic disparities in spatial access between publicly-insured and privately-insured children?

• Are there systematic disparities between children living in urban versus rural communities?

• Which communities are in need for improvement and which spatial access dimensions need to be targeted by policy makers?

The approach to addressing these questions introduces a comprehensive framework for studying disparities in spatial access. The modeling approach is data "rich," mathematically rigorous and computationally scalable, integrating large data and health policy in a systematic manner. As more data become available, the approach has the potential to provide even more specific information to target community or state-specific interventions. Material in this chapter has been published in final form at [34].

2.2 Methods

2.2.1 Modelling Overview

We estimate access by assigning patients and providers while accounting for the locations of each, the underlying need (using wellness visits by age as a proxy), patient trade-offs between distance and crowding, and some limits in the system. This modeling approach has been found to be superior to catchment approaches, which underestimate access in dense areas [35] and to simple ratios of providers and population by area [14], which inaccurately portray access, especially at lower geographical granularity. The matching model also has the advantage over both catchment methods and simple ratios of accounting for specific types of barriers to access that are of significant concern in states with high poverty rates like the southeastern states, including the willingness of providers to accept Medicaid, and the limited transportation options of some participants.

2.2.2 Data and Estimation Approach

2.2.2.1 Supply of Pediatric Primary Care

The primary care supply consists of Family Medicine [36], Internal Medicine physicians [37], and General Pediatricians and Nurse Practitioners specializing in Pediatrics. Registered nurses and public health nurses are excluded. Providers' practice location addresses are obtained from the 2013 National Plan and Provider Enumeration System (NPPES) [38]. A maximum provider caseload of approximately 2500 patients/year is assumed [39]. Caseloads of General Pediatricians and Pediatric Nurse Practitioners are assumed to be completely devoted to pediatric care while Family and General physicians are assumed to devote around 10% of their caseload. Sensitivity analysis examined other variations on these percentages.

The 2009 MAX Medicaid claims data obtained from the Centers for Medicare and Medicaid Services [40] are used to determine what providers have seen Medicaid patients. We further used the approach in [13] to inform the constraints on provider Medicaid acceptance by considering the aggregated count of providers accepting Medicaid at the county level and using a sampling technique to specify whether a provider accepts Medicaid.

2.2.2.2 Need for Pediatric Primary Care

We focus on wellness visits, thus we apply the recommendations by the American Academy of Pediatrics [41] to calculate the type and frequency of wellness visits/year by age with an average number of visits/year equal to 8, 1.6, and 1 for 0-1, 1-5 and 6-18 age groups, respectively. The patient population is aggregated at the census tract level, using the 2010 SF2 100% census data and the 2012 American Community Survey data [42] to compute the number of children in each census tract by age class along with information on poverty and ownership of cars, to estimate access to private transportation means.

An estimation of the population of children at or below the minimum income-eligibility threshold for public coverage is derived using the cutoff thresholds published by CMS [43] (Table 1). We refer to this population as eligible to be publicly insured and those above the threshold as likely to be privately insured. We recognize the distinction is imperfect as some children may have both insurance types, some neither, and additional variations in coverage eligibility exist (e.g., medically-needy).

Table 1. Medicaid/CHIP eligibility thresholds with respect to the Federal Poverty Level, April 2014

	Eligibility			
	Medicaid Ages 0-1	**Medicaid Ages 1-5**	**Medicaid Ages 6-18**	**Separate CHIP**
California	261%	261%	261%	N/A
Georgia	205%	149%	133%	247%
Louisiana	212%	212%	212%	250%
Minnesota	283%	283%	283%	N/A
Mississippi	194%	143%	133%	209%
North Carolina	210%	210%	133%	211%(6-18)
Tennessee	195%	142%	133%	250%

We assume patients do not travel to excessively distant providers (i.e., more than 25 miles) as recommended by the Health Resources Services Administration and that those without private transportation in their household will travel a maximum distance of 10 miles [44]. Street-network distances are computed using the ArcGIS Network Analyst [45].

2.2.3 Matching Model

For each of our seven selected states, we apply an optimization model similar to one introduced in [14] to estimate *served need* for pediatric primary care. This model matches the available supply and the population-based need of services under a series of access and system constraints. Decision variables represent the number of patients in each census tract of a given age class who are assigned to a specific provider, namely x_{ijk}^{M} and x_{ijk}^{O}, where index $i \in S$ represents a census tract, index $j \in P$ represents a provider, index $k = 1,2,3$ denotes a specific age class, and superscripts M and O distinguish between children covered by public insurance and children covered by private insurance respectively. Table 2 provides a summarized view of the set of parameters. We describe in detail the objective function and the constraints in the next two subsections.

2.2.3.1 Objective Function

We assume patients prefer to visit nearby and less congested/busy physicians; however, when a provider office has a high patient volume, families prefer providers or/and mid-level providers farther away [46, 47]. Under these assumptions, the objective function of the optimization model is a weighted sum of the total distance traveled (which needs to be minimized) and of the provider preference contingent upon availability of the providers (which needs to be maximized). In particular, the objective function of the model is as follows:

$$min\left((1-\lambda)\sum_{i\in S}\sum_{j\in P}\sum_{k=1,2,3} d_{ij}f_k\left(x_{ijk}^{M}+x_{ijk}^{O}\right)-\lambda\sum_{j\in P}(1-y_j)u_j\right)$$

where f_k is the yearly number of visits required by a patient in age class k, d_{ij} is the distance between the centroid of census tract i and provider j, y_j is the level of congestion at provider j computed as the ratio of assigned number of visits to maximum provider caseload, and u_j is a weight assigned to each provider to ensure that physicians are preferred to nurse practitioners. We note that the congestion level for Family/Internal Medicine is computed considering the physicians' caseload that is devoted to visits for children. We thus assume that these physicians work at their maximum capacity, respecting the general perception of shortage of primary care supply for adult population [48].

The balance between the two components is controlled by a non-negative trade-off parameter $\boldsymbol{\lambda} \in [\mathbf{0}, \mathbf{1}]$. Its value is empirically evaluated by performing several runs of the model to choose the value of the parameter such that (i) neither of the two components of the objective function dominates the other, and (ii) the resulting optimized decision reflects the fact that close neighbors experience the same travel distance and the same congestion level. Specifically for each state, we run the optimization model for different values of $\boldsymbol{\lambda}$ and compute for each run the total distance traveled (i.e. the first element of the objective function), total patient satisfaction (the second element of the objective), and the Geary spatial autocorrelation index [49] for census tract-level travel distance and congestion. We then select a value for $\boldsymbol{\lambda}$ where neither total distance nor total patient satisfaction dominate and the Geary index values are below 1, denoting positive spatial autocorrelation among neighboring census tracts. Examples are shown in Figure 1 for Georgia and California.

Table 2. Parameters used in the pediatric primary care optimization model.

Parameter	*Description*	*Value*	*Data Source*
p_{ik}^{M}	Total number of publicly-insured children at census tract i in age class k		2010 SF2 100% Census data, 2011 American Community Survey
p_{ik}^{O}	Total number of privately-insured children at census tract i in age class k		2010 SF2 100% Census data, 2011 American Community Survey
$p_{i}^{M} = \sum_{k} p_{ik}^{M}$	Total publicly-insured population at census tract i		-
$p_{i}^{O} = \sum_{k} p_{ik}^{O}$	Total privately-insured population at census tract i		-
mob_{i}^{M}	Percentage of publicly-insured population in census tract i that owns at least one vehicle		2010 SF2 100% Census data, 2011 American Community Survey
mob_{i}^{O}	Percentage of privately-insured population in census tract i that owns at least one vehicle		2010 SF2 100% Census data, 2011 American Community Survey
mi^{max}	Maximum allowed distance (in miles) between a patient and the matched provider	25	US Department of Human and Health Services [44]
mob^{max}	Maximum allowed distance (in miles) between a patient and the matched provider when the patient does not own a vehicle	10	-
d_{ij}	Distance between centroid of census tract i and provider j		ArcGIS, ESRI; NPPES (for provider location); 2010 SF2 100% Census data (for centroid location)
f_{k}	Number of yearly visits of a child in age class k	$f_1 = 8$ $f_2 = 1.6$ $f_3 = 1$	American Academy of Pediatricians [41]
λ	Weight parameter for the distance component in the objective function		Experimentally evaluated
c^{min}	The minimum percentage of the total patient population required to be assigned to providers (others are considered "uncovered").	90%	Experimentally evaluated
POP	Total patient population		2010 SF2 100% Census data
Cap_{j}	Maximum number of yearly visits of a provider	Sampled from distribution	[37, 52, 53]
pc_{j}	Percentage of the provider's caseload devoted to visits to children	100% if Pediatric Specialist 10% if Family/Internal Medicine physician	[36]
lc_{j}	Percentage of provider's caseload necessary to remain in practice	15% for NC; 10% for GA, LA, TN; 0% for CA, MN, MS	Experimentally evaluated
pam_{j}	Probability that provider j accepts publicly-insured patients	$pam_j = 1$ if provider accepts Medicaid/CHIP patients $pam_j = 0$ if provider does not accept Medicaid/CHIP patients	Medicaid Claims data
α_{k}	Percentage of the total patients in age class k that is served by pediatrics specialists	$\alpha_1 = 80\%$ $\alpha_2 = 70\%$ $\alpha_3 = 50\%$	[50]
u_{j}	Disutility perceived by patients when served by physician j	$u_j = 5$ if General Pediatric $u_j = 40$ if Family/Internal Medicine Physician $u_j = 10$ if Nurse Pediatric	Experimentally evaluated

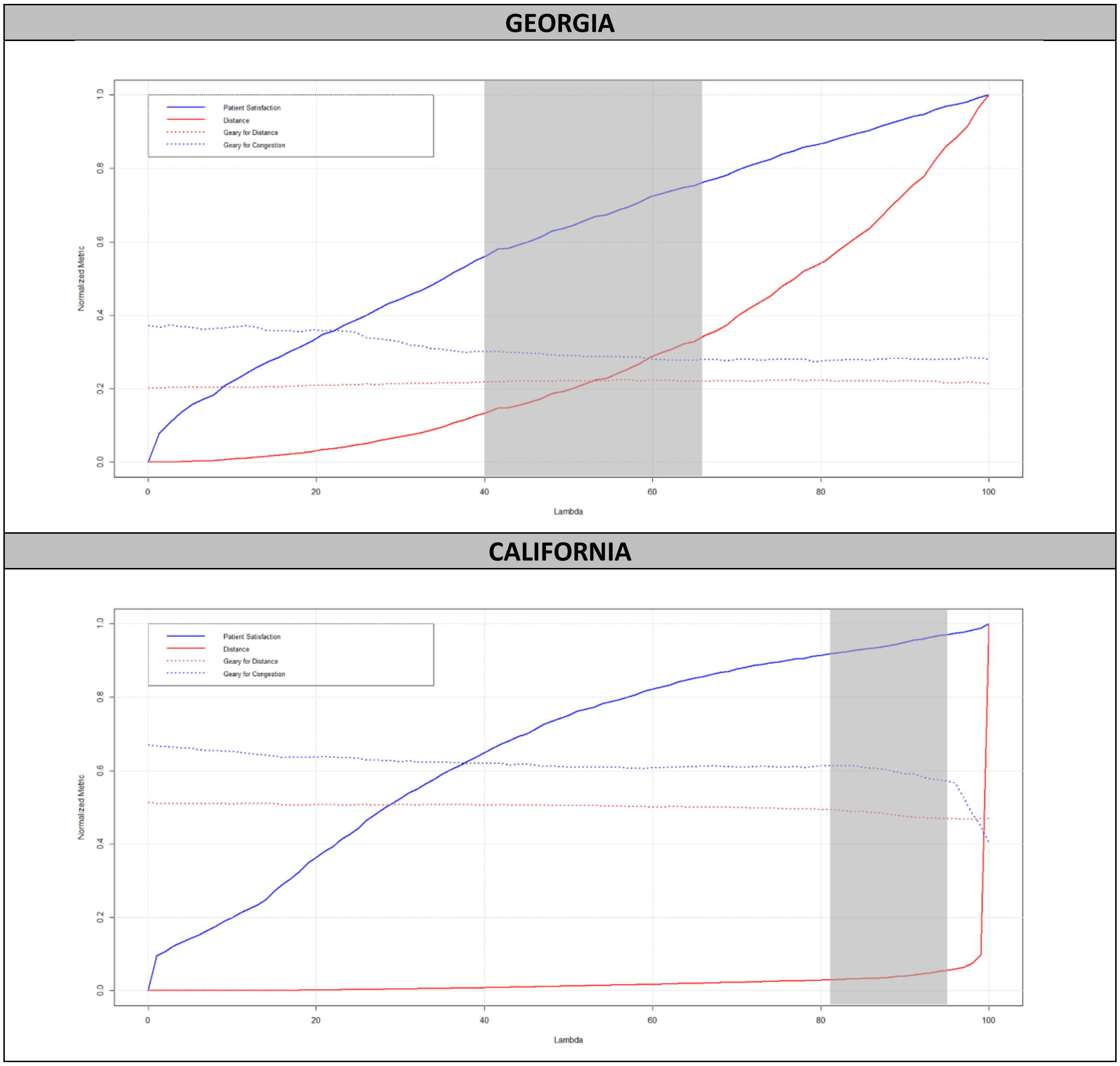


Figure 1. Normalized performance measures for different values of the trade-off parameter in the optimization model with the range of recommended values highlighted in grey, for Georgia and California.

2.2.3.2 <u>Model Constraints</u>

Constraints to the model ensure that the assignment of patients to providers mimics the process by which families choose primary care for their children. They are given below:

$$\sum_{i \in S} \sum_{k=1,2,3} f_k(x_{ijk}^M + x_{ijk}^O) / (Cap_j pc_j) = y_j \qquad \forall j \in P \qquad (2.1a)$$

$$\sum_{i \in S} \sum_{j \in P} \sum_{k=1,2,3} (x_{ijk}^M + x_{ijk}^O) \geq c^{min} POP \qquad (2.1b)$$

$$\sum_{j \in P} x_{ijk}^M \leq p_{ik}^M \qquad \forall i \in S, k = 1,2,3 \qquad (2.1c)$$

$$\sum_{j \in P} x_{ijk}^O \leq p_{ik}^O \qquad \forall i \in S, k = 1,2,3 \qquad (2.1d)$$

$$x_{ijk}^M \geq 0 \qquad \forall j \in P, i \in S, k = 1,2,3 \qquad (2.1e)$$

$$x_{ijk}^O \geq 0 \qquad \forall j \in P, i \in S, k = 1,2,3 \qquad (2.1f)$$

$$\sum_{j: d_{ij} \geq mi^{max}} \sum_{k=1,2,3} (x_{ijk}^M + x_{ijk}^O) = 0 \qquad \forall i \in S \qquad (2.1g)$$

$$\sum_{j: d_{ij} \geq mob^{max}} \sum_{k=1,2,3} x_{ijk}^M \leq mob_i^M p_i^M \qquad \forall i \in S \qquad (2.1h)$$

$$\sum_{j: d_{ij} \geq mob^{max}} \sum_{k=1,2,3} x_{ijk}^O \leq mob_i^O p_i^O \qquad \forall i \in S \qquad (2.1i)$$

$$\sum_{i \in S} \sum_{k=1,2,3} f_k (x_{ijk}^M + x_{ijk}^O) \leq Cap_j pc_j \qquad \forall j \in P \qquad (2.1j)$$

$$\sum_{i \in S} \sum_{k=1,2,3} f_k (x_{ijk}^M + x_{ijk}^O) \geq Cap_j lc_j \qquad \forall j \in P \qquad (2.1k)$$

$$\sum_{i \in S} \sum_{k=1,2,3} f_k (x_{ijk}^M) \leq Cap_j pc_j\, pam_j \qquad \forall j \in P \qquad (2.1l)$$

$$\sum_{i \in S} \sum_{j:\, cat_j = 1,3} (x_{ijk}^M + x_{ijk}^O) \geq \alpha_k \sum_i \sum_j (x_{ijk}^M + x_{ijk}^O) \qquad \forall k = 1,2,3 \qquad (2.1m)$$

The first constraint computes provider congestion y_j as used in the objective function. The second constraint ensures at least a given percentage of the total state population is assigned to providers. In particular, we set the value of parameter c^{min} to the maximum value allowing feasibility of the model. The resulting value is equal to 90% for each state. Constraints (2.1c)-(2.1f) are assignment constraints that require assignment of patients to providers to be nonnegative and not greater than the census tract population. Constraints (2.1g)-(2.1i) mimic distance barriers encountered by patients, setting a maximum allowable distance considering vehicle ownership.

The next set of constraints mimics availability barriers. In particular, constraint (2.1j) ensures that the total number of patients assigned to each provider cannot exceed his or her maximum caseload. Constraint (2.1k) acknowledges that for a provider to remain in practice, he or she must maintain a sufficiently large number of visits per year. The value of parameter lc_j is set for each state as the maximum value for which feasibility of the model was achieved. Finally, constraint (2.1l) allows for different participation in the Medicaid program by limiting the total number of publicly insured who can be assigned to each provider.

The final constraint specifies that pediatric specialists cover a greater percentage of visits to children [50, 51] with respect to Family/Internal Medicine physicians. To this end, these constraints ensure that a given percentage α_k of the total patients in age class k are served by pediatric physicians and pediatric nurse practitioners.

2.2.4 Accessibility and Availability Measures

The solution produced by the optimization model is used to compute census tract-level accessibility and availability measures for primary care for all children, children eligible for public insurance, and children likely to be privately insured. *Accessibility* is quantified as the average *distance* a child in a census tract must travel for each visit to his/her matched provider, thus smaller values of the measure indicate better accessibility. *Availability* is quantified by the *congestion* a child experiences for each visit at his/her matched provider, where patient congestion is measured as the ratio between all assigned visits to a provider and his/her maximum caseload; thus smaller values indicate better availability. Children experiencing a distance of 25 miles or greater are assumed to be "unserved" by the existing network. Hence, the output represents the *served need*, which may be smaller than the need itself.

Extensive analysis was conducted to assess the sensitivity of the access estimates to variations in input data. We first tested the sensitivity of the model with respect to the percentage of providers' caseload devoted to children by varying parameter pc_j within range 0%-10% for internists and 7%-15% for family practitioners. Output measures were not found to be very sensitive to these changes. Full results are provided in Appendix A.1.

For provider workload, 50 different parameter settings of the model were considered by varying the caseload for each provider. Specifically, for each provider, gender was identified from NPPES information [38]. The age of that provider was then sampled from a normal distribution fit on data from [52] given their gender. Finally, that provider's caseload was determined according to their gender and sampled age using data derived from [53]. Details on these distributions are given in Appendix A.2. This process was repeated for all providers 50 times, and the caseloads obtained after each repetition were input into the optimization model for Cap_j. Thus, our output consists of 50 values of accessibility and availability measures for each census tract. We summarize the results based on all 50 settings.

2.2.5 Systemic Disparities: Measures and Statistical Inference

2.2.5.1 <u>Between-State Disparities</u>

To evaluate whether between-state disparities in accessibility and availability are systematic, we apply the one-sided hypothesis test of difference in the medians using the Wilcoxon signed-ranked test, for each pair of states and for each population group. This hypothesis test applies under the independence assumption, which does not hold since the access measures are spatially dependent. Because of this limitation, the test is more conservative in detecting differences between states.

Most papers in disparities compare whether any difference exists (i.e., $\delta = 0$). We consider multiple levels of differences to gain understanding of how large differences are, if they exist. The null hypothesis difference in medians thus takes three different levels for both accessibility and spatial availability:

- $\delta = 0$, $\delta = 1$ or $\delta = 2$ miles for the accessibility measure; and
- $\delta = 0.0$, $\delta = 0.1$ or $\delta = 0.2$ patient-to-provider caseload ratio for the availability measure.

2.2.5.2 Within-Sate Disparities

We group census tracts into three categories according to their rural-urban commuting area code (RUCA) [54]. We classify the census tracts as *Large Urban Areas* (RUCA = 1-3), *Small Urban Areas* (RUCA = 4-6), and *Rural Areas* (RUCA = 7-10). We then compare disparities in accessibility and availability between publicly-eligible children and children likely to be privately insured.

2.2.5.3 Intervention Maps

We identify served, underserved and unserved census tracts if the percentage of served need is at least 80%, between 50% and 80%, and less than 50%, respectively; these levels can be adjusted depending on the coverage targeted.

Using the method described in Serban [55] we identify the specific tracts where the difference in either accessibility or availability between the children eligible for public insurance and those who are likely to be privately insured is statistically significant. Specifically, we consider the difference process $Z(s) = M(s) - O(s)$ for each spatial unit

s (i.e., census tract) within a geographic domain (e.g. state). We decompose $Z(s) = f(s) + \epsilon_s$, with $f(s)$ the regression function assumed unknown and estimated using nonparametric penalized splines regression through the *mgcv* library in the R statistical software. Subsequently, we use the existing methods proposed by Serban [55], and Krivobokova et al. [56] to estimate simultaneous confidence bands $[l(s), u(s)]$ for the regression function $f(s)$. For those spatial units s or regions such that $u(s) < 0$, the difference is significantly negative, while for those spatial units s such that $l(s) > 0$, the difference is significantly positive. The results are displayed as point maps, where the points correspond to the centroids of the census tracts where the difference process $Z(s)$ is significantly negative or positive, defined as significance maps. A significance level of 0.01 is used.

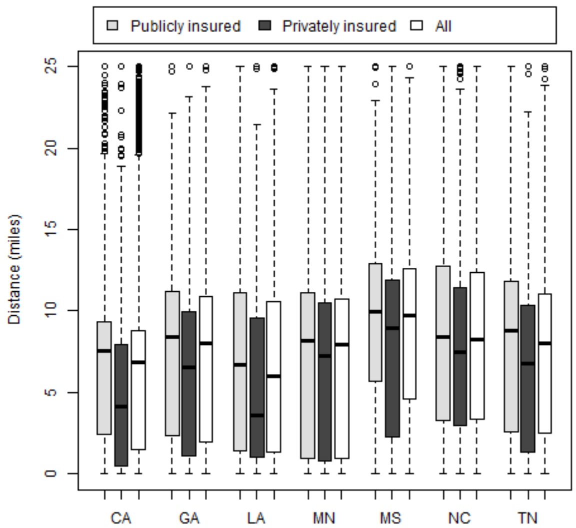
2.3 Results

The study population represents more than 9 million children across approximately 16,500 census tracts served by a network of more than 17,000 unique provider locations representing around 76,000 individual and group providers.

2.3.1 Between-State Disparities

Figure 2 displays the boxplots of the median of the access measures computed at the census tract level across all 50 settings for all census tracts in each of the seven states and for each population group. The median state-level distance to care for children eligible for public insurance ranges from 7.54 to 9.79 miles. For children likely to be privately insured, it ranges from 4.78 to 8.50 miles. The median state-level congestion for children eligible for public insurance ranges from 0.40 to 0.74. For children likely to be privately insured, it ranges from 0.39 to 0.70.

MEDIANS - DISTANCE



MEDIANS - CONGESTION

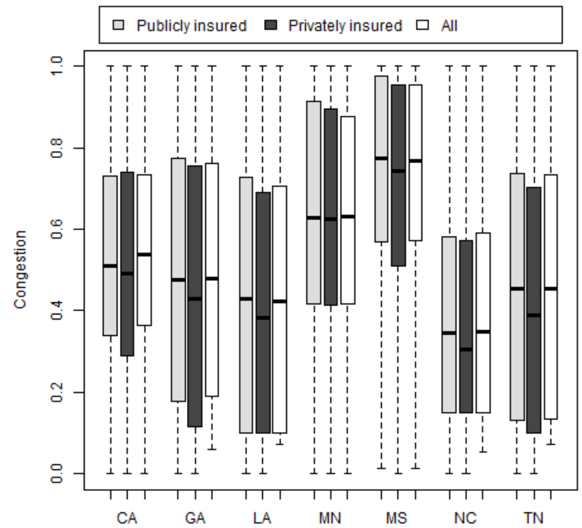


Figure 2. Distribution of medians of travel distance (in miles) and medians of congestion for different population groups. Each boxplot represents the distribution across census tracts after taking the median across the 50 runs for each census tract.

For each run, we apply the one-sided Wilcoxon test for comparison of medians of distance (in miles) for each pair of states (H_0: μ_{State1}-μ_{State2}≤δ vs. H_1: μ_{State1}-μ_{State2}>δ) for the children eligible for public insurance (Public) and children above the income threshold for public insurance (Private). Table 3 summarizes the results of these statistical comparisons with State 1 specified by the row and State 2 by the column. A symbol "*", "**", and "***" in the cell indicates a p-value less than or equal to 0.01 in at least 75% of the runs for null difference in medians δ=0, δ=1, and δ=2 respectively. The comparisons between congestion medians are similarly summarized for null difference in medians δ=0.0, δ=0.1, and δ=0.2 in Table 4.

Comparing accessibility (Table 3, null value $\delta = 0$), each state except Louisiana has a higher median distance than California for the eligible population, and all states have a higher median distance than California for the population likely to be privately insured; some differences remain significant at distance $\delta \leq 2$ miles for the population likely to be privately insured. Mississippi has higher median distance than all the other states for the eligible population, and it has a higher distance than all the other states, except North Carolina, for the population likely to be privately insured. Several states have higher median distance than Louisiana or Minnesota ($\delta = 0$ miles) for both population groups. There are no comparisons between pairs of states where the difference is statistically significant for $\delta \geq 2$ miles.

Comparing availability (Table 4, null value $\delta = 0$), Mississippi has a higher median congestion for both the population groups than all the other states. Minnesota has a higher median congestion for both the population groups than all the other states except Mississippi. All states except North Carolina have a higher median congestion than Louisiana for children eligible for public insurance insured. Additionally, all states except North Carolina and Tennessee have higher median congestion for children likely to be privately insured. All differences in medians are not statistically significant for $\delta \geq 0.1$.

Table 3. Between-state differences in median distance (in miles) a child must travel for visits to matched providers, by insurance type, averaged across 50 runs.

States	CA		GA		LA		MN	
	Public	Private	Public	Private	Public	Private	Public	Private
CA			-0.8082	-2.3116	0.8931	0.5933	-0.6064	-2.9870
GA	0.8082 *	2.3116 *		-1.0000	1.7013 *	2.9049 *	0.2018 *	-0.6754
LA	-0.8931	-0.5933 *	-1.7013	-2.9049		-1.0000	-1.4996	-3.5804
MN	0.6064 *	2.9870 *	-0.2018	0.6754	1.4996	3.5804 *		
MS	2.4092 **	4.7211 ***	1.6010 *	2.4095 *	3.3024 **	5.3144 **	1.8028 **	1.7341 *
NC	0.8453 *	3.2631 ***	0.0371 *	0.9515 *	1.7384 *	3.8564 **	0.2389 *	0.2761 *
TN	1.1832 *	2.4998 **	0.3750	0.1882	2.0763 *	3.0931 *	0.5768 *	-0.4872

States	MS		NC		TN	
	Public	Private	Public	Private	Public	Private
CA	-2.4092	-4.7211	-0.8453	-3.2631	-1.1832	-2.4998
GA	-1.6010	-2.4095	-0.0371	-0.9515	-0.3750	-0.1882
LA	-3.3024	-5.3144	-1.7384	-3.8564	-2.0763	-3.0931
MN	-1.8028	-1.7341	-0.2389	-0.2761	-0.5768	0.4872
MS			1.5639 *	1.4580	1.2260 *	2.2213 *
NC	-1.5639	-1.4580			-0.3379	0.7633 *
TN	-1.2260	-2.2213	0.3379	-0.7633		

Table 4. Between-state differences in median congestion, measured as the ratio between all assigned visits to a provider and his/her maximum caseload, by insurance type, averaged across 50 runs.

States	CA		GA		LA		MN	
	Public	Private	Public	Private	Public	Private	Public	Private
CA			0.0282 *	0.0653 *	0.0836 *	0.1127 *	-0.1192	-0.1312
GA	-0.0282	-0.0653			0.0554 *	0.0474 *	-0.1474	-0.1965
LA	-0.0836	-0.1127	-0.0554	-0.0474			-0.2028	-0.2439
MN	0.1192 *	0.1312 *	0.1474 *	0.1965 *	0.2028 *	0.2439 *		
MS	0.2619 *	0.2519 *	0.2901 *	0.3172 *	0.3456 *	0.3647 *	0.1428 *	0.1207 *
NC	-0.1632	-0.1935	-0.1350	-0.1282	-0.0796	-0.0808	-0.2824	-0.3247
TN	-0.0522	-0.0994	-0.0240	-0.0340	0.0314 *	0.0134	-0.1713	-0.2306

States	MS		NC		TN	
	Public	Private	Public	Private	Public	Private
CA	-0.2619	-0.2519	0.1632 *	0.1935 *	0.0522 *	0.0994 *
GA	-0.2901	-0.3172	0.1350 *	0.1282 *	0.0240	0.0340
LA	-0.3456	-0.3647	0.0796	0.0808	-0.0314	-0.0134
MN	-0.1428	-0.1207	0.2824 *	0.3247 *	0.1713 *	0.2306 *
MS			0.4251 *	0.4455 *	0.3141 *	0.3513 *
NC	-0.4251	-0.4455			-0.1110	-0.0942
TN	-0.3141	-0.3513	0.1110 *	0.0942		

2.3.2 Within-State Disparities

Table 5 shows differences in median travel distance (in miles) and median congestion of children eligible for public insurance vs. children above the income threshold for public insurance, averaged across the 50 runs. For each run, the Wilcoxon paired statistical test (H_0: $\mu_{Public} - \mu_{Private} \leq \delta$; H_1: $\mu_{Public} - \mu_{Private} > \delta$) was applied for each state for three different values of the hypothesized difference δ for the three different urbanicity classifications of the census tracts. A symbol "*", "**", or "***" in the cell indicates a median p-value less than or equal to α/4 (α=0.01), as specified in Bonferroni's method for correcting for multiple hypothesis tests, over the 50 runs for the three levels of difference δ respectively (δ=0, δ=1, and δ=2 for distance and δ=0.0, δ=0.1, and δ=0.2 for congestion).

Table 5. Within-state differences in median travel distance (in miles) and median congestion, averaged across 50 runs.

	Distance - Medians				Congestion - Medians			
	State	Large Urban	Small Urban	Rural	State	Large Urban	Small Urban	Rural
California	3.3381 ***	5.8216 ***	2.3172 ***	9.7767 ***	0.0133 *	0.0064 *	0.1217 *	0.3611 *
Georgia	1.8348 *	2.2379 *	1.2642 *	1.6948 *	0.0504 *	0.0474 *	0.0509 *	0.0842 *
Louisiana	3.0383 *	2.6598 *	1.0970 *	1.9829 *	0.0424 *	0.0591 *	0.0394 *	0.0497 *
Minnesota	0.9575 *	0.5092 *	1.0071 *	1.2097 *	0.0012 *	-0.0188	0.0333 *	0.0424 *
Mississippi	1.0263 *	1.3521 *	0.9263 *	1.2245 *	0.0233 *	0.0048	0.0545 *	0.0316
North Carolina	0.9203 *	0.5494 *	0.6730 *	1.3608 *	0.0436 *	0.0000 *	0.0327 *	0.0858 *
Tennessee	2.0216 *	2.2643 *	1.9465 *	2.4214 **	0.0605 *	0.0504 *	0.1124 *	0.0671 *

Median distance for the eligible children is statistically significantly higher than for children likely to be privately insured in each state and for all three urbanicity classes for a difference of $\delta = 0$ miles. The differences remain statistically significant at $\delta \leq 2$ miles for California for areas all urbanicity classes. These differences are not statistically significant for $\delta \geq 2$ for all the other states.

The eligible population has higher congestion in each state and for each urbanicity level with few exceptions at the null value $\delta = 0.0$. These differences are not statistically significant for $\delta \geq 0.1$.

Comparisons of medians of distance and congestion of children likely to be privately insured versus children eligible for public insurance across urban and rural census tracts are shown in Figure 3. The median distances for children eligible for public insurance range from 6.13 (large urban areas in Minnesota) to the maximum of 17.91 miles (rural areas in California). The median distances for children likely to be privately insured range from 4.44 (large urban areas in California) to 13.49 (rural areas in California) miles. The median congestion values for children eligible for public insurance range from 0.35 in large urban areas in North Carolina to the maximum of 0.79 in rural areas in California. The median congestion values for children likely to be privately insured range from 0.35 in large urban areas in North Carolina to 0.77 in rural areas in Mississippi.

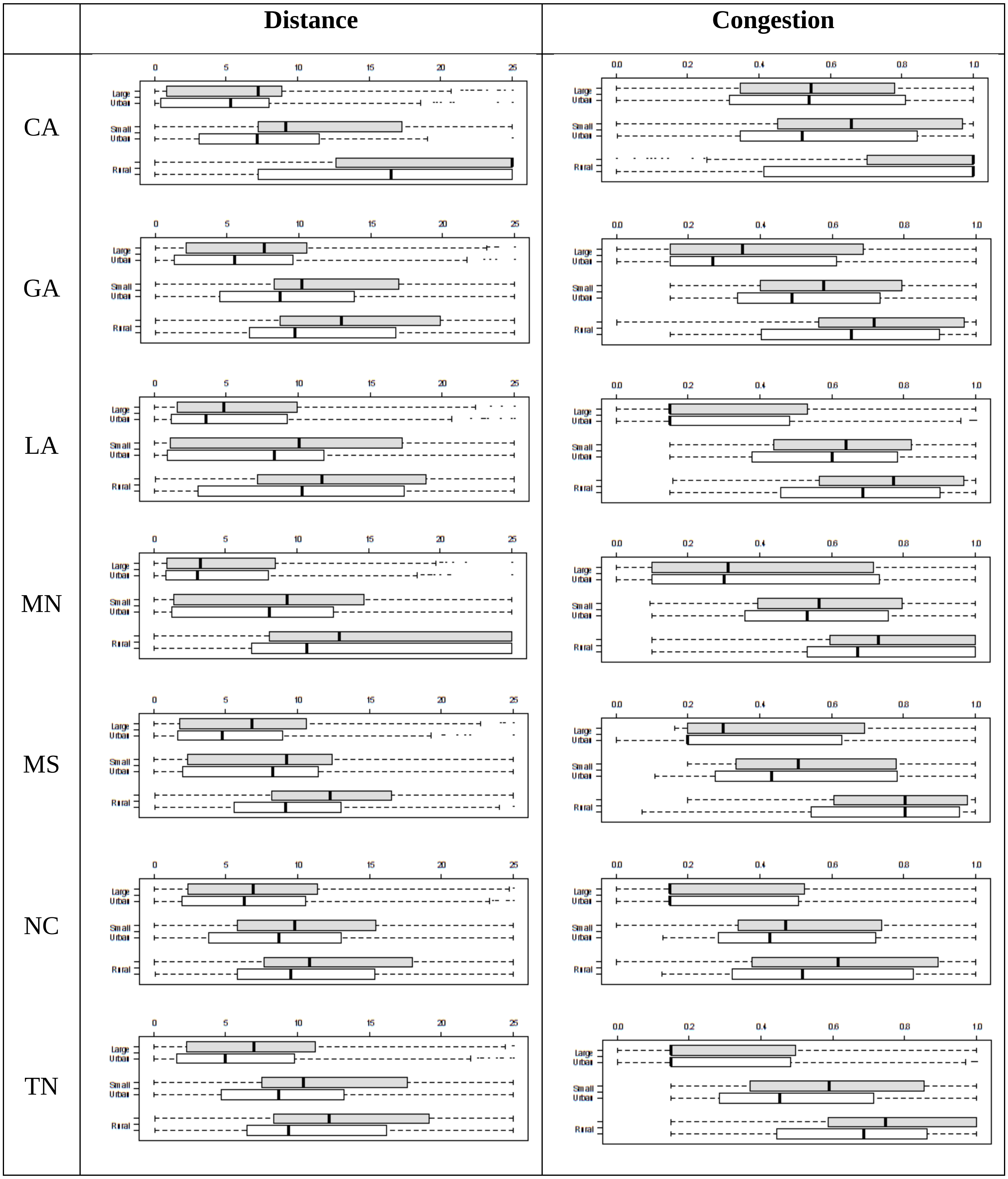


Figure 3. Distribution of census tract-level travel distance and congestion for publicly-insured (grey box) and privately-insured (white box) children in each urbanicity level for each state, after taking the median value across the 50 runs.

2.3.3 *Intervention Analysis*

For each run, we label each census tract as either served, underserved, or unserved based on its percentage of served need. Table 6 lists the average number of census tracts falling into each of the three categories across the 50 runs along with the 10^{th} percentile and 90^{th} percentile number of census tracts in parentheses. Figure 4 maps the category of each census tract based on its average percentage of served need across the 50 runs.

Table 6. Average [10^{th} percentile, 90^{th} percentile] number of census tracts across the 50 runs that are served, underserved, and unserved by state and urbanicity.

State	*Service Level*	*Entire State*	*Large Urban*	*Small Urban*	*Rural*
CA	**Served**	7046 [7041, 7051]	6795 [6790, 6800]	195 [193, 196]	56 [54, 57]
	Underserved	576 [567, 583]	481 [474, 488]	44 [43, 47]	51 [49, 54]
	Unserved	378 [375, 382]	222 [219, 225]	54 [53, 55]	102 [101, 104]
GA	**Served**	1595 [1593, 1597]	1365 [1363, 1367]	152 [151, 152]	79 [78, 79]
	Underserved	234 [231, 236]	153 [151, 156]	40 [39, 41]	41 [39, 42]
	Unserved	126 [125, 128]	72 [71, 73]	28 [27, 28]	27 [26, 28]
LA	**Served**	959 [957, 960]	818 [817, 819]	78 [77, 78]	63 [62, 64]
	Underserved	98 [96, 100]	58 [57, 59]	18 [18, 19]	22 [20, 23]
	Unserved	68 [66, 69]	42 [42, 42]	4 [4, 4]	22 [20, 23]
MN	**Served**	1118 [1116, 1120]	866 [865, 868]	116 [115, 117]	136 [135, 137]
	Underserved	122 [120, 124]	43 [41, 44]	22 [22, 23]	57 [55, 59]
	Unserved	94 [93, 95]	14 [14, 15]	15 [15, 15]	65 [64, 66]
MS	**Served**	558 [556, 560]	258 [257, 259]	194 [193, 195]	106 [104, 107]
	Underserved	76 [74, 78]	27 [26, 28]	20 [19, 21]	29 [28, 31]
	Unserved	21 [21, 22]	6 [6, 6]	9 [9, 9]	6 [6, 6]
NC	**Served**	1828 [1825, 1831]	1439 [1437, 1442]	280 [278, 283]	108 [106, 109]
	Underserved	222 [218, 225]	129 [126, 132]	50 [47, 52]	43 [41, 46]
	Unserved	120 [118, 121]	62 [61, 64]	23 [22, 24]	35 [34, 36]
TN	**Served**	1215 [1213, 1217]	963 [961, 964]	156 [154, 157]	97 [95, 98]
	Underserved	174 [170, 177]	91 [88, 92]	48 [47, 50]	35 [33, 37]
	Unserved	91 [89, 92]	35 [34, 36]	24 [23, 25]	32 [30, 33]

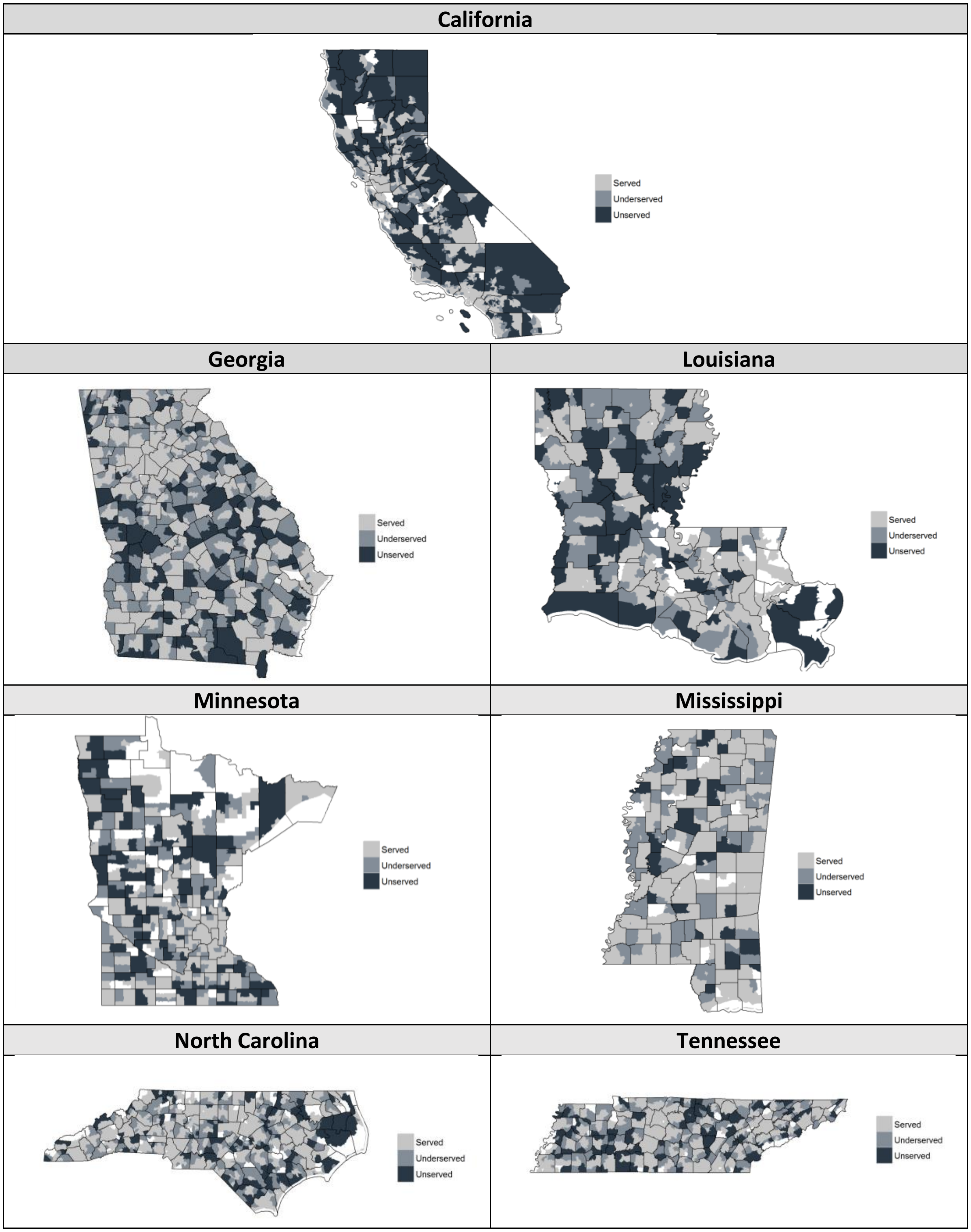


Figure 4. Map of census tracts that are served (light-grey; at least 80% of population assigned to a provider on average across the 50 runs), underserved (grey; 50-80% of population assigned on average), or unserved (black; less than 50% of population assigned on average). White-shaded census tracts were not included in the analysis.

The average percentage of served census tracts across the 50 settings ranges from 82% (Georgia and Tennessee) to 88% (California); the average percentage of underserved census tracts ranges from 7% (California) to 12% (Georgia, Mississippi, and Tennessee); the average percentage of unserved census tracts ranges from 3% (Mississippi) to 7% (Minnesota).

Census tracts identified as served or unserved tend to be located in a subset of counties, while those identified as underserved are in many counties dispersed around the state. The served tracts tend to be located in large urban areas. The percentage of large urban census tracts among the served census tracts ranges between 46% (Mississippi) to 96% (California). The unserved census tracts are located in large urban areas in all the states except Minnesota where they are mostly located in rural areas (69%) and Mississippi where they are located in small urban tracts (43%).

Results from significance maps are summarized in Table 7 and Table 8, which show for travel distance and congestion respectively the total number of census tracts where the publicly-insured population has a statistically significantly greater value (lower access) than the privately-insured population, at $\alpha = 0.01$ significance level in at least 75% of the runs. The column 'Tot' also contains the percentage of census tracts in the state meeting that criteria while the 'Large Urban', 'Small Urban', and 'Rural' columns contain the percentage of census tracts in each urbanicity category computed with respect to the total in the corresponding 'Tot' column. Results are reported for different values of the threshold δ.

The percentage of census tracts where children eligible for public insurance need to travel further to access care than the children likely to be privately insured ranges from 22% (North Carolina) to 71% (California). For δ=2 miles, the percentage varies from 0% (Mississippi and Minnesota) to 35% (California) including many in large urban areas.

There are relatively fewer census tracts where children eligible for public insurance have lower availability than the other children. The percentage of census tracts where the public insurance eligible experience higher congestion than the children likely to be privately insured ranges from 7% in Minnesota, Mississippi, and North Carolina to 24% in California. At δ=0.0, the tracts where availability is lowest for the public insurance eligible tend to be more concentrated in small urban and rural areas in Minnesota and Mississippi and more concentrated in large urban areas in the other states.

Table 7. Number (percent) of census tracts where the publicly-insured population has a significantly greater travel distance than the privately-insured population at $\alpha = 0.01$ significance level in at least 75% of the runs.

	Distance (Accessibility)											
	δ=0				δ=1				δ=2			
State	Tot	Large Urban	Small Urban	Rural	Tot	Large Urban	Small Urban	Rural	Tot	Large Urban	Small Urban	Rural
California	5711 (71%)	5402 (95%)	174 (3%)	135 (2%)	4262 (53%)	4008 (94%)	137 (3%)	117 (3%)	2778 (35%)	2566 (92%)	114 (4%)	98 (4%)
Georgia	973 (50%)	866 (89%)	60 (6%)	47 (5%)	364 (19%)	322 (88%)	17 (5%)	25 (7%)	140 (7%)	122 (87%)	4 (3%)	14 (10%)
Louisiana	425 (38%)	376 (88%)	11 (3%)	38 (9%)	147 (13%)	128 (87%)	1 (1%)	18 (12%)	37 (3%)	30 (81%)	1 (3%)	6 (16%)
Minnesota	1194 (90%)	851 (71%)	121 (10%)	222 (19%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Mississippi	592 (90%)	289 (49%)	183 (31%)	120 (20%)	125 (19%)	90 (72%)	27 (22%)	8 (6%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
North Carolina	485 (22%)	317 (65%)	105 (22%)	63 (13%)	129 (6%)	86 (67%)	24 (19%)	19 (15%)	12 (1%)	11 (92%)	0 (0%)	1 (8%)
Tennessee	593 (40%)	414 (70%)	101 (17%)	78 (13%)	358 (24%)	278 (78%)	39 (11%)	41 (11%)	183 (12%)	168 (92%)	0 (0%)	15 (8%)

Table 8. Number (percent) of census tracts where the publicly-insured population has a significantly greater congestion than the privately-insured population at $\alpha = 0.01$ significance level in at least 75% of the runs.

State	Congestion (Availability)											
	δ=0.0				δ=0.1				δ=0.2			
	Tot	Large Urban	Small Urban	Rural	Tot	Large Urban	Small Urban	Rural	Tot	Large Urban	Small Urban	Rural
California	1949 (24%)	1756 (90%)	96 (5%)	97 (5%)	727 (9%)	630 (87%)	40 (6%)	57 (8%)	179 (2%)	155 (87%)	9 (5%)	15 (8%)
Georgia	340 (17%)	217 (64%)	71 (21%)	52 (15%)	60 (3%)	60 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Louisiana	175 (16%)	140 (80%)	15 (9%)	20 (11%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Minnesota	99 (7%)	6 (6%)	38 (38%)	55 (56%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Mississippi	47 (7%)	0 (0%)	33 (70%)	14 (30%)	14 (2%)	0 (0%)	13 (93%)	1 (7%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
North Carolina	149 (7%)	96 (64%)	32 (21%)	21 (14%)	2 (0%)	0 (0%)	0 (0%)	2 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Tennessee	288 (19%)	193 (67%)	43 (15%)	52 (18%)	25 (2%)	4 (16%)	13 (52%)	8 (32%)	3 (0%)	1 (33%)	2 (67%)	0 (0%)

2.4 Discussion

This study uncovers systematic differences and disparities in accessibility and availability of pediatric primary care across seven states for public insurance eligible and children above the income threshold for public insurance. Disparities are quantified between- and within-states, comparing public insurance eligible versus likely to be privately insured children and across three urbanicity levels.

The study also introduces a framework that can be used to help support policymaking. The objective is to identify *where* the communities with the greatest need for improvement are and *which* spatial access dimensions need be targeted by policy makers in order to increase access to primary care for children. This framework will be especially useful if local data is available and the model assumptions adjust to fit the data.

The between-state pairwise comparisons reveal that children above the income threshold for public insurance have the best median accessibility in California, and public insurance eligible children have the best median accessibility in California, Minnesota and Louisiana. The median availability is the lowest in Louisiana for both population groups. While disparities between states exist, they are *not* significant for pairwise comparisons when considering intervention levels of a difference ≥1 mile in travel distance (except for comparisons with California) or a difference ≥0.1 in experienced congestion (except for comparison with Minnesota and Mississippi). This is an important finding as many disparity studies have only drawn inferences at zero absolute differences between states or between population groups [57-60]. While there are disparities between states, they are significant at low comparison levels, suggesting that within-state disparities are more relevant than those between states.

The within-state systematic disparities are more nuanced when comparing accessibility and availability for the two population groups and across urbanicity levels. In general, we *do* find that public insurance eligible children experience lower access than children above the income threshold for public insurance. However, the difference in accessibility is >*1* mile only for California, and for rural areas in Tennessee. The differences in availability are less systematic, with significant differences only for the level equal to 0.

The intervention analysis shows that the areas of lower spatial access can be found throughout a state across all urbanicity levels. Eligible children have worse spatial access than children likely to be privately insured across all the urbanicity levels. These findings highlight the importance of identifying specific areas where interventions are needed, with interventions targeted to the type of spatial access in need of improvement.

The findings for specific states may offer some guidance on where and how to target resources. For example, California has the greatest opportunity to improve accessibility for the public insurance eligible children as it has the largest percentage of communities

(~53%) where the eligible children need to travel more than 1 mile further than the other children, in contrast to all other states for which the percentage ranges between 0% in Minnesota to 24% in Tennessee.

For other states such as Georgia and Minnesota, census tracts with high accessibility are geographically clustered, especially in urban areas, while being significantly worse for publicly-insured children in some of those same areas. For the same states, communities with low availability are spread throughout the state, thus interventions to improve availability are more challenging to implement since the communities in need are spread throughout the state as compared to interventions for improving accessibility. These findings suggest interventions need to be targeted to the local need, combining both policy interventions for improving public insurance acceptance by providers already in practice and network interventions that add providers to some areas (e.g. telehealth, school-based health centers, and mobile clinics).

In states such as Tennessee, North Carolina and Louisiana, public insurance eligible children experience lower accessibility and availability throughout the state, indicating that investments in multiple types of statewide interventions would be needed, particularly policy interventions targeting access for publicly-insured children. In states such as Mississippi, spatial access is systematically low both populations, thus targeting network interventions that would lead to an increase in the primary care providers, both physician and mid-level providers, will have the highest impact.

2.5 Limitations

This study has several limitations, many of which stemming primarily from the limited availability of detailed data. First, we used income thresholds for public insurance programs to estimate the numbers of children who are publicly insured. Because the ACS data used to estimate household income are not the same as the units of measure for insurance eligibility and low income populations are more likely to live in multi-family households, the model may underestimate the number of children eligible for public insurance.

Second, because no single data source exists that identifies all providers who provide primary care to children or that quantifies caseload, we have used multiple data sources and a series of assumptions; thus, supply and locations of service may have been under or overestimated. To know the supply of health care providers, we used the NPEES database for information on geolocation for each provider and on provider type. NPPES provides provider-level data on both specialty and location; however, it has limitations. Since some nurse practitioners bill under physician's national provide index (NPI), the supply of pediatric primary care may be underestimated. This may be offset by the fact some physicians spent significant time in supervising mid-level providers as well as residents, interns and fellows. Moreover, some providers may practice from different offices, while only the business address is provided with the provider's NPI. We also use the MAX files for obtaining information on the Medicaid acceptance rates, although Medicaid MAX files can have data quality issues, especially for states with large populations on managed care [61]. We did not capture the differences among states of the variation of providers' caseload devoted to the publicly insured. It is also possible that there are some providers who would see patients on CHIP but not patients on Medicaid, and this is not captured in our data.

Third, household level data on transportation options by income thresholds for eligibility for public insurance were not available, so we compare the estimated income derived from census data with the federal net-income thresholds instead of modified adjusted-gross income (MAGI)-equivalent minimum thresholds as defined in federal public insurance coverage laws and regulations.

A final limitation is the set of assumptions specifying some of the system constraints. We assume the maximum provider capacity is the same across all providers. We assume the same maximum willingness to travel for populations in both rural and urban areas. We do not account for changes in the percentage of physicians practicing pediatric primary care after 2013. We are also estimating need for pediatric care using recommendations for wellness visits for children. We do not include visits for minor illnesses or more intensive care for children with chronic or complex conditions. Thus we underestimate the level of access for some children. We assume that the disutility of crowding is linear although in other papers we have shown how the model can incorporate nonlinear functions. We also estimate matches between patients and providers assuming a centralized framework; in other papers we have shown how the model can incorporate decentralized decision making with patients maximizing their own individual welfare.

Overall, most of the above stated assumptions can be relaxed with the acquisition of local-level, detailed data. This would be paired with minor modifications to the model used to account for the provider-specific or geographical-specific data.

2.6 Conclusions

Even though this study has limitations, it has potential implications for public health and health care policy. While concerns about the availability of primary care providers have been expressed within recent health policy, this study finds that across states the disparities in availability for pediatric primary care are not as significant as the disparities in accessibility. Moreover, contrary to some beliefs, despite potential gains in insurance coverage over the last several years, both rural and urban communities are in need for improvement of accessibility to primary care for publicly-insured children.

More generally, the findings in this study suggest that some policies will be more effective than others in addressing disparities in spatial access, while the policy recommendations depend on the state. For some states, incentivizing providers to accept public insurance could improve spatial access for public insurance eligible children, but incentivizing providers in some other states would not generate the same result since access for children likely to be privately insured also needs improvement. For all states, since unserved communities are spread across counties, interventions to provide access to pediatric primary care for these communities need to be more targeted, e.g., school telehealth clinics at school-based health centers.

The study thus shows that generating specific recommendations for small areas within states is needed to shift the needle on access to care for children. This can be done with additional data specific to local areas with minor modifications to the model. Continuing to refine the model and data will ensure that the approach is reliable and accurate, while promoting the use of interventions that are most appropriate in a given locale.

CHAPTER 3. PROJECTING THE IMPACT OF AFFORDABLE CARE ACT PROVISIONS ON ACCESSIBILITY AND AVAILABILITY OF PRIMARY CARE PROVIDERS FOR THE ADULT POPULATION IN GEORGIA

3.1 Introduction

Several policy interventions have been implemented and evaluated to improve healthcare access, to ultimately reduce health disparities [5, 62]. The most recent and comprehensive among these interventions are the provisions in the Patient Protection and Affordable Care Act (ACA). One primary emphasis of ACA is to eliminate disparities in financial access to healthcare, particularly, for the most disadvantaged populations. While affordability (i.e., financial access) is an essential dimension of healthcare access, other dimensions such as availability and accessibility are equally relevant to reduce health disparities. Improving spatial access, referring to availability and accessibility together, is especially important for the Medicaid-insured population due to a smaller network of providers accepting Medicaid insurance [11, 15, 16].

Because ACA's implementation will transform healthcare delivery in ways that are not fully understood, it is expected to have unintended consequences that could counteract its overall benefits. For example, although the ACA primarily focuses on financial access, it will also impact other forms of healthcare access. Availability and accessibility are functions of the available network of providers (supply) and of the patients accessing the healthcare services (demand/need). These will be greatly affected by the main provisions of the ACA, including the individual mandate, the exchange insurance market, the end of the pre-existing health condition exclusions, and the optional expansion of Medicaid eligibility, but also by provisions that could result in an increase in the number of primary care providers and/or the acceptance rate of the Medicaid insurance program.

Many studies [53, 63-66] forecast that the resulting increase in the demand of care due to these provisions may not be adequately supported by the supply of healthcare services, with an estimated need of primary care physicians of around 20,400 in 2020 as provided by [53], for example. This is a concern because too few physicians or inadequate supply could lead to services being delayed or forgone altogether. The delay may worsen health conditions, eventually resulting in an increase of severe health outcomes.

Although most existing studies on the impact of the ACA provisions provide nationwide or state-level projections [53, 66-68], the projected impact will vary geographically because of the pre-existing disparities in access and because of the variations in the implementation of the ACA and state-level health policies. Understanding the ACA's projected impact on other dimensions of healthcare access locally at the community-level is paramount in facilitating targeted interventions and most effective resource allocation [69-70].

The aim of this chapter is to project how spatial access is impacted by the implementation of the ACA for the non-elderly adult population. The questions we address are:

• What is the projected impact of ACA without Medicaid expansion on availability and accessibility of primary care providers geographically and over time?

• What is the projected burden of opting for Medicaid expansion on availability and accessibility of primary care providers geographically and over time?

• Does a higher rate of Medicaid insurance acceptance by providers or/and an increase of the overall supply result in an improvement in the served need for primary care services?

The methods include three models: a supply-projection model, a need-projection model, and an optimization model. The supply and need models predict the total number of available (supply) and needed primary care visits for each year from 2013 (the baseline year) until 2025. The optimization model estimates served need for primary care visits by matching the projected supply and need under a series of access constraints. Availability and accessibility are projected at the census tract level by contrasting served to needed visits.

We pilot our study for the state of Georgia, but the proposed models can be generalized and applied to other states in the U.S. Material in this chapter has been published at [71].

3.2 Methods

3.2.1 Study Population

The study population consists of all adults age 19-64 living in Georgia. The Medicare population is excluded since the Medicaid and the exchange market primarily impact the insurance status of the population younger than 65. The child population is also excluded since the Medicaid expansion does not apply to this population.

3.2.2 Data Sources

Data sources used for the supply projection model include the 2013 National Plan & Provider Enumeration System (NPPES) [38], the Georgia Board for Physician Workforce's 2013 Spotlight on Graduate Medical Education [72], the Georgia Board for Physician Workforce's 2008 Basic Physician Reports [73], the Centers for Disease Control's National Vital Statistics Reports [74], the 2007-2011 American Community Survey (ACS) County-to-County Migration Flows by Educational Attainment table [75], and the 2012 ACS Educational Attainment table [42].

Data sources used for need projections include the Governor's Office of Planning and Budget's residential population projections [76], the 2010 Census and the 2012 and 2013 American Community Surveys [42], 2006 median income data from Environmental Systems Research Institute [77], estimates from Kaiser Family Foundation/Urban Institute - Table ES-3 [78], and Congressional Budget office estimates – Table 3 [79].

An additional data source for the optimization model is the 2009 MAX Medicaid patient-level claims files [40].

Provider addresses are geocoded using the Texas A&M Geocoding Services [80], and street-network distances between census tract centroids and provider addresses are computed using the ArcGIS Network Analyst [45].

3.2.3 Supply Projection Model

According to the definition of Primary Care of the Institute of Medicine’s Committee [81], primary care providers include general and family medicine and general internal medicine, including physicians, Nurse Practitioners (NPs) and Physician Assistants (PAs). We use

NPPES to identify these providers, both to additionally obtain their specific location information and to avoid inconsistences in other databases [82]. We consider only individual provider records [83].

The supply-projection model consists of three steps: county-level projections of active workforce, distribution of projected supply across census tracts, and conversion of available supply in number of visits, all obtained yearly and for all counties. These steps, as well as alternate supply scenarios that we consider, are detailed in the next subsections.

3.2.3.1 County-level Projections

In the first step, a stock-and-flow model [84] computes the total number of active physicians yearly by considering the current level of physicians plus the net flow. The net flow is the difference between new entrants in the workforce (new graduates practicing in Georgia and immigrants) and exit from the workforce (due to retirement, death, profession change, and emigration) [53]. The model includes two modules, the Student and Workforce Modules. Output of these modules was found to be comparable to national-level projections, suggesting their validity (see Appendix B.1 for details).

The Student Module determines the number of students completing graduate medical education in Georgia and entering the workforce for the first time, assuming that students graduate after three years [72, 85]. After completing the residency, students either emigrate from Georgia or join the Georgia physician population, where they may choose to practice in other specialties or in primary care. Using data from the Georgia Board for Physician Workforce on graduate medical education [72], we estimate the input parameters of the module including the percentage of graduates practicing out of Georgia and/or choosing to practice in other specialties than primary care. (See Figure 5).

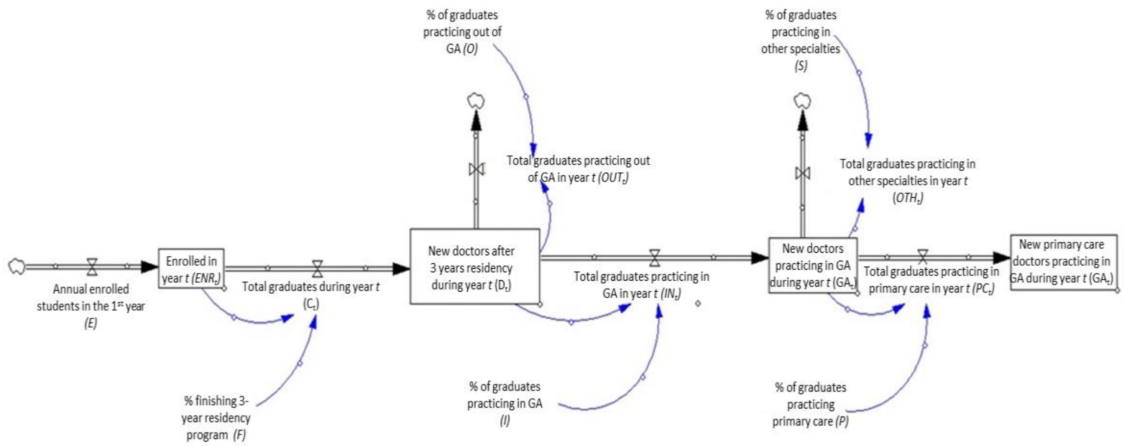


Figure 5. Student Module flowchart.

The Workforce Module determines age and county of each physician currently working. Physicians age 35 to 64 flow through the system by transitioning between stocks representing 5-year age categories. We assume physicians at the age of 75 either retire or enter administrative roles. New physicians enter the age <35 stock after graduating and new graduates are allocated to each county according to the distribution of the primary care physicians across counties in the baseline year of 2013. The initial age distribution within each county is assumed to be the same as in the 2008 reports [73]. If a county does not have a 2008 report, we use the average of the counties belonging to the same Primary Care Service Area.

To incorporate physicians' immigration from outside Georgia, each age stock has an additional inflow by which providers enter the workforce according to rates computed using ACS data on education attainment and migration flows [42, 75]. To incorporate physician attrition, each age stock has an additional outflow, again considering emigration patterns as well as death rates taken from tables I-7 and I-8 of [74].

A stock of NPs and PAs is added to the county total workforce based on data from previously published studies. In particular, the growth of PAs is based on the conservative national growth in PAs between 2013 and 2026 projected by Hooker and Muchow [86]. We assume the PA growth for Georgia is the same as the national growth and a constant number of PAs is added each year to obtain the percentage growth between 2013 and 2025. A similar procedure, based on the projection of registered nurses in Georgia between 2012 and 2025 by Health Resource and Service Administration [87], is applied to obtain the total number of NPs in each year. The county of each additional PA and NP is then determined according to the distribution of all primary care providers in the base year.

3.2.3.2 Census Tract Distribution

For the baseline year, physician locations are given in the NPPES data [38]. For future years, if a county and age class is projected to have fewer physicians than the previous year, we remove a randomly-selected physician in that county and age class.

If instead an increase is projected, we distribute the projected supply surplus across locations using a recursive sampling approach. For each additional physician, we first sample a census tract within that county using a weighted sampling procedure, where weights are estimated using the distribution of all providers (i.e. physicians, PAs, and NPs) in the baseline year with a small non-zero probability given to census tracts that had no providers in 2013. We next assign a location within that census tract to that physician by sampling from all provider locations existing in the previous years. If the census tract had no previous locations, we randomly select a location (latitude and longitude) in the census tract using information about the census tract shapefiles.

A similar procedure is applied to distribute PAs and NPs.

3.2.3.3 Conversion to Visits

The census tract-level workforce estimates are converted to number of available visits using *proficiency ratios* (i.e. the average number of yearly visits per provider). Specifically, we use data published in [53] on Average Patient Care Hours Worked per Week by General Internal Medicine Physicians. Data are reported by age class and gender in full-time-equivalent units and, by considering 45 hours per week, 50 weeks per year, and an average visit duration equal to 16 minutes (equivalent to a panel size of 2500 patients per year per physician [39] and approximately 8400 visits per year), we derived the annual number of visits per physician by age and gender. Using the gender distribution reported in [88] for which 67% of physicians are male and 33% are female, we obtain the final proficiency ratios for physicians (Table 9).

Table 9. Total number of yearly visits per primary care physician, by age.

Age	Male	Female	Overall
<40	8736	6888	8126
40-44	8988	7224	8406
45-49	9240	7644	8713
50-54	9912	8064	9302
55-59	9576	7896	9022
60-64	8904	6216	8017
> 64	7056	7560	7222

We assume NPs and PAs all have a proficiency ratio equal to 8401, the average among the age classes of the proficiency ratios of primary care physicians.

3.2.3.4 Supply Interventions

We run the model considering three growth scenarios to account for expected growth in the number of residency positions available in Georgia [89]: 0% (constant), 12% (medium) and 30% (high) growth in the number of enrolled graduate students.

Provider acceptance of publicly-insured patients is estimated using the approach in [13]. We account for possible changes in the Medicaid participation among physicians due to the Medicaid Parity Program [90], by considering: Medicaid acceptance ratios increase only in years 2013 and 2014 (without Parity), and Medicaid participation increases for the entire study period (with Parity). The increment in the Medicaid acceptance ratio due to the Medicaid Parity Program is estimated to be 13.03% [91].

3.2.4 Need Projection Model

We project need and not demand of medical care to estimate potential spatial access of primary care, which reflects important potential barriers to care. Demand depends on several factors such as income and education. For example, in the Grossman's model [92], highly educated people are expected to be more efficient producers of health. Our estimates of need, however, are driven by demographic characteristics and health status [93, 94]. We use utilization data as a measure of self-assessed health status, since "self-assessments often provide the 'trigger' that leads to consultations with primary care providers" [93].

Need is projected for three age classes (19-24, 25-44, and 45-64), by insurance status, and by gender. Insured population is divided into eligible for Medicaid and with private insurance. Under no-ACA and non-expansion of Medicaid, only adults with children under

18 and a family income of less than 36% of the federal poverty level (FPL) are eligible for Medicaid. ACA implementation with non-expansion of Medicaid additionally makes non-elderly people in families with income between 100 and 400 percent of FPL eligible for health insurance subsidizes. Under Medicaid expansion, all adults with income below 138% of FPL are eligible for Medicaid. Figure 6 summarizes the eligibility criteria for the three scenarios.

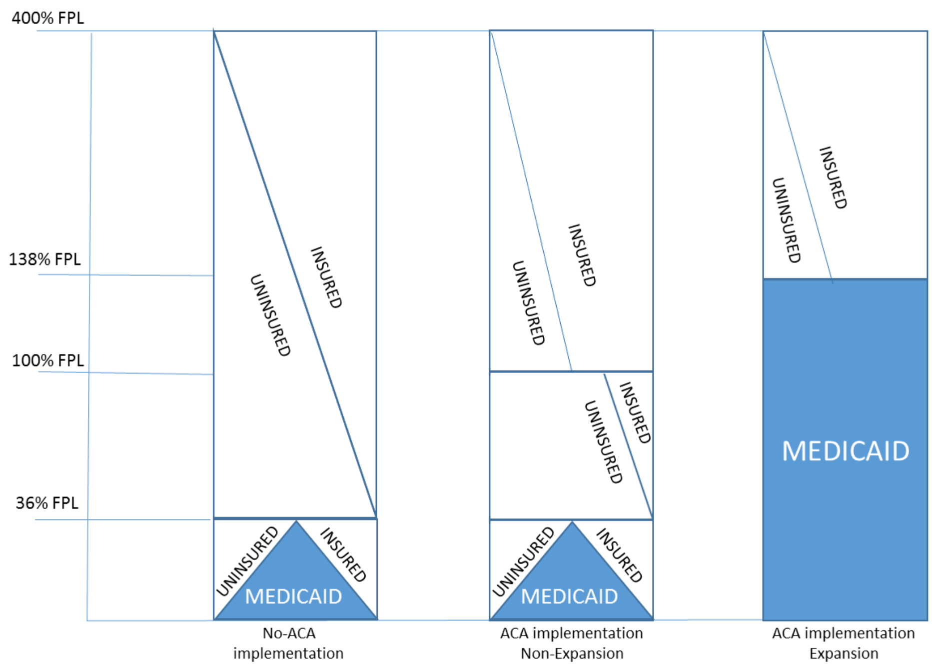


Figure 6. Medicaid eligibility criteria under different ACA implementation scenarios.

Our model consists of three steps. First, the number of adults eligible for Medicaid under each scenario is forecasted for each census tract and year. Second, we use published estimates to compute the number of uninsured and privately-insured adults in each county. These two steps are described in detail in the following subsections. Finally, adults are distributed to census tracts and split into age and gender classes according to ratios computed from 2010 Census Table PCT3.

3.2.4.1 Projecting Medicaid-insured

Regression models are used to project the total Medicaid-eligible population in Georgia in each county for each ACA implementation scenario. Specifically, for the baseline year, regression models are fit on the number of married family households with children under 18, single parent households, and family households without children in each county using characteristics such as average household size, education, age, race, average rent, and median income. Future household estimates are produced by forecasting predictors to future years. Full model details are given in Appendix B.2. The predicted household counts are divided into income ranges to determine eligibility and converted into number of nonelderly adults using ratios computed from 2010 Census and 2012 ACS data.

We assume the number of nonelderly adults in group quarters and nonfamily households stays proportional to the total number of nonelderly adults each year and that these adults do not have children. Therefore, these adults are only eligible for Medicaid under the Medicaid-expansion scenario. The proportion of these adults below 138% of FPL is assumed to be the same as the proportion of all adults within 138% of FPL given in 2012 ACS Table B17024.

3.2.4.2 Projecting Uninsured and Privately-insured

For each county, we obtain the baseline percentage of non-elderly uninsured adults with respect to FPL using the 2013 ACS Table C27016 and the population forecasted each year from the Governor's Office of Planning and Budget [76].

For the no-ACA scenario, we assume the proportion uninsured stays equal to the 2013 estimates each year.

For the Medicaid expansion scenario, we assume the percent uninsured decreases over the years due to the effect of the individual mandate. In particular, we assume that the total reduction of the uninsured population in Georgia in 2022 and in the subsequent years with respect to the baseline no-ACA implementation scenario is equal to 51.3% as estimated by the Kaiser Family Foundation/Urban Institute: State-by-State implication of ACA [78]. We project such a reduction year-by-year by using the nationwide year-by-year change estimates from the Congressional Budget Office [79], shown in Figure 7.

For the non-expansion scenario, we split the population into those under 138% of FPL and those over. Because adults under 138% of the FPL are eligible for a hardship exemption to the individual mandate if their state does not expand Medicaid, we assume for this group that the proportion uninsured each projected year stays equal to the 2013 census estimate. For adults over 138% of the FPL, we apply the reduction in uninsured that was described for the Medicaid expansion scenario. Note, combined with the uninsured under 138% of FPL, the total reduction of the uninsured population in Georgia in 2022 with respect to the baseline scenario is equal to 27.7%, close to the estimate of 28% by [78].

For each county, year, and ACA implementation scenario, we subtract our forecasted number of Medicaid-eligible adults and the estimated number of uninsured from the total nonelderly adult population forecasted by [76] to obtain the number of privately insured.

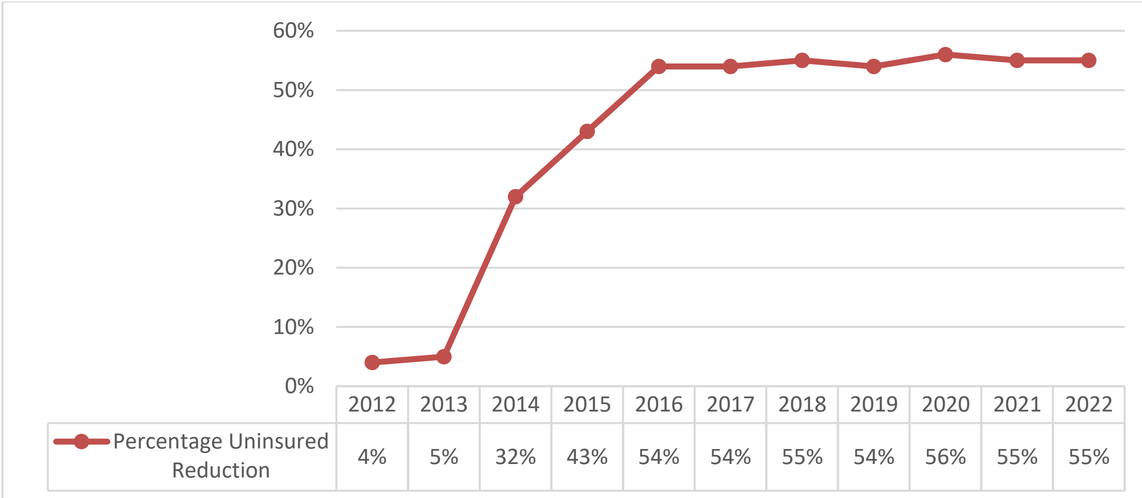


Figure 7. Congressional Budget Office's yearly estimates of proportion of uninsured that will be covered nationwide.

3.2.5 Optimization Model

We apply an optimization model similar to the one described in Chapter 2 Section 2.2.3 to match need and supply under a series of access constraints such that the travel to care is optimized.

Decision variables represent the total number of patients in each census tract of a given age class and gender assigned to a specific provider location, namely x_{ijgk}^{M} and x_{ijgk}^{O}, where index $i \in C$ represents a census tract, index $j \in P$ represents a provider location, index k denotes a specific age class, index g represents the gender, and superscripts M and O distinguish between adults covered by Medicaid and adults covered by private insurance respectively.

We assume an important factor influencing a patient's choice in provider is distance, hence, patients prefer to visit nearby physicians. Thus, our objective function is the weighted sum of the total distance traveled which needs to be minimized:

$$min\left(\sum_{i\in S}\sum_{j\in P}\sum_{k\in K}\sum_{g\in G} d_{ij}v_{kg}\left(x_{ijkg}^{M}+x_{ijkg}^{O}\right)\right)$$

where d_{ij} is the distance between the centroid of census tract i and provider location j and v_{kg} are provider utilization ratios (the average number of office visits per patient) per age class k and gender g, provided by [66].

Constraints for the model are described in Table 10 with parameter descriptions given in Table 11. Note, capacity s_j at location j returned by the supply projection is decreased by 55% to account 10% visits devoted to children [36] and for 45% visits devoted to elderly population [95]. Also, following guidelines established by the U.S. Department of Health and Human Services on rational areas for the delivery of primary medical care [44], we set a maximum possible travel distance of 25 miles for those with a vehicle and 10 miles for those without.

The output of the model consists of the optimal assignment of needed visits in each census tract to providers in the network, while the needed visits within a census tract may be assigned to different providers or/and a proportion of the need may not be served. Hence, the model provides estimates of the served visits for primary care. The difference between the needed and served visits provides the unmet need, describing patients' ability to find providers who will serve them.

Table 10. Detailed mathematical formulation of the adult primary care optimization model.

	Brief Description
$min\left(\sum_{i\in S}\sum_{j\in P}\sum_{k}\sum_{g} d_{ij}v_{kg}\left(x_{ijkg}^{M}+x_{ijkg}^{O}\right)\right)$	The objective function is the minimization of the total weighted traveled distance.
$\sum_{j} x_{ijkg}^{M} \leq p_{ikg}^{M}$ $\quad \forall i \in C, \forall k \in K, \forall g \in G$ $\sum_{j} x_{ijkg}^{O} \leq p_{ikg}^{O}$ $\quad \forall i \in C, \forall k \in K, \forall g \in G$ $\sum_{i}\sum_{j}\sum_{k,g}(x_{ijkg}^{M}+x_{ijkg}^{O}) \geq c^{min}\sum_{i}\sum_{k,g}(p_{ikg}^{M}+p_{ikg}^{O})$ $x_{ijkg}^{M} \geq 0, x_{ijkg}^{O} \geq 0$ $\quad \forall i \in C, \forall k \in K, \forall g \in G, \forall j \in P$	<u>Assignment constraints</u> that ensure total number of Medicaid-insured (privately-insured) patients assigned to providers in each census tract does not exceed the total estimated Medicaid-insured (privately-insured) population, a minimum number of patients are assigned, and assignments are non-negative.
$\sum_{j:d_{ij}\geq mi^{max}}\sum_{k,g}(x_{ijkg}^{M}+x_{ijkg}^{O}) = 0$ $\quad \forall i \in C$ $\sum_{j:d_{ij}\geq mob^{max}}\sum_{k,g} x_{ijkg}^{M} \leq mob_{i}^{M}p_{i}^{M}$ $\quad \forall i \in C$ $\sum_{j:d_{ij}\geq mob^{max}}\sum_{k,g} x_{ijkg}^{O} \leq mob_{i}^{O}p_{i}^{O}$ $\quad \forall i \in C$	<u>Accessibility constraints</u> which mimic distance barriers encountered by patients.
$\sum_{i}\sum_{k}\sum_{g} v_{kg}(x_{ijkg}^{M}+x_{ijkg}^{O}) \geq\ lc * s_j * \delta$ $\quad \forall j \in P$ $\sum_{i}\sum_{k}\sum_{g} v_{kg}(x_{ijkg}^{M}+x_{ijkg}^{O}) \leq s_j * \delta$ $\quad \forall j \in P$ $\sum_{i}\sum_{k}\sum_{g} v_{kg} * x_{ijkg}^{M} \leq pam_j * s_j * \delta_c$ $\quad \forall j \in P$	<u>Availability constraints</u> which require providers to maintain a sufficiently large number of visits to remain in paractice and to stay within their overall capacity and capacity available for Medicaid.

Table 11. Parameters used in the adult primary care optimization model.

Parameters of the Model	***Description***	***Value***	***Data Source***
$\boldsymbol{p_{kgi}^{M}}$	Total Medicaid-insured population in age class k, gender g, at census tract i.		Demand Projection Model
$\boldsymbol{p_{kgi}^{O}}$	Total privately--insured population in age class k, gender g, at census tract i.		Demand Projection Model
$\boldsymbol{p_{kgi}^{U}}$	Total uninsured population in age class k, gender g, at census tract i.		Demand Projection Model
$\boldsymbol{mob_{i}^{M}}$	Percentage of Medicaid-insured population in census tract i that owns at least one vehicle		2010 Census and 2012 American Community Surveys [42]. Assumed constant for each year.
$\boldsymbol{mob_{i}^{O}}$	Percentage of privately-insured population in census tract i that owns at least one vehicle		2010 Census and 2012 American Community Surveys [42]. Assumed constant for each year.
$\boldsymbol{mi^{max}}$	Maximum allowed distance (in miles) between a patient and the matched provider	25	US Department of Human and Health Services [44]. Assumed constant for each year.
$\boldsymbol{mob^{max}}$	Maximum allowed distance (in miles) between a patient and the matched provider when the patient does not own a vehicle	10	-
$\boldsymbol{d_{ij}}$	Distance between centroid of census tract i and provider j		Assumed constant for each year. ArcGIS Network Analyst [45], 2013 NPI data (for provider location) [38], 2010 SF2 100% Census data (for centroid location) [42].
$\boldsymbol{v_{kg}}$	Number of yearly visits of a person with insurance coverage in age class k of gender g		Assumed constant for each year [66]
$\boldsymbol{c^{min}}$	Minimum percentage to be assigned providers		Experimentally evaluated
$\boldsymbol{s_{j}}$	Total available visits at provider location j		Supply projection model
$\boldsymbol{lc_{j}}$	Percentage of provider's caseload necessary to remain in practice		Experimentally evaluated
$\boldsymbol{pam_{j}}$	Probability that providers in location j accept Medicaid-insured patients		Assumed constant for each year. MAX Medicaid Claims data [40].
$\boldsymbol{\delta}$	Percentage of provider's caseload dedicated to non-elderly population	45%	[36], [95]
$\boldsymbol{\delta_{c}}$	Percentage of Medicaid provider's caseload dedicated to non-elderly population	90%	[36]

3.2.6 Availability and Accessibility Measures

We use the results of the optimization model to measure spatial access to primary care for the adult population at the census tract level yearly.

We measure both accessibility and availability by means of two indices that vary between zero (worst value) and one (best value). In particular, accessibility is measured as one minus the ratio between the average distance a person travels to reach his/her assigned provider and the maximum allowed distance according to the guidelines established by the U.S. Department of Health and Human Services [44]. Hence, for a given census tract, if the average distance a person travels for each visit is 10 miles (25 miles), the corresponding accessibility index for the census tract is 0.6 (0.0). Availability is measured as one minus the congestion (the ratio between the visits assigned to a provider and his/her maximum caseload) a person in the census tract experiences for each visit at his/her assigned provider. Hence, if the average congestion of a physician in a given census tract is equal to 80% (the number of visits assigned to a typical provider is 80% as large as his/her maximum caseload), the availability index in the census tract is equal to 0.2. We assume people who are not assigned to a provider have the worst spatial access, hence regions whose population is not assigned to any provider are assumed to experience lowest accessibility and availability equal to 0.

Similar to Section 2.2.5 of Chapter 2, we identify the specific tracts where the difference in either accessibility, availability or served need between two given scenarios is statistically significant by considering the difference process $Z(s) = M1(s) - M2(s)$ for each spatial unit s (i.e., census tract) within a geographic domain (e.g. state). We consider multiple levels of differences to gain understanding by how large differences are, if they exist. The difference thus takes three different levels, i.e., δ=0.0, δ=0.05, or δ=0.1. We again create significance maps, where points correspond to the centroids of the census tracts where the difference process Z(s) is significantly negative or positive. With each map is an associated table containing the number of locations where the difference process is statistically significantly positive, negative and of no change. A significance level of 0.05 is used.

3.3 Results

Results are obtained for 13 possible different scenarios Table 12 of different implementations of Medicaid eligibility expansion (no-ACA, non-expansion, expansion), different supply growth rates (constant, medium, high), and different Medicaid acceptance ratios (without Parity, with Parity). The baseline scenario corresponds to no-ACA, constant supply growth and without Parity.

Table 12. Different policy scenarios considered.

	Medicaid Parity WITHOUT Expansion (without Parity)			Medicaid Parity WITH Expansion (with Parity)		
Need/Supply	Constant Growth (0% increase)	Medium Growth (12% increase)	High Growth (30% increase)	Constant Growth (0% increase)	Medium Growth (12% increase)	High Growth (30% increase)
No-ACA Implementation	1 (baseline)	-	-	-	-	-
ACA Non-expansion	2	3	4	8	9	10
ACA with Expansion	5	6	7	11	12	13

3.3.1 Supply-Projection Model

Between 2013 and 2025, the number of primary care physicians increases by 9.2% (615 total) under the constant growth, by 10.1% (677 total) under the medium growth, and by

11.7% (784 total) under the high growth scenarios. The number of NPs is projected to increase by 20%, while the number of PAs by 47%.

3.3.2 Need-Projection Model

Under Medicaid expansion, additional 980,000 people are projected to be eligible for the Medicaid program by 2025, and a decrease of over 700,000 uninsured is projected. In 2013, the percentage of Medicaid-eligible adult population is estimated to be 2%, while under the expansion scenario in 2025, it is projected to be 17% of the total population. The percentage of uninsured is estimated to be 26% of the total population in 2013 and 15% in 2025 under expansion. Population aging and growth are projected to produce an increase in the needed visits by 20% by 2025.

3.3.3 Optimization Model

Figure 8 shows the number of served visits in the state for all the projected years considering different scenarios. In 2025, the number of served visits under the baseline scenario is 7,044,866; an additional 876,124 visits are served due to the exchange market, a negligible number of additional visits are served due to supply growth and/or implementation of the parity program, while an additional 439,087 visits are served under Medicaid eligibility expansion. In the baseline scenario in 2013, the served visits are 67% of the needed visits and they remain the same in 2025 both for the baseline scenario and under non-expansion, while they increase to 80% under expansion regardless of supply growth.

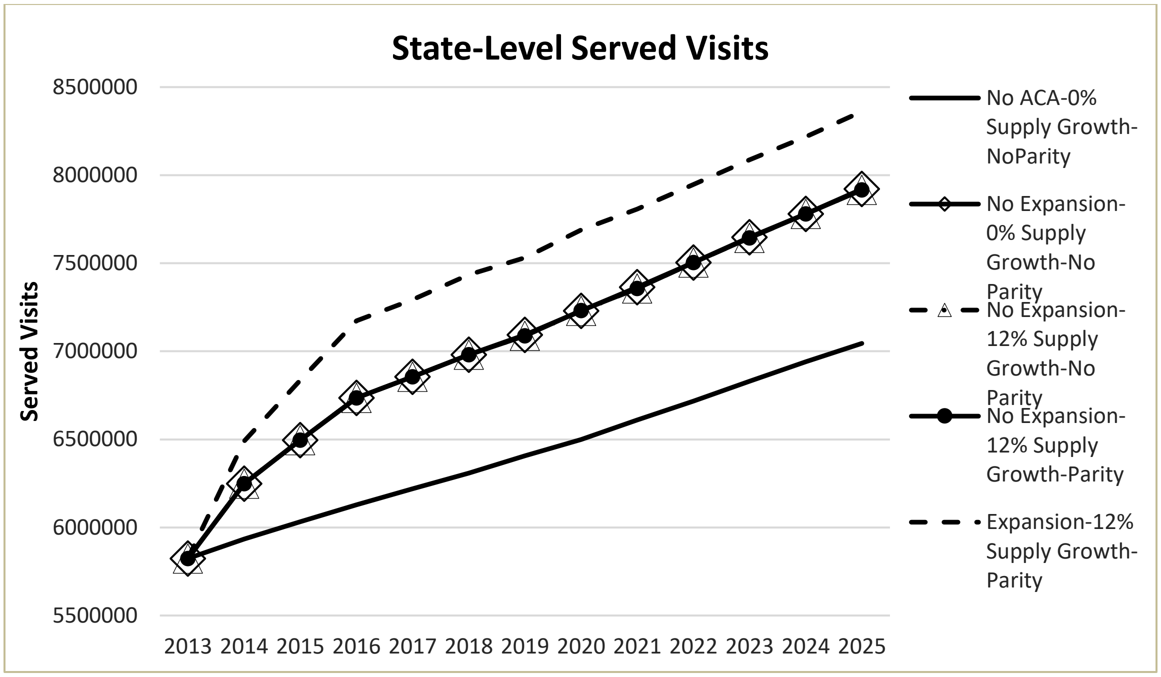


Figure 8. Total served visits in the state for all projected years and for different scenarios.

Table 13 shows the impact of the ACA provisions with and without Medicaid expansion on the served visits in year 2025 for the entire population. The impact of ACA under non-expansion is measured as the difference between the percentage of served visits under the non-expansion and no-ACA scenarios without additional supply growth or the Parity program (scenario 2 and scenario 1 in Table 12). The impact of Medicaid eligibility expansion is measured as the difference in the percentage of served visits under the expansion and non-expansion scenarios (scenario 5 and scenario 2 in Table 12). In year 2025 with δ=0.0, almost all the census tracts have a statistically significantly increment in the served visit for the entire population due to the provisions of ACA both with and without Medicaid expansion. For $\delta \geq 0.1$ the difference is not statistically significant. The significance maps for δ=0.0 are given in Figure 9, where it is shown that the positive impact is not concentrated in specific areas but affects the entire state.

Table 13. Number census tracts where the difference in the percentage of served visits is significantly positive, negative, or with no change, for three levels of the difference for the entire population in 2025.

	Change	*Difference in the percentage of served visits*		
		δ=0%	*δ=5%*	*δ=10%*
Imapct of ACA under Non-expansion	**Positive**	1954	1472	0
	Negative	0	0	0
	No Change	1	483	1955
Impact of Medicaid Expansion	**Positive**	1955	0	0
	Negative	0	0	0
	No Change	0	1955	1955

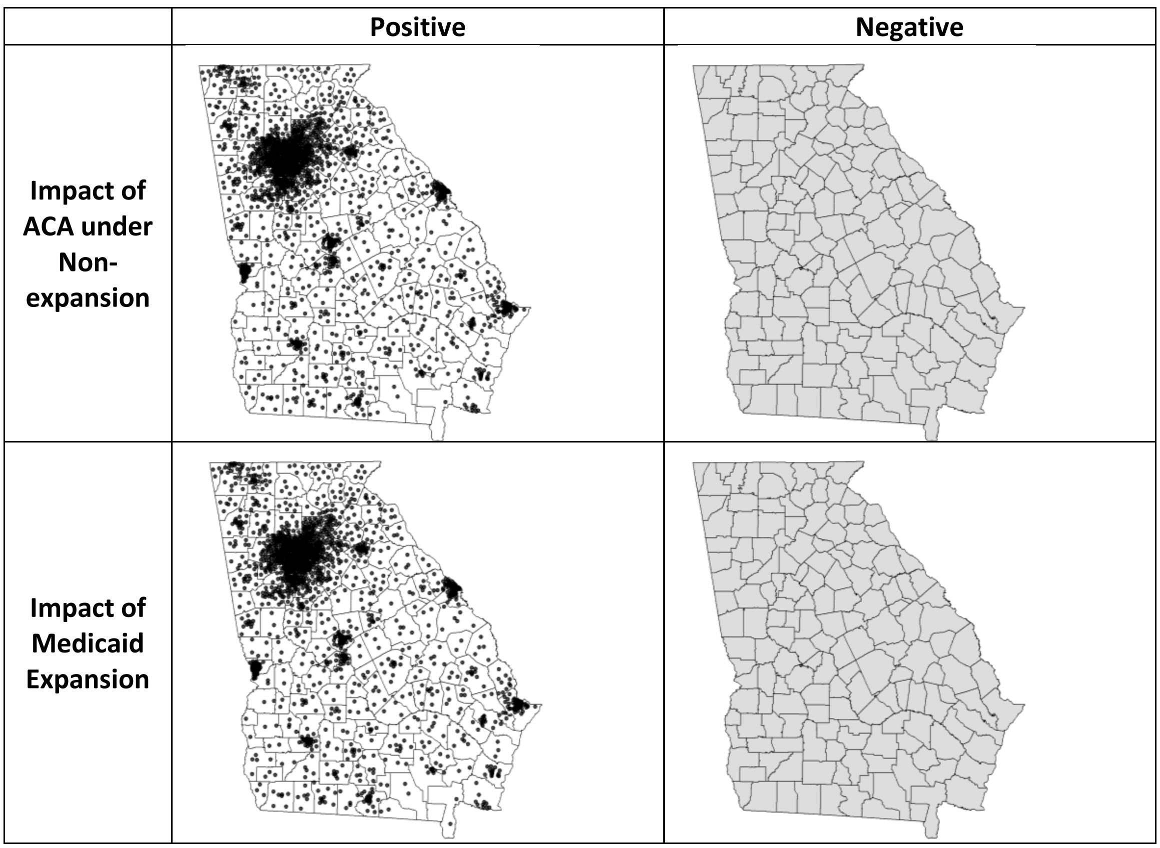


Figure 9. Significance maps marking census tracts where the difference in percentage of served visits in 2025 is significantly positive or significantly negative. Grey-shaded counties were not found to have a significant difference.

3.3.4 Availability and Accessibility Measures

3.3.4.1 Accessibility

In the baseline scenario in 2013, the median accessibility is 0.674 for the overall population, 0.919 for the publicly-insured, and 0.925 for the privately-insured.

In year 2025 under non-expansion, assuming medium supply growth with parity, median accessibility is 0.760 for overall population, 0.921 for publicly insured, and 0.926 for privately insured. Under expansion, median accessibility is 0.811 for overall population, 0.922 for publicly insured, and 0.925 for privately insured. Figure 10 shows the median level of accessibility at the state level for all the projected years considering different scenarios.

The impact on accessibility of ACA under non-expansion is measured as the difference between the level of accessibility under the non-expansion and no-ACA scenarios. In 2025, the impact regardless of the implementation of the Parity program ranges between -0.2 and 0.5, where positive values correspond to an improvement in accessibility under non-expansion. For δ=0.0, assuming medium supply growth, the majority of census tracts show a statistically significantly positive difference regardless of the implementation of the Parity program. Such a difference is not statistically significant for $\delta \geq 0.1$ (see Table 14). The corresponding significance maps for δ=0.0 show that the positive impact is not concentrated in specific areas but affects the entire state uniformly.

The measure of the impact of Medicaid eligibility expansion is measured as the difference in the level of accessibility under the expansion and non-expansion scenarios. In 2025, assuming medium supply growth with parity, impact ranges between -0.095 and 0.095 for the publicly-insured for 95% of the census tracts, and between -0.06 and 0.06 for the privately-insured, where positive values correspond to an improvement in accessibility under expansion. For δ=0.0, the number of census tracts where the difference is statistically significantly positive (negative) is 82 (61) for the publicly-insured population and 79 (156) for the privately-insured population. For $\delta \geq 0.05$ the difference is not statistically significant (Table 15). The significance maps for δ=0.0 show both the positive and negative impact are concentrated mainly in urban areas, namely, the Atlanta and Columbus areas.

Table 14. Number census tracts where the difference between the non-expansion with medium supply growth and the baseline scenarios is significantly positive, negative, or with no change, for three levels of the difference, for the entire population in 2025.

Parity Program	*Change*	ACCESSIBILITY			AVAILABILITY		
		0%	5%	10%	0%	5%	10%
No	Positive	1934	1209	0	579	0	0
	Negative	0	0	0	109	0	0
	No Change	21	746	1955	1267	1955	1955
Yes	Positive	1935	1212	0	538	0	0
	Negative	0	0	0	104	0	0
	No Change	20	743	1955	1313	1955	1955

Table 15. Number census tracts where the difference between the expansion and non-expansion scenarios, assuming medium supply growth, is significantly positive, negative, or with no change in 2025, by population group and level of the difference.

Parity Program	*Change*	ACCESSIBILITY						AVAILABILTY					
		Publicly-insured			Privately-insured			Publicly-insured			Privately-insured		
		0%	5%	10%	0%	5%	10%	0%	5%	10%	0%	5%	10%
No	Positive	88	0	0	85	0	0	0	0	0	0	0	0
	Negative	171	0	0	81	0	0	1820	0	0	1955	0	0
	No Change	1696	1955	1955	1789	1955	1955	135	1955	1955	0	1955	1955
Yes	Positive	82	**0**	**0**	79	0	0	0	0	0	0	0	0
	Negative	61	0	0	156	0	0	1955	1015	0	1955	0	0
	No Change	1812	1955	1955	1720	1955	1955	0	940	1955	0	1955	1955

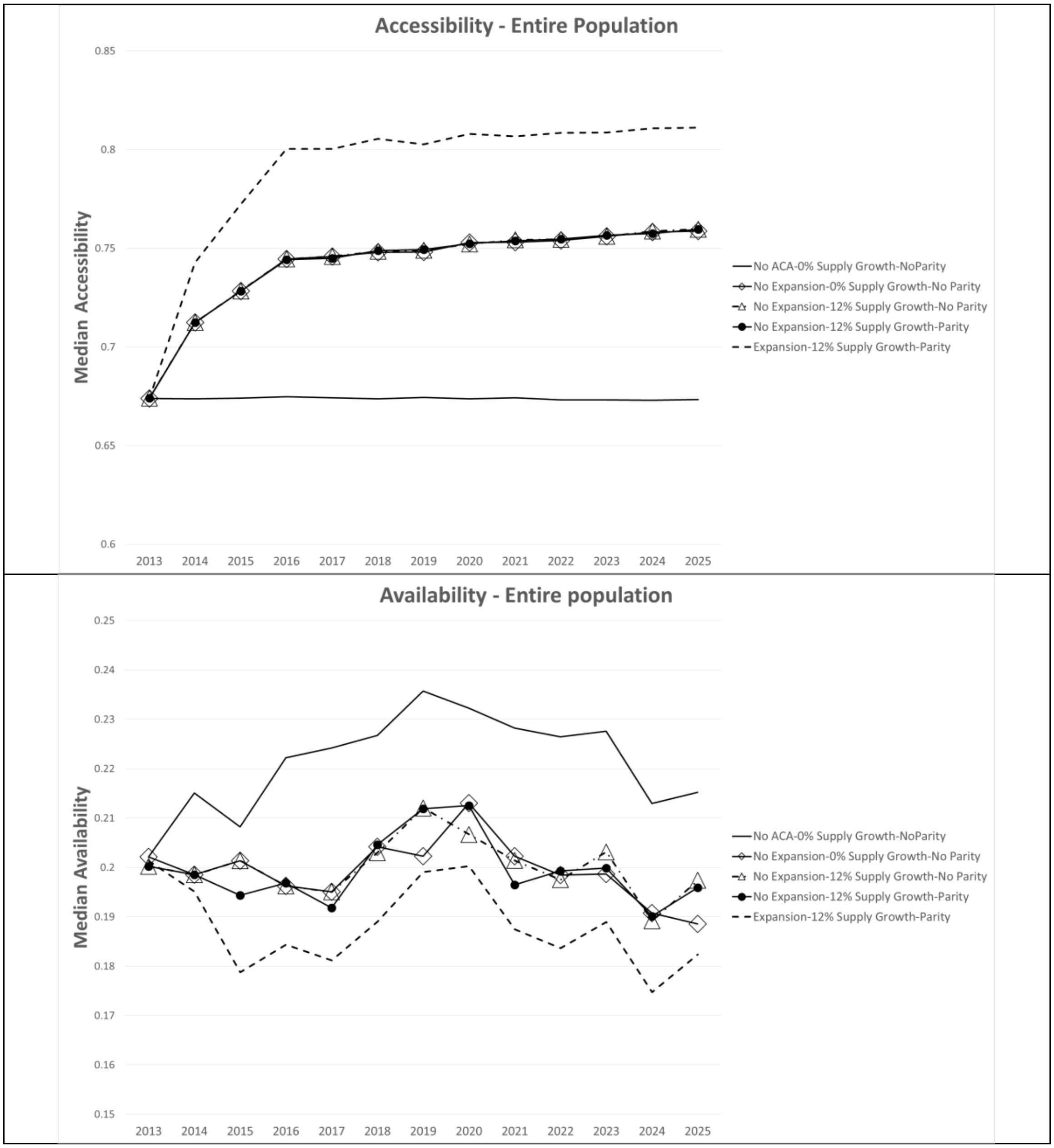


Figure 10. Median accessibility (top) and median availability (bottom) at the state level for the entire population for all the projected years and for different scenarios.

3.3.4.2 Availability

In the baseline scenario in 2013, median availability is 0.202 for the overall population, 0.418 for the publicly-insured, and 0.271 for the privately-insured.

In 2025 under non-expansion, assuming medium supply growth with parity, median availability is 0.196 for the overall population, 0.348 for the publicly-insured, and 0.234 for the privately-insured. Under expansion, median availability is 0.182 for the overall population, 0.251 for the publicly-insured, and 0.196 for the privately-insured. Figure 10 shows the median level of availability at the state level for all the projected years considering different scenarios.

In year 2025, assuming medium supply growth, the impact on availability of ACA non-expansion, regardless the implementation of the Parity program, ranges between -0.3 and 0.5, where positive values correspond to an improvement in availability under non-expansion. For δ=0.0, the number of census tracts where the difference is statistically significantly positive (negative) is 579 (109) without Parity and 538 (104) with Parity. For $\delta \geq 0.05$ the difference is not statistically significant (see Table 14).

The impact on availability of Medicaid eligibility expansion, assuming medium supply growth with parity, ranges between -0.48 and 0.48 for the publicly-insured for 95% of the census tracts and between -0.28 and 0.28 for the privately-insured, where positive values correspond to an improvement in availability under expansion. For δ=0.0, the majority of the census tracts show a statistically significantly negative difference for both the population groups regardless of the implementation of the Parity program. For $\delta \geq 0.1$ the difference is not statistically significant (Table 15).

3.4 Discussion

This chapter focuses on the projected impact of ACA implementation on spatial access to primary care for non-elderly population at the census tract level and over time for Georgia.

Existing studies project supply either for the entire workforce [67, 96, 97] or by specialization [94, 98-103] commonly at the national level. This paper is the first to report primary care supply projections by age and at the census tract level.

In contrast to existing research [53, 66, 104], we evaluate the impact of ACA (with or without Medicaid expansion) on healthcare access using served need estimated using an optimization model. This is an important contribution as it should be expected that not all supply will be available to patients in need of care due to healthcare access barriers and system constraints.

The percentage of unmet needed visits decreases to 25% under non-expansion and to 20% under expansion, both for medium and high supply growth. These results are not consistent with existing studies, which forecast that the supply shortage worsens with the implementation of the ACA [53, 66, 104]. This discrepancy is explained by the fact that our shortage measure accounts for system interactions between supply and need, unlike commonly used measures [53, 64, 66]. Additionally, these findings reveal the importance of interventions to increase supply in targeted areas so that accessibility and availability barriers can be overcome where needed.

Overall, the implementation of the ACA will have a positive impact on accessibility (increase up to 20% under expansion), while it will negatively affect availability (decrease between 13% and 19% under expansion). This finding reveals the importance of implementing interventions accounting for multiple dimensions of access simultaneously.

However, the overall impact on spatial access will minimally affect the geographic disparities in the state. We find that few communities, particularly those with predominant uninsured population, experience improved accessibility, and few communities experience reduced accessibility due to the added need. We also project that the ACA provisions excluding Medicaid expansion will minimally affect availability, although the number of communities with projected lower availability is larger than the number of communities with projected lower accessibility.

More importantly, under Medicaid expansion, the burden on the privately insured population in terms of accessibility of primary care is not substantial. There are very few communities where privately insured will experience lower accessibility of primary care services. The availability of primary care providers for both the populations will decrease in most communities. Such a decrement, however, is not greater than 0.05.

One primary challenge in this study is the limited data availability. We consider multiple data sources for different years when estimating the model parameters. A second limitation is the reliance on several model assumptions. The supply model assumes that provider productivity and its geographic distribution remain the same as in the baseline year. The supply of midlevel providers is underestimated because such providers are not captured in NPESS if they do not directly bill for services; the practice act in Georgia requires midlevel providers to practice under the supervision of a physician [105]. The projection of midlevel providers may also be underestimated as the supervision requirements may be removed. The need projection model assumes that current patterns of healthcare utilization remain the same as in the baseline year. While the need estimates are based on utilization ratios which may underestimate or overestimate need for some subpopulations, other approaches such as using the recommended care guidelines could consistently underestimate the need across most populations, particularly for those with chronic conditions. In the optimization model, the willingness to travel is assumed the same for all populations in rural and urban areas. The models introduced in this paper are general in that they allow such assumptions to be relaxed if detailed local-level data are available to inform the system constraints.

Additionally, our models account for changes in supply and need due to some provisions of the ACA (i.e., Medicaid eligibility expansion, the creation of the exchange insurance market, supply growth, and Medicaid Parity program), but they do not account other major changes in policy such as new payment models or technology oriented health care provisions as it is still unclear how such changes will impact supply. These can be addressed using our models along with simulation approaches, which can generate behavioral responses to such changes.

Even though this study has several limitations, it has some important implications for health care providers and policy makers. While there are several national-level studies highlighting the need of primary care providers for supplying the increased need due to ACA provisions [53, 63-64, 66], we find that such provisions (i.e. Medicaid eligibility expansion and health exchange markets) will reduce the total unmet need and positively impact accessibility for the overall population while reducing availability.

With respect to accessibility, the burden of the increased need due to a higher Medicaid population is not significant on the privately-insured population, while potentially reducing the availability of primary care providers for the publicly-insured and the privately-insured population.

If Georgia opts for Medicaid eligibility expansion the total level of served need will substantially increase (from 67% to 80%) in 2025. Such a policy will positively affect the total level of accessibility for the overall population, while reducing availability. Increase of supply will also positively affect the served need and the accessibility but will not uniformly overcome spatial access barriers. For a more effective impact, interventions need to be targeted locally accounting simultaneously for multiple dimensions of access.

CHAPTER 4. PROVIDER-LEVEL CASELOAD OF PSYCHOSOCIAL SERVICES FOR MEDICAID-INSURED CHILDREN

4.1 Introduction

Mental health (MH) disorders are prevalent among children but undertreated, with less than half of those with mental health disorders receiving any services [106]. For the most common disorders among this population, including depression, anxiety disorder, and attention deficit/hyperactivity disorder, psychotherapy and/or other psychosocial services are recommended as a first line of treatment [107-110]. Guidelines by the National Institute of Mental Health specify that children with mental health and behavioral disorders should all receive psychotherapeutic or psychosocial intervention, and that psychotropic medication should be complemented by provision of these services [111]. Several studies examined the efficacy of various psychosocial interventions [112-115]. About 75% of people who undergo psychotherapy show improvement for their condition [116].

Medicaid is the largest insurer of children [117] and the single largest payer of mental health services [118], but studies have documented that many Medicaid-insured children with mental health and behavioral disorders do not receive any psychosocial treatment [119-124]. Only 49% of young persons aged ≤20 years received psychosocial services before starting antipsychotics [125], and only 68% of children and adolescents aged 6-17 years received concurrent therapy [123]. Fewer than 38% of children aged 6-12 years who initiated medication for attention deficit/hyperactivity disorder received any psychotherapy visits [119]. Among children who initiate treatment, many do not receive a minimal number of psychotherapy [124, 126] or psychosocial [127, 128] visits.

Several studies have posited that lack of geographic access to treatment is one of the major barriers to psychotherapy services for this population. Not only is there an overall shortage of mental health providers in most states [129], but many mental health providers do not accept Medicaid [129-131]. A national survey of office-based psychiatrists found that the percentage of psychiatrists who accept Medicaid declined from 2010 to 2015, and only 35.4% accepted new Medicaid patients during the most recent period examined (2014-2015) [131]. Studies have also examined the geographic availability of mental health treatment facilities that accept Medicaid [132, 133] and/or serve children [134]. Those studies reported that many communities lack these resources.

Although some studies have provided information about geographic availability and distribution of Medicaid-participating providers [132-134], these studies did not describe the volume of services provided at each location. Anecdotal evidence suggests that a small percentage of mental health treatment facilities and clinics may provide the majority of services to this population (i.e., high-volume providers). These studies also focused on specialty mental health providers; however, psychosocial services can also be delivered in other settings such as primary care practices [135-138]. To date, empirical data are lacking on how the supply of psychosocial services for Medicaid-enrolled children varies across provider types (e.g., primary care, mental health specialists). A nuanced understanding has important implications for informing the accessibility of services for Medicaid-enrolled children.

This chapter links two large national databases to conduct the most comprehensive analysis to date on the supply of psychotherapy services available to Medicaid-insured children. Our objectives were to provide new information about who delivers psychosocial services to Medicaid-enrolled children and how visit volume is distributed across provider types and geography. Material in this chapter has been published in final form at [139].

4.2 Methods

4.2.1 Data Sources

We used data from the 2013 National Plan and Provider Enumeration System (NPPES) database [38] and 2012-2013 Medicaid Analytic eXtract (MAX) claims [40]. NPPES is a national database listing all health care providers with a National Provider Identifier (NPI) number. An NPI number can be assigned to a person (entity type 1) or an organization, such as a hospital or physician group (entity type 2). We used NPPES to determine whether a provider seeing Medicaid-insured children for psychosocial services specializes in a mental health–related field, as defined by the Health Resources and Services Administration [140], or another field, such as primary care, rehabilitative care, or developmental care. We considered providers who fell into one of the following 11 provider categories: psychiatrist, psychologist, counselor, social worker, mental health center, other entity 1 mental health, other entity 2 mental health, primary care, rehabilitative/developmental care, other care center (including general acute-care hospitals and federally qualified health centers), and other entity 2 related care. A full description of taxonomies in each category is available in Appendix C. We included psychiatric hospitals and residential treatment facilities in the category of mental health center because they can have outpatient clients [141].

For the MAX data, the most recent years of data available from CMS when this study began were 2013 for 28 states and 2012 for all states. We used information from the MAX Personal Summary file, which contains demographic data for Medicaid beneficiaries, and the MAX Other Therapy file, which contains claims for services received by Medicaid beneficiaries outside of inpatient hospitals, long-term care facilities, and pharmacies. We used Current Procedural Terminology (CPT) codes [142] to identify health care encounters involving psychotherapy (including individual, group, or family psychotherapy) or other psychosocial services, such as skills training and development, psychosocial rehabilitation services, and activity therapy. The selected CPT codes are level 1 Healthcare Common Procedure Coding System codes that are based on codes used in a Centers for Disease Control and Prevention study [143]. The Georgia Institute of Technology Institutional Review Board approved this study.

4.2.2 Linking NPPES Provider Database to MAX Claims

We developed an algorithm to link providers in the NPPES Provider database with the healthcare encounter data from the MAX OT file. The MAX OT file contains two separate identifiers for the billing provider (the NPI number as well as a unique Medicaid identification number) and one identifier for the service provider (a unique Medicaid identification number). We assumed that the Medicaid beneficiary received services from the provider listed in the “service provider” field, which can differ from the “billing provider”. For example, individual providers may work for a subsidiary organization but bill under the NPI number of a parent organization. Because the "service provider" field in the MAX data only contain the unique Medicaid identification number, we created an algorithm to match an NPI number to the service provider field using information from the billing provider fields. This algorithm is summarized in Figure 11 and described below.

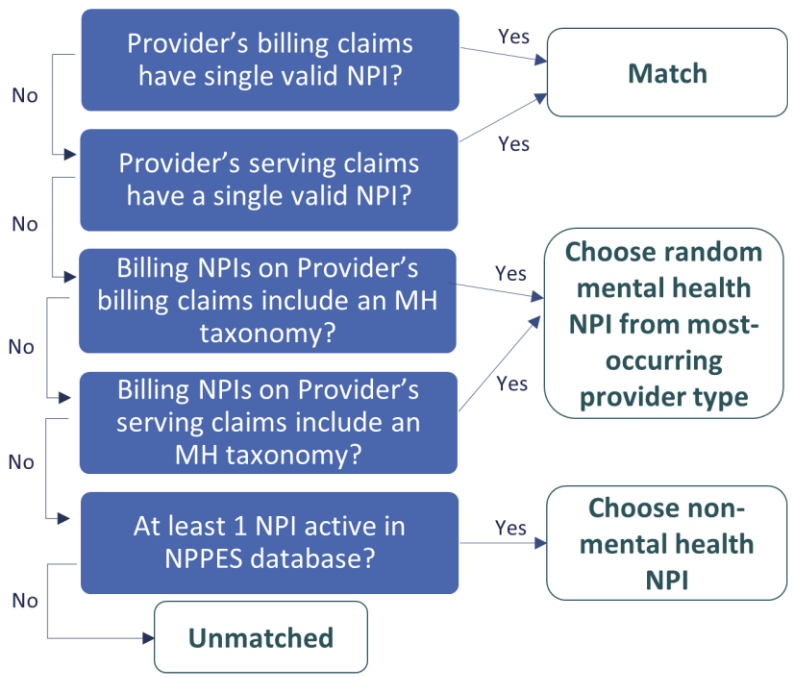


Figure 11. Procedure to match service providers to NPIs.

In Step 1, if a service provider ever appeared as a billing provider in the MAX OT file, we assessed whether all claims for which he or she was listed as the billing provider had the same NPI. In this case, we considered that NPI be a 'match'. This accounted for 33% of all matches for psychosocial service providers. If the service provider was not matched, in step 2 we assessed whether the billing NPI field was valid and identical in all claims in which he or she was listed as the service provider. If so, we considered that to be the matched NPI (42% of all matches). Service providers matched in these two steps were considered to have a single NPI match.

For service providers with multiple valid NPIs in the billing NPI field, we randomly selected a billing NPI with a MH-related primary taxonomy from the claims in which they were the billing provider if those claims had any such primary taxonomies (3.4% of all matches). If not, we randomly selected a billing NPI with a MH-related primary taxonomy from the claims in which they were the service provider (5.4% of all matches). Remaining service providers were either matched to a random non-MH-related billing NPI (4.0% of all matches) or had no associated billing NPIs that were listed in the NPPES database (12% of all matches).

In our analysis, we included 21 states from 2013 and 13 additional states from 2012 (34 states total) for which we could match at least 75% of psychosocial service providers to a single NPI number in the NPPES database. States for which we could match <75% of psychosocial service providers to a single NPI number in the NPPES database either had a large number of service providers, each with multiple potential NPI numbers (e.g., Indiana, Nebraska, Wyoming), or had a large number of billing NPI numbers not listed in the NPPES database and, therefore, service providers could not be matched to any NPI number (e.g., Michigan, Missouri, New Hampshire).

4.2.3 Address Classification

To avoid a provider's caseload being split between his or her own Entity 1 NPI number and his or her organization's Entity 2 NPI number, we additionally grouped providers with the same practice address together and performed an address-level analysis. That is, for each address where at least 1 Medicaid psychosocial service provider practices, we took the following 3 steps: (1) we identified all providers in the 2013 NPPES database sharing that practice address, (2) we determined the provider category of each of those providers using their Entity type and primary taxonomy, and (3) we categorized the practice setting of the address. We performed these steps in a hierarchical fashion based on the presence or absence of each provider category. For example, the presence of a mental health center provider resulted in a "mental health practice setting" categorization, whereas the presence of an other care center provider and absence of a mental health center provider resulted in an "other care center practice setting" categorization. Remaining categories are shown in Figure 12.

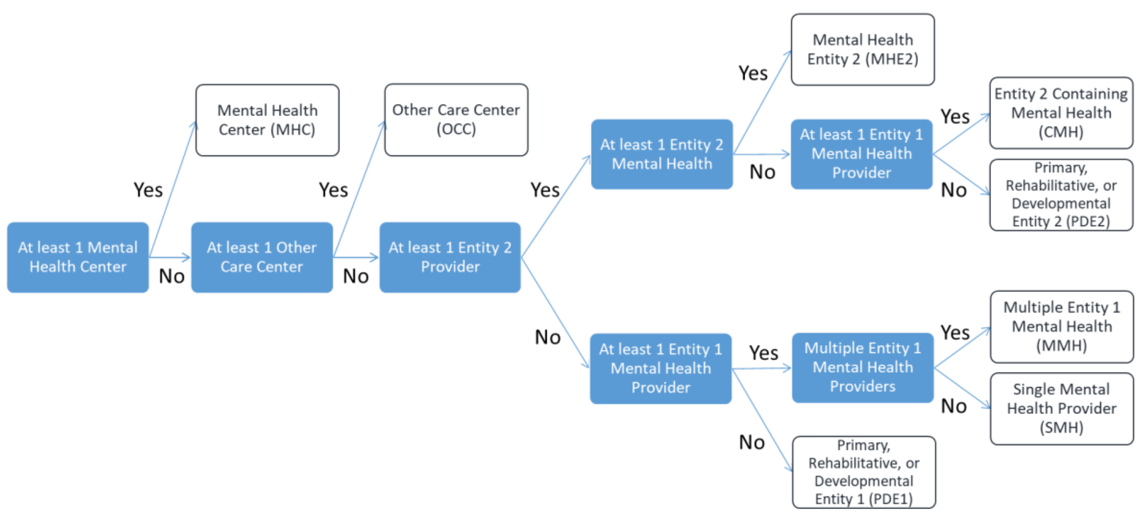


Figure 12. Classification of addresses. White boxes list each possible address categorization. Each address is categorized based on whether the description of providers located at that address given in the blue boxes applies, starting with the box furthest left.

4.2.4 Caseload Estimation

We measured the caseload of each Medicaid-participating provider delivering psychosocial services by estimating the number of Medicaid-enrolled children who received psychosocial services from that provider in a given year and adding all the psychosocial visits delivered by that provider. We obtained the unique address-level caseloads by combining the caseloads of all service providers practicing at the same address.

We examined state-level variations in the distribution of services across provider and location categories, and by practice location urbanicity. We determined urbanicity by using the zip code approximation of the rural–urban commuting area codes [144]: codes 1-3 represented large urban areas (i.e., areas with a primary flow to or within an urbanized area), codes 4-6 represented small urban areas (i.e., areas with a primary flow to or within a large urban cluster), and codes 7-10 represented rural areas.

4.3 Results

In the 34 states (21 states from 2013 and 13 states from 2012), we identified 83,727 mental health providers who provided psychosocial services to Medicaid-insured enrollees. Of these, 51,638 (61.7%) provided psychosocial services to Medicaid-insured children. We additionally identified 18,721 practitioners in related health care settings who provided psychosocial services to Medicaid-insured persons, 11,676 (62.4%) of whom served children. Combined, these providers saw more than 1.6 million Medicaid-insured children and provided more than 32 million psychosocial services visits to these children across 32 238 provider locations. Of these children, 60% were aged <13 years and 91% had a mental health diagnosis.

Mental health practitioners conducted more psychosocial treatments than non–mental health practitioners (Figure 13). More than one-third of children were treated at mental health centers, which accounted for >40% of mental health visits. Counselors, the largest group of the 11 provider types, treated 20% of children and accounted for 16% of mental health visits. Other care centers treated 16% of children and accounted for 15% of mental health visits.

More than 58% of psychosocial services occurred at addresses with at least 1 mental health center. Additionally, about 21% of children were treated and 19% of visits took place at other care center locations. Only about 12% of children were treated at locations with Entity 1 mental health providers but no organization NPI number. These locations were responsible for only 9% of visits.

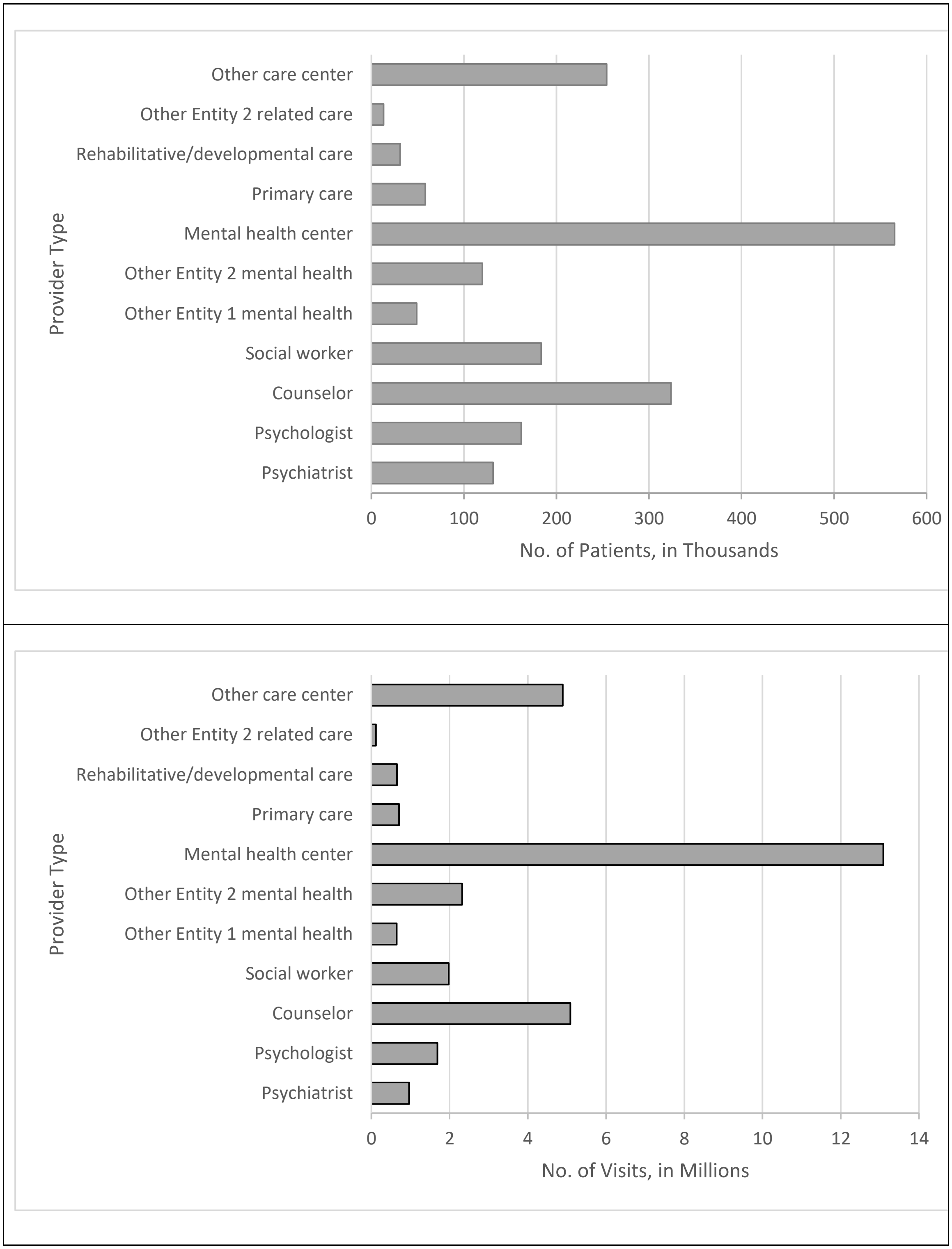


Figure 13. Total number of Medicaid-insured children seen for psychosocial services and their corresponding total number of psychosocial visits aggregated among 34 US states in 1 selected year (2012 or 2013), by provider category.

4.3.1 State-level Distribution of Services

The distribution of psychosocial services across provider and address categories varied considerably by state. The percentage of children who received psychosocial services from mental health centers ranged from 2.4% (Washington) to 81.7% (Kentucky), whereas the percentage of psychosocial service visits from mental health centers ranged from 1.2% (Iowa) to 86.8% (Kentucky). In Oklahoma and Texas, counselors treated the majority of children, whereas in Minnesota, psychologists treated the majority of children. In 3 states (Iowa, Illinois, and Washington), more children were treated by non–mental health providers than by mental health providers.

Aggregating services by location revealed that in more than half of the states, most services occurred at mental health center locations (Table 16, Table 17). However, large variations occurred. The percentage of children seeking psychosocial services at mental health center locations (vs other locations) ranged from 7.8% (Washington) to 88.6% (Kentucky). In Illinois, Iowa, Montana, and Washington, most children (54.5% to 87.2%) were treated in other care center locations. Only in Vermont were more than 50% of children seen at locations with Entity 1 mental health providers but no Entity 2 providers; however, only 28.2% of visits by children were made at those locations.

Table 16. Distribution of Medicaid-insured child psychosocial patients across address categories. Starred states use 2012 data.

State	Total No. of Patients	% of Patients MHC	OCC	MHE2	CMH	MMH	SMH	PDE2	PDE1
Alabama*	35,040	65.9	20.5	11.2	1.1	3.4	8.2	0.3	0.1
Arizona	56,045	77.0	22.9	2.9	0.2	0.1	0.3	0.3	0.02
Connecticut	29,903	51.4	36.2	12.2	7.2	5.5	6.7	0.1	0.3
District of Columbia*	5,868	58.4	41.8	7.3	0	0.3	0.9	0	0
Florida*	80,695	47.0	20.5	12.6	4.4	11.7	14.6	2.5	4.6
Georgia	67,249	55.5	10.9	27.8	1.5	6.2	8.5	1.1	1.4
Hawaii	1,551	56.0	44.7	0	0.7	0	0	0	0
Iowa	5,667	17.5	81.5	1.7	0.4	0	0	3.2	0.3
Idaho	18,394	61.6	28.5	22.1	1.5	1.7	1.0	0.7	0
Illinois*	115,650	29.6	70.5	1.8	0.7	0.8	2.3	0.5	5.6
Kentucky*	50,774	88.6	4.5	6.2	1.7	2.1	0.2	0.3	0.2
Louisiana	39,574	68.7	17.6	8.1	3.2	4.0	6.0	0.2	0.7
Massachusetts	87,878	75.0	20.5	6.2	3.1	2.5	1.8	0.1	0.0
Maryland*	39,829	65.7	23.0	8.5	1.3	3.5	6.6	0.1	0
Minnesota	35,874	47.0	25.1	34.2	0.2	7.0	1.6	0.3	0.2
Mississippi	32,157	63.2	13.1	17.4	3.9	3.9	10.9	0	0
Montana*	10,465	25.5	54.5	18.1	2.5	12.1	11.2	0.6	1.3
North Carolina*	78,468	42.0	16.8	24.1	6.0	5.6	19.3	2.7	1.0
New Jersey	31,482	73.8	13.8	16.8	0.7	0.8	3.3	0.1	0
New Mexico*	37,938	45.4	36.2	25.0	0.9	3.3	6.5	0.9	1.0
Nevada*	10,025	85.5	12.8	24.7	6.7	16.1	21.5	1.5	27.7
New York	61,925	31.9	14.4	10.0	35.2	11.5	10.9	0.5	0.6
Ohio	122,127	80.2	10.6	12.7	0.6	1.0	0.9	0.9	0.1
Oklahoma	98,125	52.7	7.4	31.5	2.5	10.3	23.5	0.0	0.8
Oregon	22,438	62.4	18.3	20.0	1.8	7.9	3.3	0.1	0
Pennsylvania	110,304	76.9	15.5	9.2	0.6	2.1	2.2	0.5	0.1
Tennessee	43,134	59.0	12.0	10.9	10.0	10.2	9.6	0.2	0.5
Texas*	145,564	26.9	30.1	24.7	5.7	11.4	18.6	0.2	0.2
Utah	13,963	49.1	6.0	43.2	0.9	11.6	6.5	0	0.2
Virginia*	35,166	47.0	20.3	29.0	4.2	9.2	9.1	0.4	0.1
Vermont	10,530	42.0	7.7	21.2	7.3	29.6	21.0	0	0
Washington	50,662	7.8	87.2	4.8	1.8	1.7	1.8	0.3	0.7
Wisconsin*	34,200	45.3	23.2	18.1	12.4	10.2	7.0	0.5	0.9
West Virginia	14,364	10.7	5.9	28.4	2.1	3.8	3.4	0.1	0.2

Table 17. Distribution of Medicaid-insured child psychosocial visits across address categories. Starred states use 2012 data.

State	Total No. of Visits	% of Visits							
		MHC	OCC	MHE2	CMH	MMH	SMH	PDE2	PDE1
Alabama*	840,858	80.3	13.0	3.0	0.1	0.8	2.7	0.1	0.03
Arizona	745,061	84.2	13.1	2.4	0.1	0.1	0.2	0.02	0.01
Connecticut	517,747	40.1	34.7	8.4	6.2	4.0	6.4	0.1	0.1
District of Columbia*	138,044	69.8	18.8	11.0	0	0.1	0.3	0	0
Florida*	1,030,037	45.6	15.0	9.2	2.8	8.9	11.5	1.6	5.4
Georgia	1,186,922	73.5	5.2	13.5	0.7	2.1	3.5	0.8	0.8
Hawaii	32,971	83.9	16.0	0	0.1	0	0	0	0
Iowa	368,572	3.82	95.7	0.1	0.04	0	0	0.3	0.03
Idaho	878,843	45.7	43.7	10.1	0.1	0.2	0.1	0.1	0
Illinois*	1,706,700	33.7	56.0	0.9	0.2	0.3	2.1	0.4	6.5
Kentucky*	513,478	91.0	2.9	3.9	0.6	1.5	0.04	0.1	0.04
Louisiana	1,076,208	84.4	4.7	7.2	1.0	0.8	1.7	0.1	0.1
Massachusetts	2,635,936	80.0	11.9	4.7	1.7	0.9	0.7	0.02	0.01
Maryland*	762,003	64.9	18.8	7.1	0.9	2.1	6.0	0.3	0
Minnesota	778,272	47.5	16.9	28.3	0.04	6.1	1.0	0.2	0.1
Mississippi	821,511	61.6	9.1	17.4	1.4	2.1	8.5	0	0
Montana*	467,083	16.2	70.4	4.9	0.6	3.3	3.9	0.2	0.5
North Carolina*	1,745,610	45.6	24.5	11.7	2.2	2.1	11.1	2.4	0.4
New Jersey	466,525	63.6	14.5	18.5	0.2	0.5	2.7	0.01	0
New Mexico*	940,717	50.0	29.6	13.8	0.5	1.3	3.4	0.8	0.6
Nevada*	620,908	54.2	3.0	8.1	2.5	6.1	8.2	0.7	17.3
New York	571,711	27.8	10.3	11.2	31.7	9.9	8.7	0.2	0.3
Ohio	2,571,918	87.2	3.5	8.5	0.1	0.3	0.3	0.1	0.03
Oklahoma	3,224,014	46.4	2.8	25.7	1.5	6.5	16.7	0.02	0.4
Oregon	249,955	61.6	12.8	16.2	0.8	6.4	2.4	0.04	0
Pennsylvania	2,987,005	77.5	12.8	6.7	0.5	1.3	1.2	0.03	0.01
Tennessee	368,921	61.5	10.9	6.8	5.8	6.8	7.6	0.1	0.6
Texas*	1,377,028	25.4	22.7	18.7	4.8	8.5	19.8	0.1	0.2
Utah	396,217	44.7	8.6	40.6	0.2	3.8	2.2	0	0.02
Virginia*	531,231	51.8	12.6	18.7	2.4	5.7	8.5	0.3	0.01
Vermont	342,033	42.1	2.5	24.9	2.3	18.1	10.1	0	0
Washington	752,035	8.4	84.2	3.2	1.6	0.9	1.1	0.2	0.6
Wisconsin*	351,274	49.1	14.0	14.7	8.8	6.4	6.3	0.3	0.4
West Virginia	152,185	65.6	2.5	27.2	0.8	2.4	1.3	0.1	0.2

4.3.2 *Per-provider Distribution*

Most providers saw <25 children and provided <250 psychosocial service visits during their selected year of data (Table 18, Figure 14). More than 75% of Entity 1 mental health providers saw at most 20 Medicaid-enrolled children per year or provided <170 psychosocial visits to Medicaid-enrolled children. Among Entity 1 mental health providers, counselors had the highest 75th-percentile child–patient caseload, with 25 children, and the highest 75th-percentile and 90th-percentile child–visit caseloads, with 302 and 730 visits, respectively. However, psychiatrists had the highest 90th-percentile child–patient caseload, with 84 children. Social workers generally had the lowest caseloads.

Table 18. Total number of addresses seeing Medicaid-insured children for psychosocial services (no.) and mean (mean), 50th percentile (50%), 75th percentile (75%), and 90th percentile (90%) caseload among those addresses, by zip code urbanicity and address category. Blank cells indicate a caseload below 11.

		Patients								Visits							
		MHC	**OCC**	**MHE2**	**CMH**	**MMH**	**SMH**	**PDE2**	**PDE1**	**MHC**	**OCC**	**MHE2**	**CMH**	**MMH**	**SMH**	**PDE2**	**PDE1**
Overall	No.	7092	7071	4236	1391	2944	7247	648	1609	7092	7071	4236	1391	2944	7247	648	1609
	Mean	140	53	57	36	34	20	15	12	2629	762	695	327	352	257	161	186
	50%	30	—	15	—	—	—	—	—	296	66	103	48	76	64	—	59
	75%	108	35	47	30	34	22	—	14	1571	381	401	204	297	256	54	235
	90%	331	109	124	77	78	47	32	30	5820	1423	1165	596	785	680	402	495
Large urban	No.	5661	5396	3582	1183	2377	5749	504	1402	5661	5396	3582	1183	2377	5749	504	1402
	Mean	146	61	56	35	32	20	15	12	2742	821	681	317	316	258	144	188
	50%	29	—	14	—	—	—	—	—	285	66	93	43	62	60	—	63
	75%	109	39	44	27	30	20	—	15	1561	381	381	182	252	233	52	236
	90%	348	130	120	69	71	46	31	30	6296	1473	1162	549	697	663	435	487
Small urban	No.	859	795	431	143	336	793	96	132	859	795	431	143	336	793	96	132
	Mean	149	38	64	47	43	21	18	—	2744	702	678	428	481	264	266	179
	50%	41	—	23	14	18	11	—	—	420	64	164	80	170	88	16	31
	75%	132	35	66	53	50	27	13	13	1971	410	511	377	490	363	77	245
	90%	334	85	153	117	110	50	47	26	5802	1529	1121	889	1109	759	276	495
Rural	No.	555	866	220	63	224	683	48	72	555	866	220	63	224	683	48	72
	Mean	70	22	51	26	39	19	—	12	1310	449	927	294	540	239	127	173
	50%	28	—	19	—	22	—	—	—	225	73	169	78	167	87	—	30
	75%	73	20	51	32	48	25	—	15	1131	347	584	173	500	310	30	200
	90%	157	56	122	59	96	45	25	28	3050	1120	1327	601	1174	691	245	527

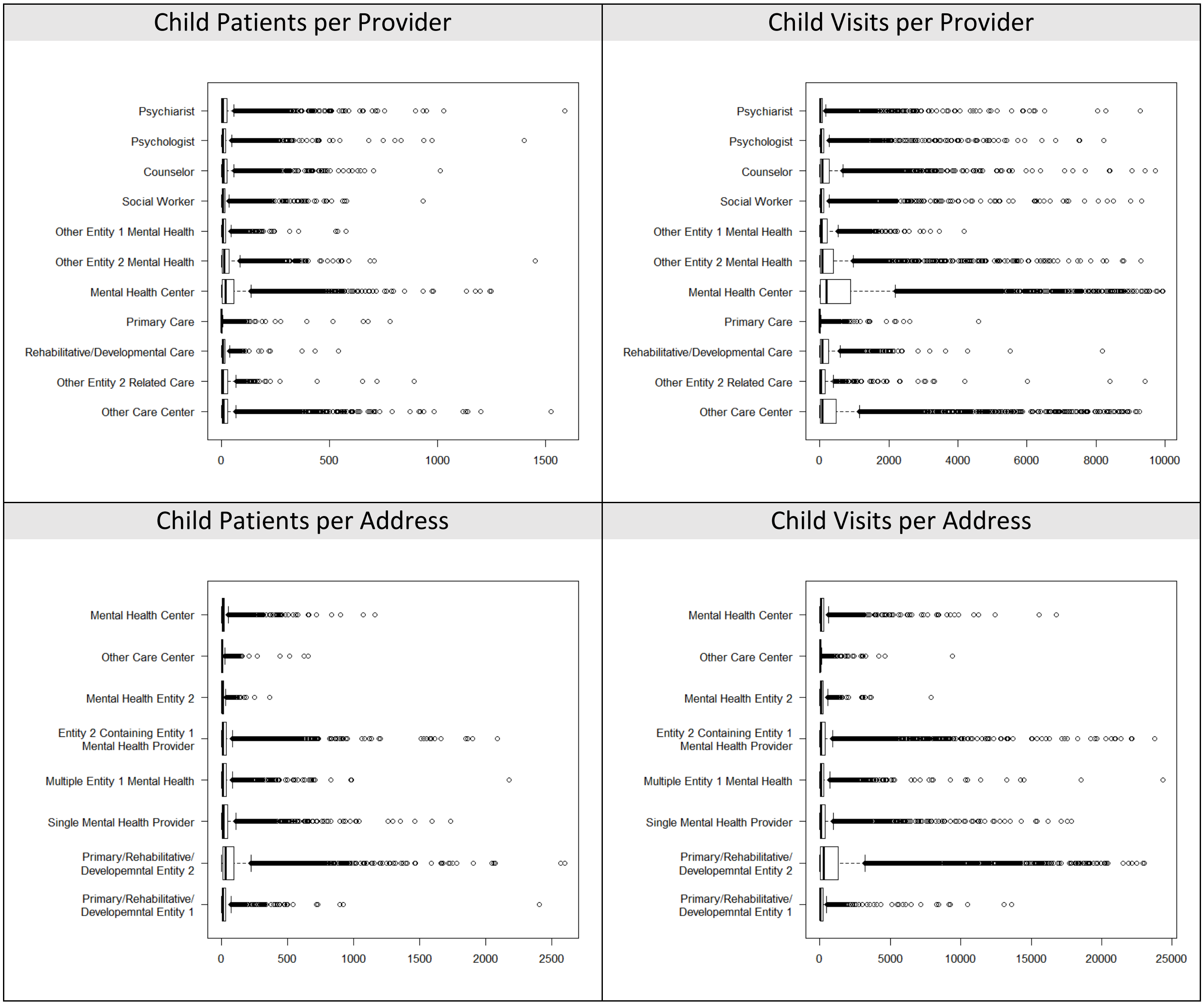


Figure 14. Boxplots displaying per-provider per-year and per-address per-year caseloads of Medicaid-insured child psychosocial patients and visits across 34 US states, by provider and address category.

Across address categorizations, median caseload was at most 30 children and 296 visits. Mental health centers had the highest mean, median, 75th percentile caseload, and 90th percentile caseload, both in patients and visits, which was at least twice those of the next highest category (generally locations with other Entity 2 mental health). Caseload was generally lowest at locations without mental health providers. All these caseload distributions were heavily skewed (Figure 14). For example, about 7% of locations with Entity 1 mental health providers but without Entity 2 mental health providers saw half of the Medicaid-enrolled children seeking psychosocial services from such locations. Similarly, 4% of mental health centers saw half the children seeking psychosocial services at mental health center locations.

Patient caseloads for Entity 1 mental health providers were generally lowest in large urban zip codes and highest in small urban areas (75th percentile of 18 children in large urban areas vs 29 children in small urban areas). Entity 1 mental health provider visit caseloads, however, were highest in rural zip codes (75th percentile of 144 visits from children in large urban areas versus 312 visits from children in rural areas). Small urban zip codes generally had the highest patient caseload across all address categories and the highest child visit caseloads for mental health center, other care center, and single mental health provider locations. Rural zip codes had the lowest patient and visit caseloads for both mental health centers and other care centers (Table 18).

4.4 Discussion

This chapter provides a comprehensive analysis of the current supply of psychosocial services available for Medicaid-enrolled children across provider types, revealing the important role of mental health centers, especially those that serve a high volume of Medicaid-enrolled children. More than half of the visits occurred in a mental health center, yet only 4% of mental health centers saw half the children seeking psychosocial services.

Across all practice settings, fewer than 10% of locations were responsible for more than half of the patients served and more than half of the visits provided. This finding suggests that Medicaid-insured children have little choice in treatment location. Concentrating the supply of psychosocial services to few locations may partly explain why many studies cite distance as a barrier to care [145-147]. These findings underscore the limits of studies that assess geographic accessibility of mental health treatment by only examining where mental health clinics and providers are located, without taking into account the volume of services provided at those location.

Fewer than 15% of patients who seek psychosocial services receive these services from providers not associated with a center or organization. This concentration of treatment at centers and organizations may be due to barriers against Medicaid participation among providers, such as reimbursement rates and administrative costs. Administrative requirements and the cost of overhead to handle paperwork and insurance billing have been reported as a barrier to psychiatrists participating in Medicaid [148, 149]. This barrier may be even more pronounced for therapists in solo or small group practices. Easing these burdens may enable providers to accept more Medicaid-insured patients.

Service distribution is not consistent across states, which may be explained, in part, by differences in the organization of mental health care systems available to serve Medicaid-insured children and/or differences in state policies. For example, Florida required behavioral health clinicians such as psychologists to work under physician supervision, which may explain why it has more services provided by psychiatrists and related care providers than most other states [150]. In Massachusetts, private practice psychologists can only provide therapy through licensed mental health clinics, which may account for its low rate of services from Entity 1 providers [151].

Our findings have key implications for policy makers and program planners who aim to improve the accessibility of psychosocial services for Medicaid-enrolled children. These decision makers should recognize that high-volume mental health clinics play an important role in providing psychosocial services to Medicaid-insured children. Policy makers can provide incentives and resources to encourage increased geographic accessibility of services provided by high-volume clinics. One approach would be for these facilities to partner with schools to deliver psychosocial services on school grounds [152-153]. Another approach would be to incentivize these clinics to provide home-based services, in which counselors or therapists travel to the child's home to deliver care [154].

Policy makers could also consider approaches to encourage all providers to increase their supply of psychosocial services. These approaches would include increasing current levels of investment in policies to expand the mental health workforce capacity in clinics and practices that accept Medicaid, such as loan forgiveness programs [155, 156]. Another option would entail increasing Medicaid reimbursement rates for psychosocial services to enable clinics and practices to offer higher salaries than could be offered without the increased reimbursement rates as a strategy to improve recruitment and retention efforts of these providers [157].

4.4.1 Limitations

This study had several limitations. First, our results were for 34 states; patterns in these states may differ from patterns in the rest of the country. Second, the latest data available were for 2013, before the Affordable Care Act went into effect. With an increase in the proportion of mental health services covered by health insurance after implementation of the Affordable Care Act, the proportion of their caseload that providers dedicate to persons insured by Medicaid may have changed in recent years. For example, one study comparing a 2013-2014 survey with a 2016-2017 survey found that among outpatient substance use disorder treatment programs, the total number of clients remained constant but more clients used Medicaid during 2016-2017 than during 2013-2014 [158].

Third, our data relied on Medicaid claims. To be registered as a service to a child, a claim must have a child listed as the beneficiary rather than an adult family member. However, family therapies listing an adult family member as the beneficiary would still be of benefit for the child. Medicaid-enrolled children may also have other resources for obtaining psychosocial services, such as community or school programs, which do not bill Medicaid. However, we were unable to capture these data [122, 159].

Fourth, some providers bill solely through their organization's NPI number. Our matching algorithm would link these providers only to the organization's NPI number, preventing us from identifying the type of practitioner providing the service. This linkage of providers solely to an organization's NPI number occurred for 20% of the psychosocial service providers. Similarly, some providers working for an organization may still bill as individuals, resulting in a lower caseload captured for that organization in the per-provider results than if the provider had billed through their organization. Although our address-level analysis reduced the likelihood of these errors, it did not allow us to distinguish among individual provider types. Additionally, we assumed that all providers worked at their single practice address listed in NPPES, but some providers may travel to treat patients. A study in Georgia found that primary care providers had on average 2.6 practice locations whereas psychiatrists had 1.8 [160]. Finally, we examined only the caseload of psychosocial services. Some providers may still see Medicaid beneficiaries for other mental health–related treatment, such as prescribing medication.

4.5 Conclusions

To our knowledge, this chapter presents the largest and most comprehensive to date examining Medicaid caseload for psychosocial services by a broad range of mental health providers. Most providers across all provider types had relatively low caseloads. Fewer than 10% of providers were responsible for more than half of services, with the largest proportion of services provided by mental health treatment centers. Services concentrated in few locations would reduce geographic access to services for the Medicaid-insured population.

CHAPTER 5. INTEGRATION OF PRIMARY AND SPECIALIZED CARE: A DECENTRALIZED APPROACH

5.1 Introduction

Currently, the US healthcare system is highly fragmented, with specialists and primary care physicians working independently of each other. A patient with multiple chronic conditions may have to visit up to 16 healthcare providers in a year [161]. This leads to system inefficiencies and treatment inconsistencies, such as patients having to undergo redundant tests due to missing information [161-163]. Surveys among adults with chronic conditions found that if patients were seeing at least four physicians, medical records were not made available in time for a scheduled visit or duplicate tests were ordered 43% of the time whereas these mistakes occurred only 22% of the time if patients were seeing a single physician [164]. A study of pediatrician referrals found that the referred specialist received no information 49% of the time while the referring physician received no feedback 45% of the time [165]. Service duplication, unnecessary hospitalizations, medical complications, and patient non-adherence to care resulting from poor coordination was responsible for an estimated $25-$45 billion in wasteful spending in 2011 [166]. These redundancies and costs can be reduced while maintaining the same or better health outcomes by effective collaboration among specialty and primary care providers [167-169].

Collaborative care is defined as “ongoing working relationship between clinicians, rather than a specific product or activity" [170]. In collaborative care, healthcare providers combine their skills and knowledge to identify problems and treatments, and continually adapt provision of healthcare as needed. The terms such as integrated care, coordinated care, and care coordination have been used in the medical community to represent closely related concepts [170]. Collaborative care in the healthcare sector is crucial for more effective and efficient delivery of healthcare services [171, 172], and it has been recognized by the Institute of Medicine as a key strategy for transforming healthcare quality that could potentially make the US healthcare system more effective, more efficient, and safer [173].

In this chapter, we particularly focus on collaborative care for children with mental health disorders. Nearly one in five U.S. children suffer from mental health conditions [174]. Among those children, at least 80% do not receive treatment for their mental health conditions [175]. However, almost 75% of these patients are seen in the pediatrician's office, and hence primary care providers (PCPs) often provide the first line of treatment, identifying, diagnosing, and sometimes treating mental health disorders. After proper diagnosis by PCPs, these children should be referred to mental health specialized providers (MHPs) to receive specialty care. During the treatment, regular communication between PCPs and MHPs is necessary, and effective coordination of mental health, medical, and social needs is crucial to prevent unnecessary hospitalizations and emergency department use [175, 176]. Despite this, communication between MHPs and PCPs is historically known to be poor, and unlikely to improve without a systematic approach [175]. To estimate the impact of such an approach on access to healthcare services, realistic partnerships among participating providers must first be determined.

This study evaluates the potential impact of a systematic approach to collaboration between MHPs and PCPs by developing a congestion game framework to connect PCPs with MHPs. More specifically, this framework captures preferences of both PCPs and MHPs, and its resulting solution is an equilibrium of the game that specifies each PCP needs to work with which MHP to provide collaborative care to children. The congestion game framework is a simplified perspective into the collaboration of PCPs and MHPs; however it is useful in understanding how access to mental health services could improve under such collaboration.

Congestion games were originally introduced by Rosenthal [177], whose model involves a set of players who must choose a subset from among a set of resources. The cost of using each resource depends on congestion, defined as the number of players who selected that resource, and each player's goal is to minimize her own total cost. [177] demonstrated the existence of a pure Nash equilibrium, where no player can unilaterally reduce her cost.

Ever since [177] seminal work, there have been various extensions in the structure of congestion games. To model the collaborative care problem as a congestion game, we consider each PCP as a player and each MHP as a resource. However, none of the existing models in congestion game literature can fully describe the main elements of the interaction between PCPs and MHPs. The best available model for our purpose is that of [178], which would allow MHPs to limit the number of PCPs with whom they can work and prioritize PCPs according to their own preferences. However, it imposes a restrictive assumption, specifically, that the cost of working with an MHP should be the same for all PCPs. Motivated by this shortcoming, in this chapter, we extend congestion games into a more general setting in which resources have capacities and preferences and the cost to use a resource can vary by player. Our contributions in this paper are both methodological and applied.

The methodological contributions of this paper are: (i) We establish the existence of a pure Nash equilibrium for our more general setting by developing a polynomial-time algorithm to find such an equilibrium. (ii) We investigate the more challenging problem of finding the minimum social cost pure equilibrium, which we show to be NP-hard. (iii) We develop a mixed-integer program (MIP) to solve this problem.

We apply our methodological results to the problem of providing collaborative care by PCPs and MHPs to children with mental health conditions using real data provided by the Centers for Medicare & Medicaid Services. We show that our equilibrium solution would nearly double the number of children receiving mental health services under the coordinated care approach versus the traditional healthcare delivery, while meeting preferences of both PCPs and MHPs, without significantly increasing the workload of the majority of MHPs. We additionally provide results demonstrating the efficiency of this healthcare delivery solution with respect to social cost. Finally, our model may be applied in other collaborative care applications, particularly between PCPs and secondary care providers.

The remainder of this chapter is organized as follows. In Section 5.2, we review the relevant literature. In Section 5.3, we formally introduce our congestion game setting. In Section 5.4, we present theoretical results regarding the existence of a pure equilibrium and the computational complexity of finding the minimum social cost pure equilibrium. Section 5.5 provides an MIP formulation for the problem of finding the minimum social cost pure equilibrium. In Section 5.6, we describe the parameters of the collaborative care approach and the results of applying the congestion game model to evaluate collaborative care between PCPs and MHPs. Finally, concluding remarks are presented in Section 5.7.

5.2 Related Literature

In this section, we review the relevant congestion game models to delineate distinctions of our model over the existing literature.

Following the introduction of congestion games by [177], this class of games has been extended in various ways. Two particular classes of extensions which are of interest include (i) player-specific cost functions, and (ii) resources with preferences. We will elaborate on these two extensions below.

Congestion games with player-specific cost functions (i.e., player-specific congestion games) allow players using the same resource to each have different cost rather than sharing the same cost function. Such games are useful for modeling interference in wireless networks [179, 180], the service chain composition problem in network function virtualization [181], and the assignment of distribution facilities to population groups [182]. Congestion games with player-specific costs do not necessarily have a pure Nash equilibrium [183], and deciding in general whether a game has a pure Nash equilibrium is NP-complete [184]. To guarantee the existence of a pure Nash equilibrium, it is necessary and sufficient that for each resource the cost functions for every pair of players are affine transformations of each other [185]. However, in the case where each player chooses only a single resource (called *singleton congestion games*), a pure Nash equilibrium has been proven to always exist when all cost functions are non-decreasing in congestion by [186] using the concept of finite improvement path introduced by [187]. This result has been established more generally for matroid games, in which each player's action space has a special combinatorial structure, i.e., the bases of a matroid, over the resources [188].

The other class of extensions is in allowing each resource to have its own preferences over the set of players. This may be further subclassified into uncapacitated games and capacitated games. In uncapacitated games, the resource only accommodates the most preferred players who have proposed to the resource. Note that a resource may have the same preference for multiple players, and there is no capacity limit for each resource. [189] showed that such games with player-specific costs and a matroid structure for the action space of each player, including singleton games, possess a pure Nash equilibrium that can be computed in polynomial time.

The other subclass, capacitated games, with resources having their own capacities and preferences over players but not player-specific cost functions, has been studied by [178]. They provided polynomial time approaches to compute a pure Nash equilibrium in singleton capacitated congestion games and in capacitated congestion games with only two resources. However, they showed that determining whether such an equilibrium exists in non-singleton games with at least three resources is NP-complete, even in the case of two players and symmetric strategies.

What distinguishes our study from the literature is that we consolidate the two above-mentioned directions of extensions into a single general setting. More specifically, we introduce a class of singleton congestion games with both player-specific costs and resource capacity. For our more general setting, the results of [178] imply that identifying the existence of a pure Nash equilibrium is NP-complete. Hence, we impose the assumption of non-decreasing cost in congestion under which we provide a polynomial-time approach to identify a pure Nash equilibrium. This assumption is natural and holds in many practical settings including our collaborative care problem. Moreover, we show that the more challenging problem of finding the least social cost pure equilibrium is NP-hard, which we solve by developing an MIP formulation.

5.3 Capacitated Singleton Congestion Game Model

A capacitated singleton congestion game, as studied by [178], may informally be described as a set of players and resources, in which each player should choose only one resource among the available resources to the player. Moreover, each resource has a limited capacity and a preference rule over players to select among the players who have proposed the resource. The player's cost of choosing each resource only depends on the number of players who have chosen that resource. The structure of this game makes it a natural choice for modeling of the collaborative care problem. To illustrate this, consider a general overview of interactions between PCPs and MHPs, described below.

Each PCP based on her own preference offers an MHP to collaborate. Once each MHP has received the offers of collaborations from different PCPs, he should select which one to accept, based on his preference and his available capacity. Moreover, the utility of each PCP is only affected by the number of PCPs who work with the same MHP, and each MHP has his own preference over different PCPs to work with. Therefore, it seems reasonable to model this application as a congestion game where PCPs and MHPs correspond, respectively, to players and resources. However, there is a major shortcoming in the congestion game model of [178] which prevents us from directly applying it to our collaborative care setting. More specifically, in the model of [178], the cost of choosing a specific resource is identical for all players while in our application, this cost varies across different players. This has motivated us to extend capacitated singleton congestion games into a more general setting with player-specific costs. We formally define this generalized class of congestion games in the rest of this section.

Our capacitated singleton congestion game with player-specific costs consists of a set $\mathcal{N}$ containing n players and a set $\mathcal{R}$ containing m resources. Each player i has her own private cost function for utilizing resource j, denoted by $d_{ij}(\cdot)$. Each resource j has its own positive capacity K_j and ranking for each player i, denoted by p_{ij}, with lower ranks indicating higher preference. We assume preferences are strict, meaning at each resource, no two players share a rank. Each player's strategy consists of proposing to a single resource, and we denote σ_i as the resource player i proposed to and $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_n)$ as a vector containing the strategies of all players. We allow our games to be asymmetric, meaning player's action space Σ_i (that is, the set of all possible strategies player i can choose from) can be a nonempty subset of $\mathcal{R}$ (i.e., $\sigma_i \in \Sigma_i \subseteq \mathcal{R}$).

Once a player i has proposed to a resource j (i.e., $\sigma_i = j$), the resource can decide whether to *accommodate* that player based on its capacity. If the player is not accommodated, that player will incur infinite cost. If the player is accommodated, that player will incur a cost according to her cost function for that resource, $d_{ij}(n_j)$, where n_j denotes the *congestion* at resource j, defined as the number of players who are being accommodated by this resource. Motivated by our healthcare application, we assume that $d_{ij}(n_j)$ is non-decreasing in congestion. Under strategy profile σ, the player's final cost f_i will therefore equal the following:

$$f_i = \begin{cases} d_{i\sigma_i}(n_{\sigma_i}), & \sigma_i \text{ accommodates } i \\ \infty, & otherwise \end{cases}$$

All players act simultaneously in this game, and a resource must accommodate all players that propose to it until its capacity is met. If the number of players who propose to a resource exceeds its capacity, the resource only accommodates players who are the most preferred based on the previously defined notion of rank. We say a resource is *saturated* if its congestion equals its capacity (i.e., $n_j = K_j$). Otherwise, the resource is called *unsaturated*.

5.4 Equilibrium: Existence, Selection, and Complexity

In this section, we present our methodological results regarding the existence of an equilibrium and the computational complexity of finding one with minimum social cost. We provide all the proofs Appendix D. We start by demonstrating the existence of a pure equilibrium in our generalized setting of congestion games when all player-specific cost functions d_{ij} are non-decreasing in congestion. To fulfill this, we follow an inductive approach to construct an equilibrium of an n-player game using an equilibrium of an $(n-1)$-player game. This constructive approach is formally presented in the next theorem.

Theorem 1: *Suppose we have a player-specific singleton capacitated congestion game on $n-1$ players at a pure equilibrium. Assume that all player cost functions accommodated by a resource j are non-decreasing with the congestion of resource j. If an additional player P_n, with a cost function non-decreasing in congestion, is added, the new game can again reach a pure equilibrium.*

The existence of a pure equilibrium is an immediate consequence of Theorem 1, which is formalized in the next theorem. The proof of Theorem 1, provided in Appendix D, also gives the algorithm to find such an equilibrium. For a game with n players and m resources, this algorithm is able to reach an equilibrium with at most $O(n^3m^2)$ strategy changes.

Theorem 2: *A pure Nash equilibrium exists for any player-specific singleton capacitated congestion game for which all player cost functions are non-decreasing with resource congestion.*

The proof of this theorem is in Appendix D. Theorem 2 establishes the existence of a pure Nash equilibrium, but we have not ascertained its uniqueness. In fact, each congestion game may have multiple pure equilibria; this naturally leads to the following equilibrium selection problem: *Given a social cost function, which pure equilibrium has the minimum social cost?* In this paper, we adopt the commonly used utilitarian social cost function, defined as the sum of all players' costs. The equilibrium selection problem is important for a couple of reasons as discussed below.

In many applications, including the motivating application of this paper, there exists a social planner who is in a higher level of decision making. This planner is interested in complying with the autonomy of the players while reaching a socially optimal outcome. This means the planner has the opportunity to choose an equilibrium with minimum social cost, which results into the above-mentioned equilibrium selection problem. The planner cannot enforce the obtained equilibrium, but she can provide recommendations to the players about which action they need to follow. Each player would not be better off by a unilateral deviation from the prescribed recommendation; this implies the enforceability of the minimum cost equilibrium.

Measuring inefficiency of equilibria has gained considerable attention in game theory, when the social cost of the game is compared with that of a centrally designed system [190]. In other words, we measure how much cost the system incurs due to the autonomy of players. This cost is insightful for the social planner since it indicates how well the current system works. In fact, if the cost is high, the social planner may need to pursue possible initiatives to decrease it. *Price of stability* is one of the well-known metrics to measure such an inefficiency, and it is defined as the ratio of the social cost of a minimum cost equilibrium to that of a minimum cost strategy profile [191]. A variation of this notion is *pure price of stability*, for which the set of pure equilibria is considered in the numerator of the ratio. By finding a minimum cost pure equilibrium, we can compute the pure price of stability which has the above-mentioned managerial insights.

In the following, we establish the computational complexity of the equilibrium selection problem. For the congestion game setting of [177], [192] showed that the problem of finding a pure equilibrium is PLS-complete. For our congestion game, the proof of

Theorem 2 presents a polynomial-time approach to find a pure equilibrium. However, the problem of finding a best pure equilibrium intuitively seems more challenging. The next theorem addresses this question formally.

Theorem 3: *The problem of finding a minimum social cost pure equilibrium is strongly NP-hard.*

5.5 MIP Formulation of Equilibrium Selection

As the problem of finding a minimum cost pure equilibrium is NP-hard, no polynomial-time algorithm can solve it unless $P = NP$. However, it is crucial to develop a solution method that can solve it in practice. Mixed-integer programming (MIP) is a powerful tool to model and solve discrete optimization problems, and it has already been used in the literature to identify equilibria of game theory models [193, 194]. In this section, we develop an MIP formulation to characterize pure equilibria of the congestion game, and subsequently find the one with the least social cost. The parameters and decision variables of our model are as follows:

- $\mathcal{N} \coloneqq \{1,2, \dots, n\}$ denotes the set of players.
- $\mathcal{R} \coloneqq \{1,2, \dots, m\}$ denotes the set of resources.
- $\mathcal{K}_j \coloneqq \{1,2, \dots, K_j\}$ denotes the set of possible positive values for congestion of each resource $j \in \mathcal{R}$.
- y_{ij}: A binary variable where $y_{ij} = 1$ means that player i chooses resource j, and $y_{ij} = 0$ otherwise.
- c_j: A variable denoting the congestion level of resource j. Clearly, $c_j = \sum_i y_{ij}$.

- x_{ijk}: A binary variable used to model the nonlinear cost function of player i. More specifically, $x_{ijk} = 1$ if and only if $y_{ij} = 1$ and $c_j = k$.
- z_{jk}: A binary variable used to model the nonlinear cost function of player i if she chooses to switch to resource j. More specifically, $z_{jk} = 1$ if and only if congestion of resource j is k. Note that $z_{jK_j} = 1$ implies that resource j is saturated. Note that the index k may take any integer value from 0 to K_j.
- f_i: A variable denoting the cost of player i.
- o_{ij}: A binary variable where $o_{ij} = 1$ if and only if resource j is saturated, and player i is accommodated by the resource in the case where she chooses to switch her decision to resource j.
- q_{ij}: A binary variable where $q_{ij} = 1$ if and only if resource j is saturated, and player i is not accommodated by the resource in the case where she chooses to switch her decision to resource j.

We present the following MIP polyhedron to characterize pure equilibria of the game.

$$\sum_{j \in \mathcal{R}} \sum_{k \in \mathcal{K}_j} x_{ijk} = 1 \qquad \forall i \in \mathcal{N} \qquad \text{(5.1a)}$$

$$x_{ijk} \leq y_{ij} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R}, k \in \mathcal{K}_j \qquad \text{(5.1b)}$$

$$\sum_{j \in \mathcal{R}} y_{ij} = 1 \qquad \forall i \in \mathcal{N} \qquad \text{(5.1c)}$$

$$c_j = \sum_{i \in \mathcal{N}} y_{ij} \qquad \forall j \in \mathcal{R} \qquad \text{(5.1d)}$$

$$c_j = \sum_{k \in \{0\} \cup \mathcal{K}_j} k\, z_{jk} \qquad \forall j \in \mathcal{R} \qquad \text{(5.1e)}$$

$$\sum_{k \in \{0\} \cup \mathcal{K}_j} z_{jk} = 1 \qquad \forall j \in \mathcal{R} \qquad \text{(5.1f)}$$

$$0 \leq c_j - \sum_{k \in \mathcal{K}_j} k\, x_{ijk} \leq K_j \left(1 - y_{ij}\right) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad \text{(5.1g)}$$

$$f_i = \sum_{j \in \mathcal{R}} \sum_{k \in \mathcal{K}_j} d_{ij}(k) x_{ijk} \qquad \forall i \in \mathcal{N} \qquad \text{(5.1h)}$$

$$f_i \leq \sum_{k \in \mathcal{K}_j} d_{ij}(k) z_{j(k-1)} + M z_{jK_j} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \tag{5.1i}$$

$$f_i \leq d_{ij}(K_j) + M(1 - o_{ij}) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \tag{5.1j}$$

$$\sum_{i': p_{i'j} > p_{ij}} y_{i'j} \leq M(1 - q_{ij}) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \tag{5.1k}$$

$$o_{ij} + q_{ij} \geq z_{jK_j} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \tag{5.1l}$$

$$x_{ijk}, y_{ij}, z_{jk}, o_{ij}, q_{ij} \in \{0,1\} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R}, k \in \mathcal{K}_j \tag{5.1m}$$

$$z_{jk} \in \{0,1\} \qquad \forall j \in \mathcal{R}, k \in \{0\} \cup \mathcal{K}_j \tag{5.1n}$$

$$c_j, f_i \quad \text{unrestricted} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \tag{5.1o}$$

where M denotes a large number. A specific number should be substituted for the big-M coefficients in constraints (5.1i), (5.1j), and (5.1k) when the polyhedron (5.1a)-(5.1o) is given to an MIP solver. For this purpose, the big-M coefficients should be appropriate upper bounds such that the polyhedron (5.1a)-(5.1o) includes all pure equilibria. The big-M coefficient may be replaced by $\max_{\bar{j} \in \mathcal{R}}\{d_{i\bar{j}}(K_{\bar{j}})\}$, $\max_{\bar{j} \in \mathcal{R}}\{d_{i\bar{j}}(K_{\bar{j}})\} - d_{ij}(K_j)$, and the size of the set $\{i': p_{i'j} > p_{ij}\}$ for constraints (5.1i), (5.1j), and (5.1k), associated with each $i \in \mathcal{N}$ and $j \in \mathcal{R}$, respectively. Note that constraints (5.1a), (5.1c), and (5.1f) are specially ordered sets of type 1, a set of variables of which exactly one member may be nonzero in each feasible solution. Moreover, we need an objective function to be able to choose among all pure equilibria, and the utilitarian objective function (i.e., $\sum_{i \in \mathcal{N}} f_i$) is a natural choice here as noted earlier.

Theorem 4: *When the sum of capacity of all resources are greater than or equal to the number of players, i.e.,* $\sum_{j \in \mathcal{R}} K_j \geq n$, *the polyhedron (5.1a)-(5.1o) characterizes all pure equilibria of the congestion game.*

The above theorem needs the regularity condition $\sum_{j\in\mathcal{R}} K_j \geq n$. If this condition is violated, we can easily transform the game to one which satisfies such a condition, and its equilibria has a one-to-one correspondence with those of the original game. For this purpose, we only need to add a dummy resource which has an unlimited capacity, and the cost of choosing this resource is strictly larger than the highest possible cost of choosing any other resource. An interesting special case of the game is when the cost function is linear with respect to congestion, i.e., $d_{ij}(c_j) = d_{ij}c_j + b_{ij}$. For such a case, we can present a more parsimonious MIP formulation to characterize pure equilibria of the game. In fact, we no longer need the variables x_{ijk} and z_{jk}, of the formulation (5.1a)-(5.1o). Following the same line of arguments as that of the formulation (5.1a)-(5.1o), we can develop the following formulation:

$$\sum_{j\in\mathcal{R}} y_{ij} = 1 \qquad \forall i \in \mathcal{N} \qquad (5.2a)$$

$$c_j = \sum_{i\in\mathcal{N}} y_{ij} \qquad \forall j \in \mathcal{R} \qquad (5.2b)$$

$$c_j = \tilde{z}_j + \overline{z}_j \qquad \forall j \in \mathcal{R} \qquad (5.2c)$$

$$-M(1 - y_{ij}) \leq f_i - d_{ij}c_j - b_{ij} \leq M(1 - y_{ij}) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2d)$$

$$f_i \leq d_{ij}c_j + d_{ij} + b_{ij} + M\overline{z}_j \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2e)$$

$$f_i \leq d_{ij}(K_j) + M(1 - o_{ij}) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2f)$$

$$\sum_{i':p_{i'j}>p_{ij}} y_{i'j} \leq M(1 - q_{ij}) \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2g)$$

$$o_{ij} + q_{ij} \geq \overline{z}_j \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2h)$$

$$\tilde{z}_j \leq K_j - 1 \qquad \forall j \in \mathcal{R} \qquad (5.2i)$$

$$y_{ij}, \overline{z}_j, o_{ij}, q_{ij} \in \{0,1\} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R}, k \in \mathcal{K}_j \qquad (5.2j)$$

$$\tilde{z}_j \in Z_+ \qquad \forall j \in \mathcal{R} \qquad (5.1k)$$

$$c_j, f_i \quad \text{unrestricted} \qquad \forall i \in \mathcal{N}, j \in \mathcal{R} \qquad (5.2l)$$

Note that the new variables $\overline{z_j}$ and $\widetilde{z_j}$ are introduced to identify whether resource j is saturated. In fact, $\overline{z_j} = 1$ if and only if resource j is saturated.

5.6 Primary Care Physicians and Behavior Care Specialists Integration

We can use the congestion game model introduced in Section 5.3 to obtain a potential matching between primary care providers (PCPs) and mental health (specialized) providers (MHPs) that could be used to coordinate primary care and mental health services, specifically, focusing on psychosocial services. We specifically consider collaborative care, in which PCPs and MHPs form an ongoing relationship and work together to deliver care to patients [170]. There are different levels of collaborative care ranging from minimal collaboration, in which providers rarely communicate, to merged practices where providers share a practice space and act as a unified team [195]. We focus on collaborative care in which PCPs regularly consult with MHPs about their patients. Such collaboration is especially important for children as most children with behavioral health conditions are treated in primary care settings rather than mental health settings [196]. Communication and treatment can occur through the use of telehealth tools such as videoconferencing rather than co-location [197-200]. This is particularly useful in areas where patients do not have access to mental health providers. Collaborative care has been implemented in various clinics and has been shown to be effective [195, 201].

We illustrate our analysis for the Medicaid-insured child population (age ≤ 18) in the state of New York. New York was selected since we were able to attribute over 90% of psychosocial services in that state to individual mental health providers. However, our methodology can be applied to any state and healthcare setting for which the necessary provider data can be obtained.

Data primarily comes from two sources: the 2013 National Plan and Provider Enumeration System (NPPES) [38], which lists the National Provider Identifier (NPI) of all providers that electronically bill for services along with their primary taxonomy and practice address, and the 2013 Medicaid Analytic eXtract (MAX) [40], which contains all Medicaid claims made in 2013 as well as the age, county, and zip code of Medicaid beneficiaries. Urbanicity of each provider was determined using the 2010 Rural-Urban Commuting Area (RUCA) code [144] of their practice location census tract and urbanicity of each child was determined using Zip Code RUCA Approximation [144], with RUCA codes 1-3 representing large urban areas, codes 4-6 representing small urban areas, and codes 7-10 representing rural areas.

5.6.1 Model Calibration

In this subsection, we illustrate how we apply the congestion game framework to model our healthcare application. For this purpose, we should identify components of the game, i.e., players, resources, costs, capacities, preferences, and action spaces.

Players, resources, and action space: We identified individual PCPs and MHPs in New York through their primary taxonomy code and practice location as listed in the NPPES data. We considered only those serving Medicaid-insured children, that is PCPs who billed at least 11 Medicaid-insured children and MHPs who provided psychosocial services to at least 11 Medicaid-insured children, determined using the MAX claims. A minimum of 11 children was selected because that is the minimum required to maintain patient confidentiality when using the MAX claims. We assumed PCPs working in the same office as an MHP already have a working relationship with that MHP and would therefore collaborate with that MHP. Thus, we further considered only PCPs not co-located with an MHP and MHPs not co-located with a PCP.

We additionally assumed that PCPs sharing an office with each other would realistically work with the same MHP when possible. For such a restriction to be incorporated into our model, PCPs sharing a location should be treated as the same player. However, a location with a large number of PCPs or especially busy PCPs matched to a single MHP may overwhelm that MHP. Therefore, we grouped PCPs sharing a location together up to a limit representing the demand an MHP can handle. We set this limit to be the median number of Medicaid-insured child visits among all PCPs. Specifically, we grouped PCPs together such that the number of PCP groups (PCPGs) at each primary care location was $\min\left(q, \left\lceil \frac{v}{250} \right\rceil\right)$, where q is the number of PCPs at the location, v is the number of visits by Medicaid-insured children observed from those PCPs in 2013, and 250 is the median number of Medicaid-insured child visits among all PCPs in 2013. We used these PCPGs as our players. Thus, our player set $\mathcal{N}$ consisted of 4,337 PCPGs (representing 4,637 PCPs), and our resource set $\mathcal{R}$ consisted of 1,000 MHPs. We assumed any MHP could be matched to any PCPG. That is, $\Sigma_i = \mathcal{R}\ \forall i \in \mathcal{N}$.

Cost Functions: The cost d_{ij} for player i to utilize resource j was set equal to $w_i \frac{dist_{ij}}{M} + (1 - w_i)\frac{n_j}{C}$ where w_i is a weight associated with PCPG i which was randomly generated from a uniform distribution between 0 and 1, $dist_{ij}$ is the travel distance between the practice locations of PCPG i and MHP j (obtained using ArcGIS software), M is the maximum permissible distance between two providers (set to be 500 miles), n_j is congestion of resource j, and C is the maximum capacity across all resources. Note that both the distance and congestion measures are normalized so that d_{ij} is within the interval [0,1].

Capacities and preferences: Capacity K_j of resource j was assumed to scale with the number of psychosocial service visits provided to Medicaid-insured children in 2013. Specifically, it was equal to 1 if the number of observed visits was less than 500 (representing approximately 10 visits available a week), equal to 2 if the number of observed visits was between 500 and 1,000, and equal to 3 if the number of observed visits was greater than 1,000. Finally, for each MHP, PCPGs at locations that share patients with the MHP were given first preference, in order of the number of patients shared between that location and the MHP. Remaining PCPGs followed in order of distance between the MHP and the PCPG location.

Before concluding this subsection, we highlight a simplification that we have made in the decision-making sequence of the congestion game, compared to our collaborative care problem. The interaction between PCPGs and MHPs occur over a dynamic setting where PCPGs are not enforced to act simultaneously. Despite this, the congestion game captures important characteristics of this interaction for the following reasons: (i) When a PCPG finds an MHP, it barely changes its decision over a short period of time due to the inconvenience of finding a new MHP. (ii) In our proof for the existence of a pure equilibrium for the congestion game, we add one player at a time and allow players to iteratively follow their cost minimizing strategy, and show that players will converge to an equilibrium in a finite number of iterations. This informally implies that in a dynamic environment where PCPGs choose their favorite MHPs with available capacity at each point of time, they will reach within a finite time to the equilibrium derived from our static simultaneous-move congestion game.

5.6.2 *Computation and Efficiency of Equilibria*

In this subsection, we report and derive insights from our computational results regarding finding an equilibrium and measuring its inefficiency, as discussed earlier in Section 5.4. For this purpose, we have investigated the following three decision-making approaches, and have measured the performance of their outputs using the utilitarian objective function (i.e., the sum of all players' costs).

(i) The proof of Theorem 2 provides a polynomial-time algorithm to find an equilibrium of the game. We refer to this approach as *Algorithm*.

(ii) The MIP formulation (5.2a)-(5.2l) presents an approach to find the least social cost equilibrium. We refer to this approach as *Decentralized MIP*. Note, in our implementation, we provided the equilibrium found by the first approach as a warm-start solution for this MIP.

(iii) A centralized decision-making setting is defined as when players have no autonomy, and each player has to follow the strategy prescribed by a social planner who seeks to minimize the utilitarian objective function. This strategy profile prescribed by the social planner may be computed by dropping the equilibrium constraints, i.e., (5.2e)-(5.2h), in the MIP formulation (5.2a)-(5.2l). We refer to this approach as *Centralized MIP*.

Note, since the total number of players is higher than the total capacity across all resources, we added a dummy resource with a cost of 1.1 to Decentralized MIP and Centralized MIP for the technical reasons discussed after Theorem 4.

All three approaches were implemented in Python 2.7.16 and run through HTCondor version 8.8.9. Decentralized MIP and Centralized MIP were solved using CPLEX version 12.8.0 through the Python API with a maximum runtime of 10 hours and maximum memory available for working storage of 16GB. As expected, both Decentralized MIP and Centralized MIP were computationally demanding, exceeding memory limitations when trying to solve the instance associated with the complete set of PCPGs and MHPs in our application. Hence, we generated and solved smaller-size instances selected by randomly sampling a subset of PCPGs and MHPs.

The specifications of these instances and the computational results for the three above decision-making approaches are reported in Table 19. In this table, "PCPG" and "MHP" are the number of players and resources, respectively, and "Accom" is the total number of accommodated players. "Tot Cost" is the total cost over all players, with unaccommodated players assigned a value of 1.1 while "Acc Cost" is the cost over only the accommodated players. "Gap" is the relative optimality gap of the given solution, computed within CPLEX.

Table 19 indicates that Algorithm is able to quickly find an equilibrium that is desirable with respect to the utilitarian objective function as demonstrated in the following. Centralized MIP searches over all strategy profiles while the search space of Decentralized MIP is only restricted to equilibria. Hence, the optimal objective value of Centralized MIP provides a lower bound on that of Decentralized MIP, and on the objective value of the resulting equilibrium from Algorithm. Since all these values are close to each other, it indicates that Algorithm finds an equilibrium with nearly the least social cost among all pure equilibria. As the social cost of the equilibrium is close to that of Centralized MIP, it implies that there is not much gain to move into a centralized setting as illustrated in more detail next.

Table 19. Solution quality and runtime under three decision-making approaches for small-size instances.

PCPG	MHP	Accom	Algorithm		Decentralized MP		Centralized MP	
			Tot Cost	Acc Cost	Tot Cost	Acc Cost	Tot Cost	Acc Cost
251	140	154	140.02	33.319	140.02	33.319	124.22	17.522
469	244	269	276.31	56.309	276.31	56.309	271.62	50.519
1050	342	378	819.01	79.807	819.00	79.807	790.82	51.616
628	400	446	304.54	104.343	304.54	104.343	304.54	104.343
PCPG	**MHP**	**Accom**	**Algorithm**		**Decentralized MP**		**Centralized MP**	
			Time (s)		Time (s)	Gap (%)	Time (s)	Gap (%)
251	140	154	0.1		36035.9	19.4	36011.6	14.1
469	244	269	0.4		36077.9	20.4	36031.9	19.0
1050	342	378	3.3		36578.2	9.4	36078.7	6.5
628	400	446	1.9		36112.6	34.3	36013.4	34.3

Recall that in a centralized setting, players have no autonomy and are imposed to act according to the decision making of the social planner. Since in such a setting, the social planner only seeks to minimize the social cost without being restrained by incentives of individual players, it always leads to a lower social cost compared to a decentralized setting. However, this advantage comes at the cost of depriving the players from their ability to choose, which makes the proposed solution unstable and not necessarily enforceable. When the difference of social cost between the centralized and decentralized settings are small (i.e., the price of stability is close to 1), it implies that the marginal gain of a centralized setting is low, and hence there is not enough motivation and justification to the social planner to intervene in the natural interaction among the players presented by the decentralized setting. In summary, our discussion implies that the resulting equilibrium from Algorithm is efficient.

For the full-size instance of our congestion game model with 4,337 PCPGs and 1,000 MHPs, Algorithm finds an equilibrium within 18 seconds. Under this equilibrium, 1,100 PCPGs (25.36%) were accommodated by a resource. Total cost among those accommodated was 233.2632. The MIP was unable to find a solution for this instance within the memory limits. However, the result of Centralized MIP suggests that this equilibrium is efficient. In the remainder of this paper, we will investigate this equilibrium with respect to other criteria and measure its gains over the existing practice.

5.6.3 Implications for Patients

For the equilibrium solution to be beneficial if implemented, it must increase access to mental healthcare for children, quantified as the number of children who receive psychological service. Our algorithm does not directly maximize the number of children with access to collaborative care. Instead, it assigns as many PCPGs to MHPs as possible. We assumed that if a child's PCP was accommodated by an MHP, that child received access to collaborative care. In this subsection, we first quantify the proportion of children granted access to collaborative psychosocial services, overall and by urbanicity. We then verify that access improved under our model when compared with a matching approach based on current practices; this improvement occurred throughout the entire state.

To quantify access resulting from our congestion game model, we used the MAX data to assign each Medicaid-insured child to a single PCP. This was the PCP in the state (not limited to those in our player set) with whom they had the most visits. If that PCP belonged to a PCPG within our player set, we defined that child's assigned PCPG to be that PCPG. We then measured the percentage of children with access, that is, the percentage of children assigned a PCPG within our player set that received access to collaborative psychosocial services under our model equilibrium solution. We additionally computed this percentage considering only children that received psychosocial services in 2013 since these are the children most likely to utilize psychosocial services. Results are shown in Table 20.

Table 20. Access metrics under two matching scenarios.

Metric	Congestion Game Algorithm	Observation-based Matching
PCPGs Accommodated (%)	25.36	15.40
Children with Access (%)	48.74	14.13
Psychosocial service-receiving children with access (%)	52.10	15.25

As intended, our algorithm granted children access to psychosocial services via their PCP. In particular, the proportion of children who received access and the proportion of psychosocial service-receiving children who received access under the collaborative framework were both around twice as high as the proportion of PCPGs accommodated by an MHP, suggesting our parameter settings for MHP preferences resulted in our algorithm giving some priority to PCPGs responsible for more children. That is, MHPs shared more of their patients with PCPGs who had a large patient caseload than with PCPGs who had a smaller caseload, leading to high-patient-volume PCPGs being more preferred and therefore being more likely to be accommodated. Specifically, while only 25.36% of

PCPGs were accommodated by an MHP using our algorithm, these accommodated PCPGs accounted for 48.74% of children and 52.10% of the children who received psychosocial services. Of the 414 PCPGs that were assigned to fewer than 30 children, only 5.8% were accommodated whereas of the 456 that were assigned to more than 1,000 children, 63.8% were accommodated.

Access was expanded throughout the state rather than concentrated in one geography. Across urbanicity levels, the percentage of players accommodated ranged from 20% in rural areas to 25% in large urban areas to 30\% in small urban areas, and the percentage of psychosocial service-receiving children ranged from 44.96% in small urban areas to 47.15% in rural areas to 53.56% in large urban areas (Table 21).

Table 21. Access metrics by urbanicity, under two matching scenarios.

Metric	Congestion Game Algorithm			Observation-based Matching		
	Large Urban	Small Urban	Rural	Large Urban	Small Urban	Rural
PCPGs Accommodated (%)	25.38	29.92	20.17	13.91	21.65	32.77
Children with Access (%)	49.06	46.57	44.68	12.98	25.61	23.51
Psychosocial service-receiving children with access (%)	53.56	44.96	47.15	12.69	26.72	25.25

To determine whether access has increased, we should compare our algorithm with current practices. However, as we do not know exactly which PCPGs already practice collaborative care, we instead compared our algorithm with an alternate matching method that more closely resembles how providers were behaving, which we called the observation-based matching approach. This approach was used to represent current practices and provide a baseline access measurement. In this observation-based matching approach, for each PCP location, we considered the Medicaid-insured children that were assigned a PCPG at that location and sought psychosocial services. If a large proportion of these children visited the same MHP, we assumed PCPs at that location had a collaborative relationship with that MHP. Specifically, for every 1/3 of these children visiting the same MHP, we matched one PCPG at that location with that MHP.

Our algorithm does perform better than matching PCPs with MHPs based on current behaviors. Compared with the observation-based matching approach, our algorithm accommodated 9.95% more PCPGs, granting integrated care to over twice as many children (48.74% versus 14.13%). For all urbanicity levels and for 55 of New York's 62 counties, more psychosocial service-receiving children had integrated care access under our algorithm than under the observation-based method (Figure 15). Much of this difference can be explained by all MHPs being assigned to at least one PCP under our algorithm while only 29.1% of MHPs were under the observation-based method.

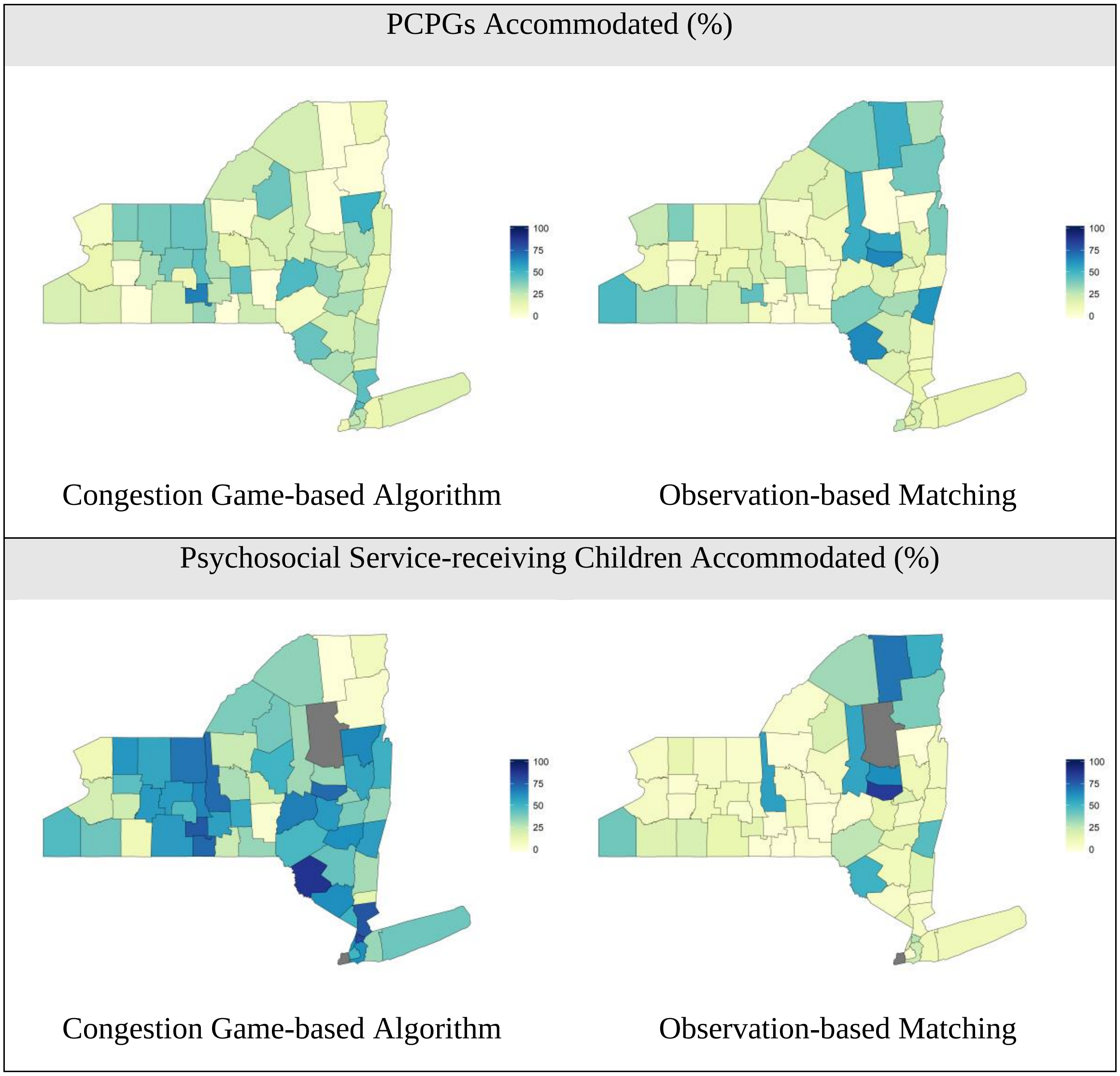


Figure 15. County-level maps of percent of primary care groups (PCPGs) and percent of psychosocial service-receiving children accommodated under two matching methods. Grey counties had fewer than 11 children assigned to PCPGs in our player set.

5.6.4 Implications for Providers

For providers to elect to participate in collaborative care using our equilibrium solution, their preferences must be met and their workload cannot heavily increase. In this subsection, we examine the effect our solution would have on providers. Specifically, we first investigate the extent that preferences of both PCPs and MHPs are met and we next assess that MHP caseload is not negatively impacted.

We assumed that PCPGs would prefer nearby MHPs and MHPs with less congestion. These preferences were incorporated into the cost functions of each PCPG as described in subsection 5.6.1, and our congestion game-based algorithm was designed to make the least-cost move for each PCPG in each iteration. Among the 1,100 accommodated PCPGs, average cost per PCPG was 0.2121, but it ranged from 0.0008 to 0.9612. The resulting distances ranged from near 0 miles to around 364 miles, with the majority being under 12 miles (Figure 16). Costs and distances do depend on the selected components of the player cost functions. For example, under our parameter settings, costs per PCPG at equilibrium are generally positively correlated with the weight given to congestion (i.e. $1 - w_i$, as described in subsection 5.6.1). That is, PCPGs placing more importance on reducing distance generally had lower costs due to the wider range of possible distances. Some PCPGs, however, were forced to have large distances despite having a higher weight on distance than congestion due to few nearby MHPs. For example, Chautauqua county, the westernmost county in New York, had 31 PCPGs in their player set but only 6 MHPs in their resource set, each with a capacity of 1 and some preferring PCPGs in the neighboring counties, resulting in 3 PCPGs being accommodated by MHPs 364 miles away who had the available capacity and 25 remaining unaccommodated. Providers matched at such large distances can still communicate with each other and provide care to patients through telehealth services, thus these distances should not prevent our solution from being implementable.

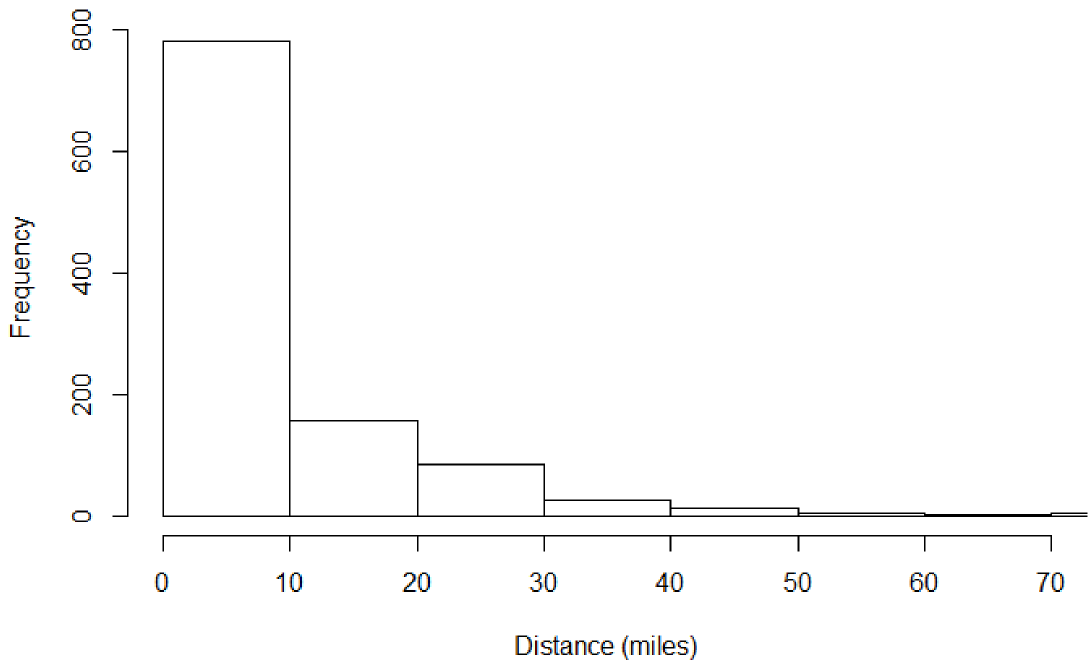


Figure 16. Histogram of the distance between each accommodated player and their matched resource.

Although each step of our algorithm involved finding the least-cost MHP for each PCPG rather than finding the most-preferred PCPG for each MHP, MHPs still generally received their preferred choices of PCPG. This is due to children typically seeking providers to whom they can easily travel, creating a relationship between providers being close in distance (considered in PCPG preferences via their cost functions, with lower distances preferred) and providers sharing patients (considered in MHP preferences, with more shared patients preferred). Statistically, 38% of MHPs were paired with their most preferred PCPG, and 65.8% only work with PCPGs that were among their three most preferred. Only 0.62% of MHPs had to work with a PCPG outside their top ten, with the worst preference rank being 40.

Next, we examine the effect of collaborative care on MHP caseload. We consider for each MHP their child caseload, defined as the number of Medicaid-insured children receiving psychosocial services from that MHP in 2013, and their visit caseload, defined as the total number of psychosocial service visits they provided to Medicaid-insured children in 2013. We compare the caseloads observed in 2013 with those after implementing collaborative care, estimated by considering a scenario where children assigned to accommodate PCPGs received all their psychosocial service visits in 2013 from the matched MHP rather than from their original providers.

The majority of MHPs were not heavily burdened by increased annual caseload after collaborative care implementation. In 2013, median child psychosocial patient caseload and visit caseload for the MHPs were observed to be 19 patients and 129 visits. Boxplots comparing the psychosocial caseload per MHP observed in the 2013 claims, after collaboration under our algorithm, and after collaboration under the observation-based matching approach described in subsection 5.6.3 are shown in Figure 17. Per provider caseload under both matching methods was similar to that observed in the 2013 claims. Using our algorithm, median caseload was only 1 child and 7 visits higher than that observed. In fact, only 101 of the 1,000 MHPs (10.1%) experienced a caseload increase of at least 10 children under our algorithm as compared with that observed in 2013. Only 9.5% experienced an increase of at least 100 visits. This means most MHPs would have needed to add no more than 2 visits a week to satisfy the demand observed in 2013.

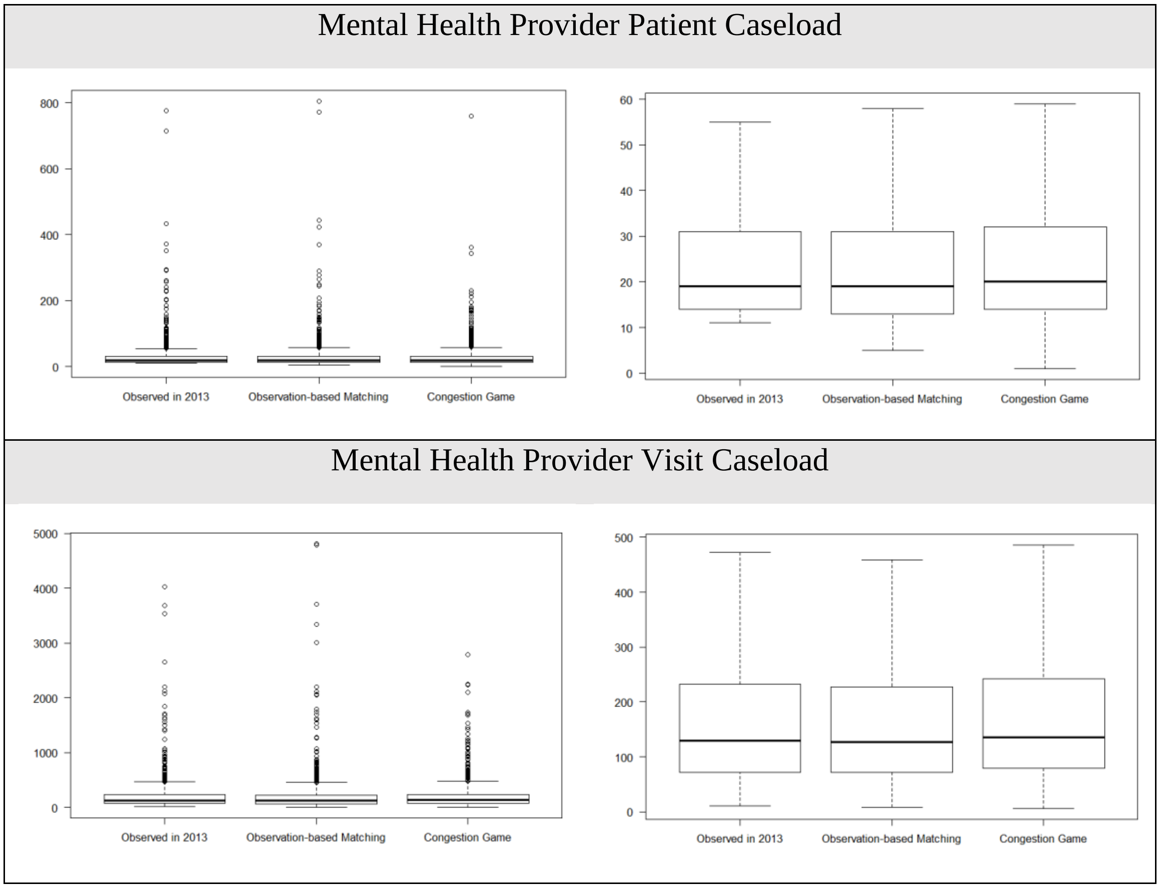


Figure 17. Boxplots of mental health provider caseload, measured in visits and children, as observed in 2013 and under two matching methods, with and without outliers displayed.

County-level maps displaying median caseload are given in Figure 18, and caseload by urbanicity is given in Table 22. Caseload increase was primarily driven by large urban areas, where 89.3% of the MHPs practice. For rural areas, the difference was lessened, with median caseload under our algorithm being just 1 visit higher. For small urban areas, median caseload was instead reduced by 13 visits.

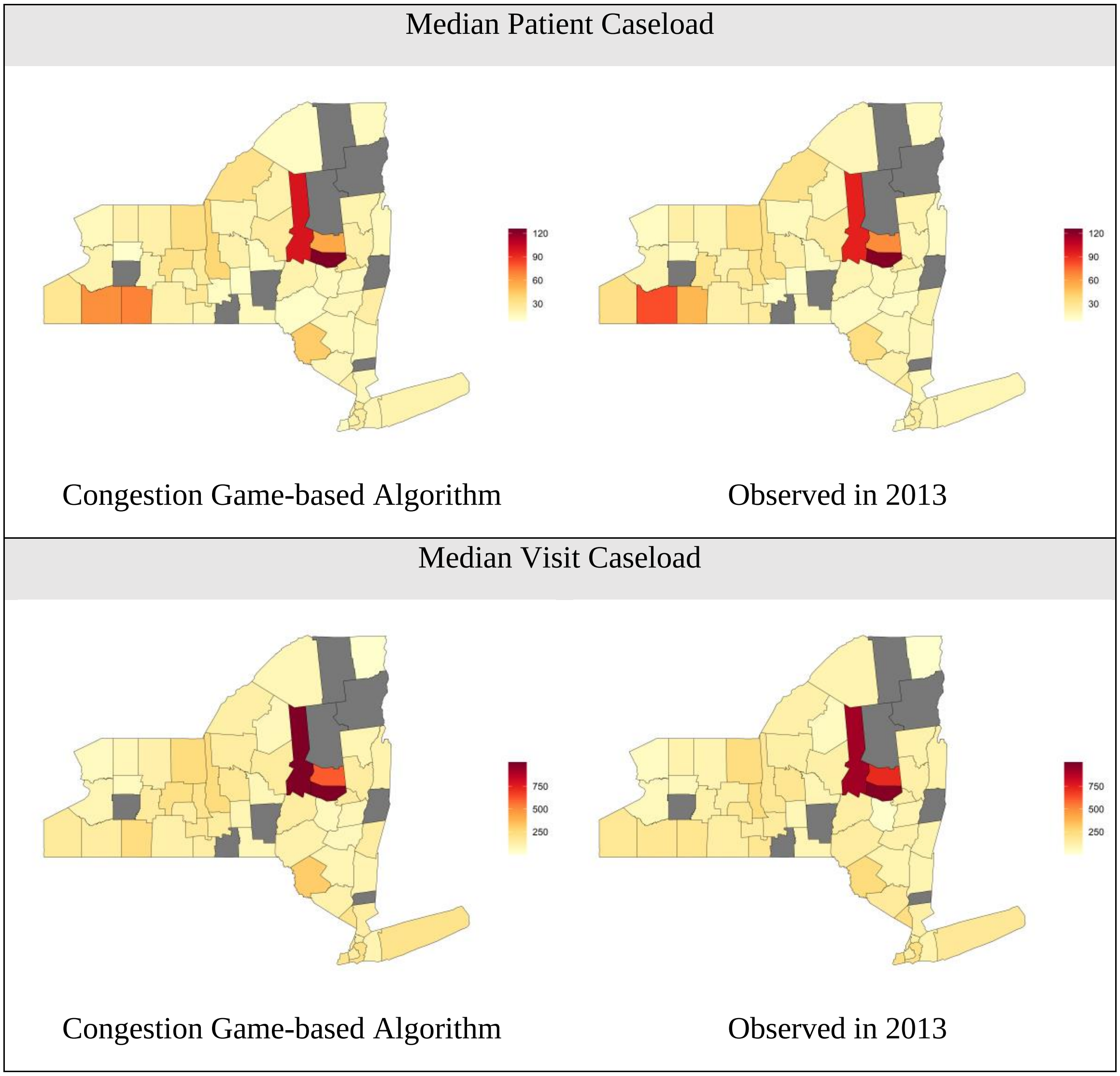


Figure 18. County-level maps of median psychosocial caseload per mental health provider, in children and visits, observed in 2013 and under our algorithm. Grey counties had no mental health providers in our resource set.

Table 22. Median caseload among mental health providers, by urbanicity.

	Congestion Game Algorithm				Observed in 2013			
	Full State	Large Urban	Small Urban	Rural	Full State	Large Urban	Small Urban	Rural
Child Caseload	20	20	22	21	19	19	21	21
Visit Caseload	136	136	140	123	129	129	153	122

5.7 Conclusion

In this chapter, we introduced a method of partnering PCPs with MHPs while considering the capacities and preferences of both provider types for the purpose of evaluating collaborative care. This method extends singleton congestion games to consider cases in which each player has its own private cost function and each resource has a capacity and preferences over the players. In proving that such games have a pure Nash equilibrium, we developed a polynomial time algorithm to find an equilibrium solution. While this algorithm may not produce the Nash equilibrium resulting in the greatest social good, in the context of collaborative primary care and psychosocial services in New York, it can still produce a solution comparable to the optimal found using an MIP in a fraction of the time. If the solution would be implemented, it suggests that collaborative care can increase access to mental health services without greatly burdening healthcare providers. Specifically, 49% of children would have access to psychosocial services via their PCP. Increase in access occurs for all three urbanicity levels and for the majority of counties, suggesting that it does not favor one portion of the state over the rest. In spite of this increase, the median patient caseload for MHPs would only have to increase by 1 child.

CHAPTER 6. CONCLUSION

Understanding disparities in healthcare access is important when designing effective policy interventions to improve the healthcare system. In this thesis, we demonstrated the value of using local-level data to obtain spatial access estimates that can be used to identify significant disparities and inform on their underlying cause. We also simulated policy interventions to assess their impact on access to care. We focused on three healthcare settings: pediatric primary care, adult primary care, and pediatric mental health.

For pediatric primary care, we found among our seven selected states, between-state and within-state differences in median travel distance and median congestion were mostly not significantly greater than 1 mile and 10%, respectively. However, significance maps created using nonparametric regression and simultaneous confidence bands revealed variations in the locations where children eligible for public insurance had significantly lower access than those not eligible. For some states such as Georgia and Minnesota, locations where these children had lower accessibility were concentrated in large urban areas despite such areas having high accessibility overall, suggesting the need to improve public insurance acceptance in these areas. For other states such as Tennessee and North Carolina, eligible children had lower accessibility and availability throughout the state, suggesting the need for statewide interventions.

For adult primary care, our projections to year 2025 showed implementation of the Affordable Care Act in Georgia would overall decrease the percentage of unmet needed primary care visits, improving accessibility while reducing availability. Additionally expanding Medicaid does not substantially burden the privately-insured population.

Implementing a statewide Medicaid parity program or increasing the number of residency positions have little impact on reducing unmet need and improving access to care.

Finally, for pediatric mental health, we found that the majority of psychosocial services available to publicly-insured children were concentrated to only a few locations. Only 15% of children received services from providers not associated with a mental health center or other organization. We designed a system to match mental health specialists with primary care providers while considering both groups' preferences using a novel extension of congestion games to evaluate the potential impact of collaborative care on access to psychosocial services. Results for New York indicated 49% of children could be granted access to collaborative services without greatly increasing mental health provider caseload.

Overall, our results suggest interventions to improve access to primary care should be targeted for specific communities and that access to psychosocial services would benefit from increased community-based services or collaborative care. While our analyses were performed on only a select number of states, the models we use are flexible and can be extended to other states and even other healthcare services given appropriate data on the supply and need of those services. We hope the findings of this thesis and the methodology introduced will be used to make more informed health policy decisions.

APPENDIX A. SUPPLEMENTARY MATERIAL FOR CHAPTER 2

A.1 Sensitivity Analysis on Child Allocation

In order to assess the sensitivity of the optimization model with respect to the assumption that 10% of the workload of internists’ and family practitioners' practices is allocated for children, we perform a sensitivity analysis of the model by varying these parameters. In particular, we run the model multiple times by varying the percentage of the internists workload devoted to children between 0% and 10%, and by varying the percentage of the family practitioners workload devoted to children between 7% and 15%.

The analysis shows that the results of the optimization model are not very sensitive to a change in the values of these parameters, being the level of accessibility (i.e., distance), availability (i.e., congestion) and coverage (i.e., served visits) very close to each other when parameters’ values change.

We report in Figure 19 the graphs for accessibility, availability and coverage at the state level for the each state and for each population when the values of these parameters are varied.

Figure 19. State-level travel distance, congestion, and coverage versus family medicine, internist percent caseload devoted to children.

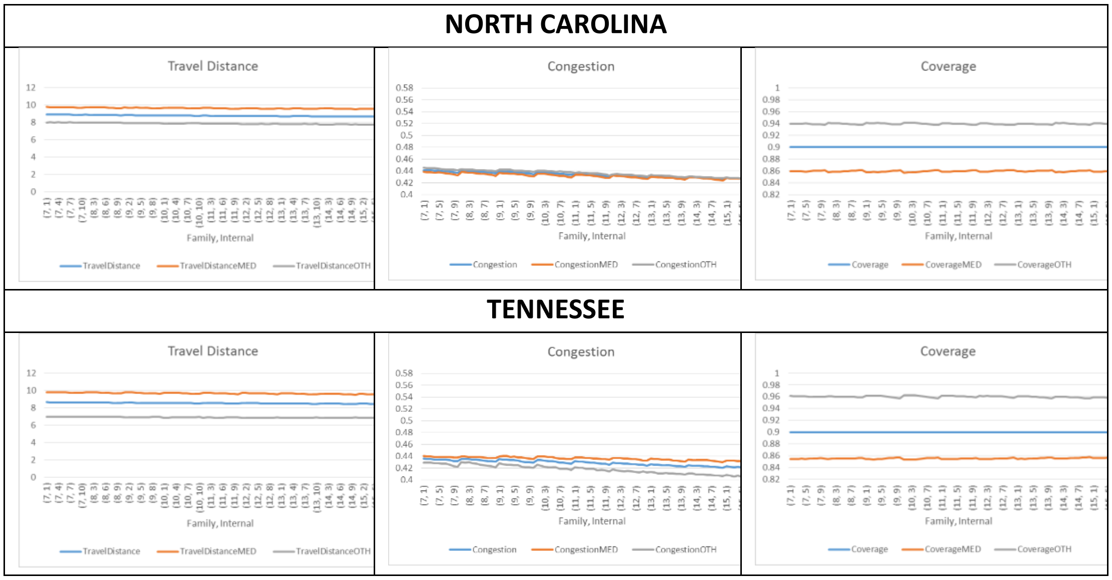


Figure 19 continued.

A.2 Experimental Settings for Total Caseload

This section describes the experimental analysis we carry out to test the sensitivity of the optimization model with respect to providers' workload parameter. Each model is run 50 times, where the caseload of each provider is sampled each run.

We use data from the Health Resources and Services Administration (HRSA) [53] and Organization for Economic Co-operation and Development (OECD) [52] to determine our sampling distributions. Specifically, based on surveys conducted in 2002, 2003, and 2006, the HRSA data reports Average Patient Care Hours Worked per Week by General Internal Medicine Physicians, by age class and gender in full-time equivalent (FTE) units. By considering a work schedule of 45 hours per week, 50 weeks per year, and an average visit duration equal to 16 minutes (equivalent to a panel size of 2500 patients per year per physician [39] and approximately 8400 visits per year), we derived the annual number of visits per physician by age and gender (Table 23).

OECD provides the number of physicians in each of five age classes separated by gender for the United States in 2013 using data from the American Medical Association (Table 24). We fit a Normal Distribution to the data for each gender by calculating the sample mean and standard deviation assuming frequency weights are at the midpoints of each age interval (Figure 20).

Table 23. Annual number of visits per primary care physician by age and gender.

Total Number of yearly visits		
Age	**Male**	**Female**
<40	8736	6888
40-44	8988	7224
45-49	9240	7644
50-54	9912	8064
55-59	9576	7896
60-64	8904	6216
> 64	7056	7560

Table 24. Physicians by age and gender (from OECD).

Number of Physicians		
Age	**Male**	**Female**
<35	71867	13174
35-44	112769	83115
45-54	130264	67710
55-64	137081	45240
65-74	81787	13174

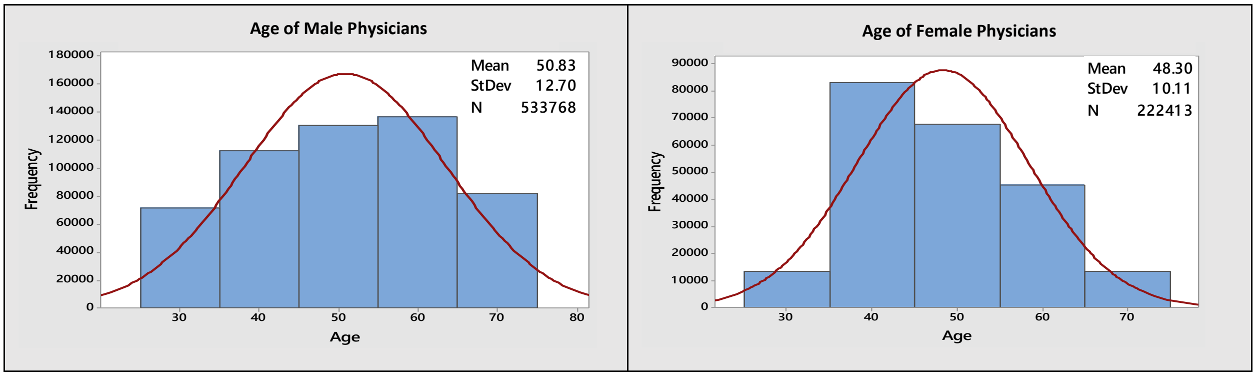


Figure 20. Age distribution with fitted normal curve for male physicians and for female physicians.

For our sampling procedure, we follow three steps:

First, we determine the gender of each physician at physician location j. A physician's gender can be found in the NPI database [38]. However, not all physicians list their gender. We use the NPI database to obtain the gender of all physicians at j who have their gender listed. We then calculate the proportion of physicians who are female at j based on the providers who have their genders listed. If no providers' genders are known at j, we instead use the 2013 national ratio of 0.3409 female found in the OECD data table. Then for each physician of unknown gender, we generate a random number between 0 and 1. If the number is less than the proportion female at j, we say that physician is female. Otherwise we say they are male.

Second, we generate a random age for each physician based on their gender by sampling from the corresponding Normal Distribution depicted in Figure 20. Finally, using each physician's sampled age and gender, we find the total yearly visits for that physician in Table 23.

APPENDIX B. SUPPLYMENTARY MATERIAL FOR CHAPTER 3

B.1 Supply Model Validation

This section presents a comparison of our results with existing results in the literature for a validation of our supply projection model.

To validate the Student Module, we compared our output with data from the Georgia Board for Physician Workforce's Graduate Medical Education Survey Reports, 2002-2013 [202]. Results are shown in Figure 21 for different growth scenarios. We found the number of Georgia GME graduates projected by the Student Module to be comparable to the number of graduates recorded in previous years.

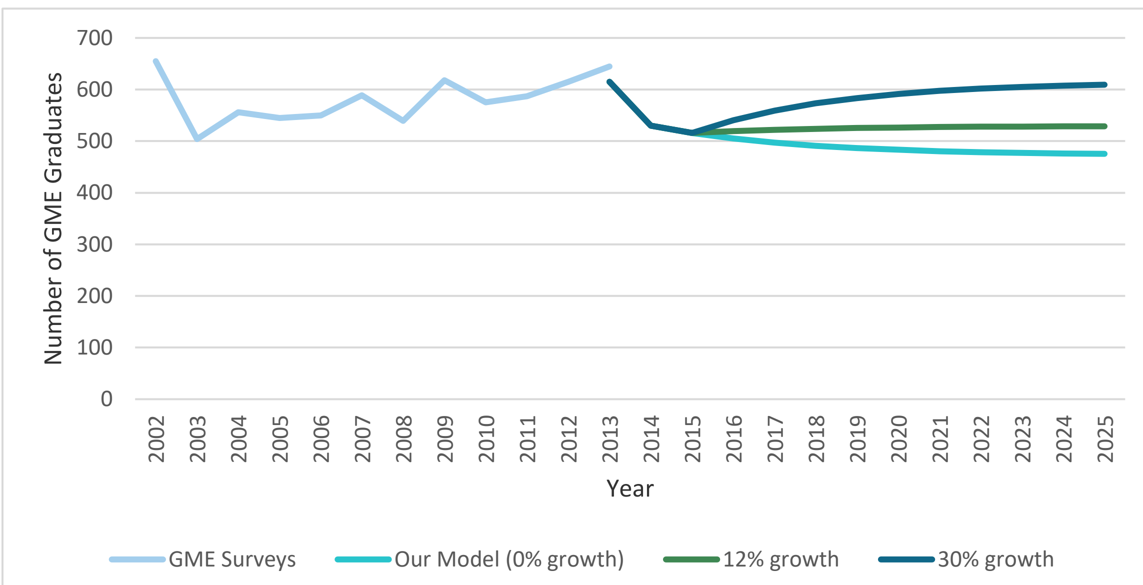


Figure 21. Number of Georgia GME graduates, 2002-2025.

To validate the Workforce Module, we compare our predicted growth in physicians to national projections made by HIS Inc in 2013 [97] and HRSA in 2006 [203] and 2013 [53].

Because the 2014 numbers were not explicitly given, we assumed a constant increase in providers per year between 2010 and 2015 for the HRSA 2006 study and between 2010 and 2020 for the HRSA 2013 study. Results including the different scenarios for growth in GME entrants are given in Table 25 and Table 26. Our projected increase is consistent with those produced by HIS Inc. and HRSA.

Table 25. Percent growth in primary care providers, 2013-2025.

Source	Physicians in 2013	Physicians in 2025	Percent Growth (%)
GA model (0% growth)	6,699	7,314	9.1
GA model (12% growth)	6,699	7,376	10.1
GA model (30% growth)	6,699	7,483	11.7
IHS	240,800	266,700	10.8

Table 26. Percent growth in primary care providers, 2014-2020.

Source	Physicians in 2014	Physicians in 2020	Percent Growth (%)
GA model (0% growth)	6,794	7,241	6.6
GA model (12% growth)	6,814	7,290	6.9
GA model (30% growth)	6,800	7,285	7.3
HRSA 2013	211,320	220,800	4.5
HRSA 2006 – Total PCPs	280,998	298,680	6.3
HRSA 2006 – FTE PCPs	205,204	216,890	5.7

We additionally compared the age distribution projected for year 2020 by our Workforce Module with the age distribution of all physicians at the national level in 2020 as given in the HRSA 2006 study [203] and by [68] considering initial numbers both from the US Census Bureau Current Population Survey (CPS) and from the American Medical Association Physician Masterfile (Masterfile). This is shown in Figure 22.

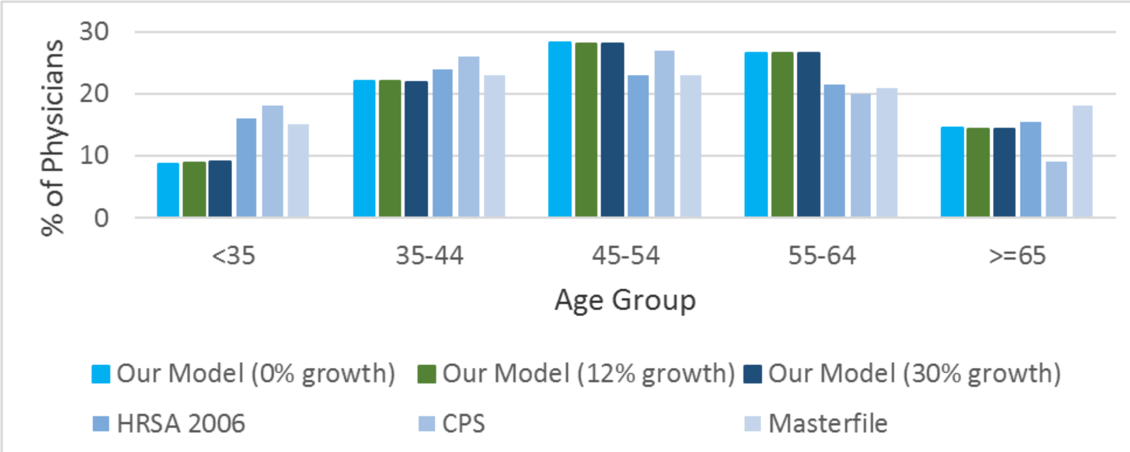


Figure 22. Primary care provider age distribution, 2020.

B.2 Medicaid Insurance Eligibility Forecast Model

This section details the steps taken to produce estimates of the number of adults eligible for Medicaid each year between 2013 and 2025 under each of the three ACA implementation scenarios. That is, our intended output is:

- $T_{c,t}^{MED,NE}$: The number of nonelderly adults eligible for Medicaid under non-expansion in county *c* in year *t*
- $T_{c,t}^{MED,E}$: The number of nonelderly adults eligible for Medicaid under expansion in county *c* in year *t*
- $T_{c,t}^{MED,NP}$: The number of nonelderly adults eligible for Medicaid under the no-ACA implementation scenario in county *c* in year *t*

The Medicaid eligibility criteria are the same under the no-ACA implementation scenario and the no-expansion scenario, hence $T_{c,t}^{MED,NP} = T_{c,t}^{MED,NE}$.

To obtain these values, the following data are needed:

- $A_{c,t}^{M}$and $A_{c,t}^{F}$: Median age for males and females in county *c* in year *t* (2012 ACS Table B01002)

- $C_{c,t}$: Proportion of the population age 25 and over with a bachelor's degree or higher in county *c* in year *t* (2012 ACS Table S2301)

- $D_{c,t}$: Average gross rent in county *c* in year *t* (2012 ACS Table B25064)

- $E_{c,t}^{1}$and $E_{c,t}^{2}$: Average household size over 18 and under 18 in county *c* in year *t* (2010 Census Table PCT7)

- $G_{c,t}$ and $G_{c,t}^{N}$: Total population and total non-elderly adult population in county *c* in year *t* (Governor's Office of Planning and Budget Population Projections)

- $q_{c,t}$: Proportion of the total population that is non-elderly adults in county *c* in year *t* (2010 Census Table PCT3)

- $p_{c,t}^{M}$, $p_{c,t}^{F}$ and $p_{c,t}$: Proportion of male adults, proportion of female adults, and proportion of all adults that are non-elderly in county *c* in year *t* (2010 Census Table PCT3)

- $H_{c,t}$: Proportion of Caucasian residents in county *c* in year *t* (2012 ACS Table B02001)

- $I_{c,t}$: Median income in county *c* in year *t* (ESRI)

- $Q_{c,t}$: Population in group quarters in county *c* in year *t* (2012 ACS Table B26001)

- $S_{c,t}$: Number of non-elderly adult householders living alone in county *c* in year *t* (2012 ACS Table B11010)

- $T_{c,t}$: Number of nonfamily householders not living alone in county *c* in year *t* (2012 ACS Table B11010)

- $u_{c,t}$: Proportion of adults with income less than 138% of the FPL in county *c* in year *t* (2012 ACS Table B17024)

The method for obtaining the final outputs takes the following steps:

1. <u>Forecast family household counts</u>

Multiple regression models were used to forecast the following:

- $N^{MA}_{c,t,\cdot}$: The number of households with married families with children under 18 in county *c* during year *t* in all income ranges

- $N^{SF}_{c,t,\cdot}$: The number of households with single fathers with children under 18 in county *c* during year *t* in all income ranges

- $N^{SM}_{c,t,\cdot}$: The number of households with single mothers with children under 18 in county *c* during year *t* in all income ranges

- $N^{NC}_{c,t,\cdot}$: The number of family households with no children under 18 in county c during year t in all income ranges

The regression models are as follows:

- $\log N^{MA}_{c,t,\cdot} = .0253 \log C_{c,t} + .0393 \log D_{c,t} + .1329 E^2_{c,t} - .0060 E^1_{c,t} + 1.1728 \log G_{c,t} + .1657 H_{c,t}$

- $\log N^{SF}_{c,t,\cdot} = -.0471 A^F_{c,t} + .0878 E^1_{c,t} + 1.1509 \log G_{c,t}$

- $\log N^{SM}_{c,t,\cdot} = -.0964 \log C_{c,t} - .0466 \log D_{c,t} + .0370 E^2_{c,t} - .0582 E^1_{c,t} + 1.2801 \log G_{c,t} - .1705 H_{c,t}$

- $\log N^{NC}_{c,t,\cdot} = .0407 A^M_{c,t} + .0686 A^F_{c,t} - .0665 E^2_{c,t} + .0361 E^1_{c,t} + 1.1796 \log G_{c,t} + .0346 H_{c,t} + .0024 \log I_{c,t}$

The predictors $C_{c,t}, E^1_{c,t}, E^2_{c,t}$, are assumed constant with time through year 2025 whereas the other predictors had to be forecasted for future years. $A^M_{c,t}$ and $H_{c,t}$ are forecasted using Holt-Winters method with historical median age data from the UN database. $D_{c,t}$ and $I_{c,t}$ are forecasted using Holt-Winters method with historical Consumer Price Index data from the Bureau of Labor Statistics. Forecasts for $G_{c,t}$ are given in the census tables.

2. Split the household count into income ranges

Each of the resulting household counts is divided into income-to-poverty (IPL) ranges using the 2012 household proportions from ACS Table B17022. For example, the proportion of married adults in county c that are in income range i is $N^{MA}_{c,2012,i} / N^{MA}_{c,2012,\cdot}$ with

$$i = \begin{cases} 1, & if\ IPL \leq 0.37 \\ 2, & if\ 0.37 < IPL \leq 1.00 \\ 3, & if\ 1.00 < IPL \leq 1.38 \end{cases}$$

3. <u>Calculate the number of eligible adults in family households</u>

Define $F_{c,t}^{MED,NE}$ to be the number of nonelderly adults living in family households that are eligible for Medicaid in county *c* and year *t* under the non-expansion scenario and $F_{c,t}^{MED,E}$ to be the same number under the Medicaid-expansion scenario. These numbers can be calculated using the following equations based on the eligibility criteria:

- $F_{c,t}^{MED,NE} = \left(p_{c,2010}^{M} + p_{c,2010}^{F}\right) * N_{c,t,1}^{MA} + p_{c,2010}^{M} * N_{c,t,1}^{SF} + p_{c,2010}^{F} * N_{c,t,1}^{SM}$

- $F_{c,t}^{MED,E} = \left(p_{c,2010}^{M} + p_{c,2010}^{F}\right) * \left(N_{c,t,1}^{MA} + N_{c,t,2}^{MA} + N_{c,t,3}^{MA}\right) + p_{c,2010}^{M} * \left(N_{c,t,1}^{SF} + N_{c,t,2}^{SF} + N_{c,t,3}^{SF}\right) + p_{c,2010}^{F} * \left(N_{c,t,1}^{SM} + N_{c,t,2}^{SM} + N_{c,t,3}^{SM}\right) + p_{c,2010} * E_{c,2010}^{1} * (N_{c,t,1}^{NC} + N_{c,t,2}^{NC} + N_{c,t,3}^{NC})$

4. <u>Calculate the number of adults in group quarters and nonfamily households</u>

The number of non-elderly adults $NF_{c,t}$ living in group quarters and nonfamily households in county *c* and year *t* is determined as follows.

For year 2012 we have:

- $NF_{c,2012} = (Q_{c,2012} * q_{c,2010}) + S_{c,2012} + (T_{c,2012} * E_{c,2010}^{1} * p_{c,2010})$

For future years, we assume the ratio of non-elderly adults in group quarters and nonfamily households to all non-elderly adults remains the same:

- $NF_{c,t} = \left(\frac{NF_{c,2012}}{G^N_{c,2012}}\right) * G^N_{c,t}$

5. <u>Calculate the number of eligible adults in group quarters and nonfamily households</u>

We assume only adults in family households have children under age 18. Thus, adults in group quarters and nonfamily households are only eligible for Medicaid under the Medicaid-expansion scenario.

- $NF^{MED,E}_{c,t} = NF_{c,t} * u_{c,2012}$

6. <u>Compute the desired outputs</u>

- $T^{MED,NE}_{c,t} = F^{MED,NE}_{c,t}$

- $T^{MED,E}_{c,t} = F^{MED,E}_{c,t} + NF^{MED,E}_{c,t}$

Final values are given at the county level. These are distributed to census tracts according to the percent of the county's population that reside in each census tract.

APPENDIX C. SUPPLEMENTARY MATERIAL FOR CHAPTER 4

Table 27 shows how taxonomy codes were classified into the 11 different provider categories used in our analysis. The National Uniform Claim Committee structures taxonomy codes into three levels: Provider Type, Classification, and Area of Specialization. Each of our provider categories consists of all taxonomy codes with an Area of Specialization listed under the corresponding "Included Specializations" or with a Classification listed under the corresponding "Included Classifications" except for codes that also have an Area of Specialization listed under the corresponding "Excluded Specializations". For example, federally qualified health centers (taxonomy code 261QF0400X) and rural health clinics (261QR1300X) are both specializations listed under the Classification Clinic/Center (261Q00000X) and would therefore be categorized as 'Other Care Centers'.

Table 27. Taxonomy code classification.

	Provider Category	Included Entity Types	Included Specializations	Included Classifications	Excluded Specializations
Mental Health	Psychiatrist (PST)	1		Psychiatry & Neurology	Clinical Neurophysiology, Diagnostic Neuroimaging, Neurodevelopmental Disabilities, Pain Medicine, Sports Medicine, Vascular Neurology
	Psychologist (PSG)	1		Psychologist, Clinical Neuropsychologist	
	Counselor (CLR)	1		Counselor	
	Social Worker (SW)	1		Social Worker	
	Other Entity 1 Mental Health (OM1)	1	Psychiatric/Mental Health Registered Nurse, Psychiatric/Mental Health Nurse Practitioner, Psychiatric/Mental Health Clinical Nurse Specialist	Marriage and Family Therapist, Psychoanalyst, Behavior Analyst	
	Other Entity 2 Mental Health (OM2)	2	Psychiatric/Mental Health Registered Nurse, Psychiatric/Mental Health Nurse Practitioner, Psychiatric/Mental Health Clinical Nurse Specialist	Psychiatry & Neurology, Psychologist, Clinical Neuropsychologist, Counselor, Social Worker, Marriage and Family Therapist, Psychoanalyst, Behavior Analyst	Clinical Neurophysiology, Diagnostic Neuroimaging, Neurodevelopmental Disabilities, Pain Medicine, Sports Medicine, Vascular Neurology
	Mental Health Center (MHC)	1,2	Adolescent and Children Mental Health Clinic/Center, Adult Mental Health Clinic/Center, Mental Health Clinic/Center	Community/Behavioral Health Agency; Psychiatric Residential Treatment Facility; Community Based Residential Treatment Facility, Mental Illness; Residential Treatment Facility, Emotionally Disturbed Children; Psychiatric Hospital; Psychiatric Unit	

Table 27 continued.

	Provider Category	Included Entity Types	Included Specializations	Included Classifications	Excluded Specializations
Related Care	Primary Care (PC)	1		Registered Nurse, Nurse Practitioner, Clinical Nurse Specialist, Physician Assistant, General Practice, Family Medicine, Internal Medicine, Obstetrics & Gynocology, Pediatrics	Psychiatric/Mental Health Registered Nurse, Psychiatric/Mental Health Nurse Practitioner, Psychiatric/Mental Health Clinical Nurse Specialist, Surgical Physician Assistant
	Rehabilitative/ Developmental Care (RC)	1	Neurology, Neurology with Special Qualifications in Child Neurology, Clinical Neurophysiologist, Neuromuscular Medicine (Psychiatry & Neurology), Pain Medicine (Psychiatry & Neurology), Sports Medicine (Psychiatry & Neurology), Vascular Neurology (Psychiatry & Neurology)	Art Therapist, Dance Therapist, Developmental Therapist, Kinesiotherapist, Massage Therapist, Music Therapist, Occupational Therapist, Occupational Therapy Assistant, Orthotist, Pedorthist, Physical Therapist, Physical Therapy Assistant, Prosthetist, Recreation Therapist, Rehabilitation Counselor, Rehabilitation Practitioner, Respiratory Therapist Certified, Respiratory Therapist Registered, Poetry Therapists, Speech Language Pathologist, Physical Medicine & Rehabilitation, Pain Medicine	
	Other Entity 2 Related Care (PR2)	2	Neurology, Neurology with Special Qualifications in Child Neurology, Clinical Neurophysiologist, Neuromuscular Medicine (Psychiatry & Neurology), Pain Medicine (Psychiatry & Neurology), Sports Medicine (Psychiatry & Neurology), Vascular Neurology (Psychiatry & Neurology)	Registered Nurse, Nurse Practitioner, Clinical Nurse Specialist, Physician Assistant, General Practice, Family Medicine, Internal Medicine, Obstetrics & Gynocology, Pediatrics, Art Therapist, Dance Therapist, Developmental Therapist, Kinesiotherapist, Massage Therapist, Music Therapist, Occupational Therapist, Occupational Therapy Assistant, Orthotist, Pedorthist, Physical Therapist, Physical Therapy Assistant, Prosthetist, Recreation Therapist, Rehabilitation Counselor, Rehabilitation Practitioner, Respiratory Therapist Certified, Respiratory Therapist Registered, Poetry Therapists, Speech Language Pathologist, Physical Medicine & Rehabilitation, Pain Medicine	Psychiatric/Mental Health Registered Nurse, Psychiatric/Mental Health Nurse Practitioner, Psychiatric/Mental Health Clinical Nurse Specialist, Surgical Physician Assistant

Table 27 continued.

	Provider Category	Included Entity Types	Included Specializations	Included Classifications	Excluded Specializations
Related Care	Other Care Center (OCC)	1,2		Multi-Specialty Group; Single Specialty Group; Day Training, Developmentally Disabled Services; Early Intervention Provider Agency; Home Health Agency; Home Infusion Agency; Hospice Care, Community Based; In Home Supportive Care Agency; Local Education Agency; Nursing Care Agency; PACE Provider Organization; Public Health or Welfare Agency; Supports Brokerage; Voluntary or Charitable Agency; Alzheimer Center/Dementia Center/ Dementia Special Care Unit; Assisted Living Facility; Custodial Care Facility; Hospice, Inpatient; Intermediate Care Facility, Mentally Retarded; Intermediate Care, Mental Illness; Nursing Facility/Intermediate Care Facility; Skilled Nursing Facility; Community Based Residential Treatment Facility, Mental Retardation and/or Developmental Disabilities; Residential Treatment Facility, Mental Retardation and/or Developmental Disabilities; Residential Treatment Facility, Physical Disabilities; Substance Abuse Disorder Rehabilitation Facility; Respite Care; Clinic/Center; Epilepsy Unit; Rehabilitation Unit; Rehabilitation, Substance Use Disorder Unit; Chronic Disease Hospital; General Acute Care Hospital; Long Term Care Hospital; Military Hospital; Rehabilitation Hospital; Religious Nonmedical Health Care Institution; Special Hospital	Adolescent and Children Mental Health Clinic/Center, Adult Mental Health Clinic/Center, Mental Health Clinic/Center

APPENDIX D. SUPPLEMENTARY MATERIAL FOR CHAPTER 5

D.1 Proofs for Nash Equilibrium Existence

In this section, we provide the necessary background for the proofs of Theorems 1 and 2 regarding the existence of a pure equilibrium. For this purpose, we allow players to iteratively change their strategy to one that will result in their lowest cost given the current state of the game. Specifically, we define a *step* s ($s = 1,2, ...$) as the act of a single player changing strategy or of a newly added player playing her initial strategy. We define *stage* s as the state of the game (i.e. the values of all variables determined by σ) after step s. Stage $s = 0$ represents the initial game state before any players move. When referring to a variable at a specific state, we use superscripts (σ_i^s is player i's strategy at stage s, f_i^s is player i's final cost at stage s, etc.). We further define $f_{ij}(\sigma^s)$ as the cost player i will incur if it moves to resource j during step $s + 1$. We say resource j is player i's least-cost resource during stage s if $\sigma_i^s = j$ and $f_i^s \leq f_{ij'}(\sigma^s)\ \forall j' \in \Sigma_i$. Finally, we say a game is at equilibrium at stage s, if players cannot reduce their cost by unilaterally changing their strategy (i.e. $f_i^s \leq f_{ij}(\sigma^s)\ \forall i \in \mathcal{N}, j \in \Sigma_i$). We breakdown the proof of Theorem 1 into four lemmas.

When a player proposes to a saturated resource, the resource will accommodate that player if her rank at that resource is lower than the rank of at least one player currently accommodated by that resource. We define a resource j's *cutoff rank* p_j as the rank a player must be below in order to be accommodated by j. That is,

$$p_j = \begin{cases} \max\{p_{ij} | \sigma_i = j, i \text{ is accommodated}\}, & j \text{ is saturated} \\ \infty, & j \text{ is unsaturated} \end{cases}$$

If a player gets accommodated by a saturated resource, for the resource to stay within its capacity, the highest-ranked accommodated player at that resource must be *displaced*, meaning the player will no longer be accommodated and her incurred cost will rise to infinity. If a player accommodated by a saturated resource decides to change her strategy (i.e., leave her current resource and newly propose to a different resource), that saturated resource must immediately accommodate the lowest-ranked player that is proposing to it but had not been accommodated, if any such player exists.

The next lemma shows that if initially all players are at equilibrium and a new player has proposed to her least-cost resource, at each stage, only one resource's players will have an incentive to change strategies.

Lemma 1: *Suppose a congestion game is at equilibrium. If a new player i_n joins to the game and proposes to her least-cost resource j_1 at step 1, either the game remains at equilibrium, or both the following hold: (1) the only players that could achieve lower cost changing strategies at the next step are also at j_1 and (2) once one of those players leaves j_1 for a different resource j_2, all players except those at j_2 will again be playing their least-cost resource.*

Proof. If cost incurred for each player is still minimum after player i_n proposes to j_1, the game remains at equilibrium. We consider the case when the game has not remained at equilibrium. Note because an additional player was added to resource j_1, we have $n_{j_1}^1 \geq n_{j_1}^0$ and $n_j^1 = n_j^0 \ \forall j \neq j_1$. Consider the player i at some resource $j' \neq j_1$. Since player costs functions are non-decreasing with congestion, we have $f_i^1 = f_i^0 = \min_{\mathrm{j}}\left(f_{ij}(\sigma^0)\right) = \min_{\mathrm{j}}\left(f_{ij}(\sigma^1)\right)$. Thus players not at j_1 are still matched to their lowest cost resource, so any player that may want to move must be at j_1. This shows (1). To show (2), we consider two cases:

1. j_1 was initially unsaturated
2. j_1 was initially saturated

In the first case, let any player i at resource j_1 move to some other resource j_2 at the next step. Then we have $n_j^2 = n_j^0\ \forall j \neq j_2$ and $n_{j_2}^2 \geq n_{j_2}^0$. Additionally, $p_j^2 = p_j^0\ \forall j \neq j_2$ and $p_{j_2}^2 \leq p_{j_2}^0$. This means all congestions and cutoff ranks stay the same as they were initially at every resource except at j_2 (whose congestion does not decrease and cutoff rank does not increase). Since all players were initially matched to their least-cost resource, all players not at j_2 must still achieve their lowest cost. Note as a consequence of this, if the game is still not at equilibrium, the next player to change strategy must be at j_2.

In the second case, a single player i at j_1 will be displaced by player i_n. Note the other players at j_1 would retain their lowest-possible costs since $n_j^1 = n_j^0\ \forall j \in \mathcal{R}$ and $p_j^1 = p_j^0\ \forall j \neq j_1$ (i.e. all congestions and cutoff ranks at the other resources would not have changed from their initial state), so the displaced player must change strategy. Let the displaced player i move to some other resource j_2 at the next step. Then we have $n_j^2 = n_j^0\ \forall j \neq j_2$ and $n_{j_2}^2 \geq n_{j_2}^0$. Additionally, $p_j^2 = p_j^0\ \forall j \neq j_1, j_2$, $p_{j_1}^2 < p_{j_1}^0$, and $p_{j_2}^2 \leq p_{j_2}^0$. Again, this means all congestions stay the same as they were initially except at j_2 (where it does not decrease), and all cutoff ranks stay the same as they were initially except at j_1

and j_2 (which do not increase). Since all players were initially matched to their least-cost resource, all players not at j_2 must still achieve their lowest cost. ■

As a consequence of this lemma, after each step, it is enough to focus on the behavior of the players at the resource that just got added a player. This leads to the following definition:

Definition 1: *The addition of a player starts a **chain**, that is a sequence of resources where the k-th resource in the sequence is the resource that a player newly proposed to at step k. If $k > 1$, that player would have previously been proposing the $k-1$-th resource in the sequence. A resource can appear multiple times in the chain.*

An example chain resulting from a new player i_1 proposing to a resource j_1 is depicted in Figure 23. At each proceeding step k, a player i_k leaves her previous resource j_{k-1} to be accommodated by a lower-cost resource j_k. The chain ends after step n when no players can achieve lower cost by leaving resource j_n.

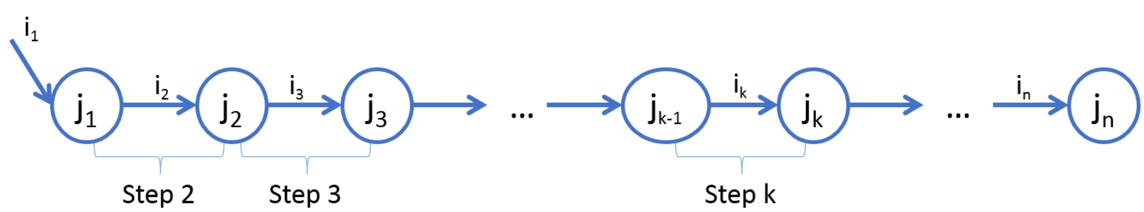


Figure 23. Chain Consisting of Resources j_1,j_2,j_3,...,j_{k-1},j_k,...,j_n

Given a chain, we can know the congestions of every resource relative to its initial value.

Corollary 1: *Suppose resource j is added to the chain at steps $S = s_1, s_2, \dots, s_n$. Then for all steps $s \notin S$, $n_j^s = n_j^0$. For steps $s \in S$, if resource j was initially saturated, $n_j^s = n_j^0$, and if resource j was initially unsaturated, $n_j^s = n_j^0 + 1$.*

Proof. From the definition of chain, the players proposing to j will remain unchanged until j is added to the chain, meaning its congestion will remain n_j^0 until that first occurs, if that occurs at all. Say j is added to the chain at step s_1. That is, $n_j^s = n_j^0 \; \forall s < s_1$. Then at step s_1, a player i will newly propose to resource j.

If j was saturated (i.e. $n_j^0 = K_j$), that player would either not be accommodated (indicating the game is at equilibrium) or that player would displace a previously-accommodated player. This means the congestion will remain the same (i.e. $n_j^{s_1} = n_j^0$). If s_1 is not the last step, by Lemma 1, the displaced player must leave j. A displaced player leaving does not affect the congestion at j, so the congestion will not change at the following step (i.e. $n_j^{s_1+1} = n_j^0$).

If j was unsaturated (i.e. $n_j^0 < K_j$), player i would be accommodated, causing the congestion to increase by 1 (i.e. $n_j^{s_1} = n_j^0 + 1$). Again if s_1 is not the last step, by Lemma 1, a player must leave j at the next step, reducing the congestion by 1. That is, $n_j^{s_1+1} = n_j^{s_1} - 1 = n_j^0$.

Thus in both the saturated and unsaturated case, we have $n_j^{s_1+1} = n_j^0$. Again by definition of chain, the congestion at j will remain unaffected until the next step j appears in the chain if such a step exists. If there is no such step, we have $n_j^s = n_j^{s_1+1} = n_j^0 \; \forall s \geq s_1 + 1$.

Otherwise if s_2 denotes the next step j is added to the chain, we have $n_j^s = n_j^{s_1+1} = n_j^0 \; \forall s \in [s_1, s_2 - 1]$. Then at step s_2 the same consequences from a player newly proposing to j will occur. ■

As a consequence of this corollary, a resource that was saturated at stage 0 will remain saturated for all stages, and a resource that was unsaturated at stage 0 will remain unsaturated for all stages not immediately following a step where a player newly proposed to that resource (i.e. the step the resource appears in the chain). Thus, we can characterize each resource by its initial saturation.

We can additionally characterize subsequences of a chain.

Definition 2: *We refer to any contiguous subsequence of the chain where the first resource was either the first resource in the chain or saturated at stage 0, the last resource was either the last resource in the chain or saturated at stage 0, and any resources in between were unsaturated at stage 0 as a* ***leg*** *of the chain. The length of a leg refers to the number of these unsaturated resources.*

An example chain with four legs is depicted in Figure 24. In this figure, Shaded circles are saturated resources while unshaded circles are unsaturated resources. The four legs consist of resources 1,2,3 (a leg of length 2); 3,4 (of length 0); 4,5,6 (of length 1); and 6,7 (of length 1).

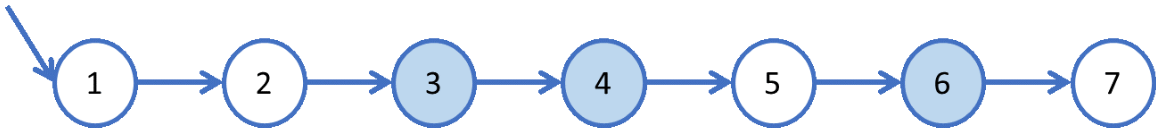


Figure 24. An example chain consisting of seven resources and four legs.

We can also find limits for the length of a chain.

Lemma 2: *Whenever a player newly proposes to and is accommodated by a saturated resource, the cutoff rank of that resource must decrease.*

Proof. Let i_1 be the player, j the saturated resource, and s the step in which i_1 proposed to j. Additionally, let $\mathcal{J}^{s-1}$ and $\mathcal{J}^{s}$ denote the set of all players accommodated by j during stages $s-1$ and s respectively. Before i_1 proposed, j's cutoff rank p_j^{s-1} is by definition j's ranking of its least-preferred (or equivalently, its highest-ranked) accommodated player, say i_2. That is, $p_j^{s-1} = p_{i_2 j} > p_{ij}\ \forall i \in \mathcal{J}^{s-1} \setminus \{i_2\}$. For i_1 to be accommodated by j during step s, it is required that $p_{i_1 j} < p_j^{s-1}$. When i_1 is accommodated, i_2 must be displaced. Therefore we have $p_j^{s-1} > \max\left(p_{ij}: i \in \{i_1\} \cup \mathcal{J}^{s-1} \setminus \{i_2\}\right) = \max\left(p_{ij}: i \in \mathcal{J}^{s}\right) = p_j^s$.■

Lemma 3: *Within a chain, a player cannot return to a resource from which they have been displaced.*

Proof. If a player i is displaced from resource j at step s, the cutoff rank of j must decrease, as described in Lemma 2. (i.e. we have $p_j^s < p_j^{s-1} = p_{ij}$). For player i to return to resource j at some future step $s+d$, we would need $p_{ij} < p_j^{s+d-1} \leq p_j^{s-1} = p_{ij}$, a contradiction. Note the middle inequality holds because each step, if a player is added to a saturated resource, it must displace another player with a higher rank p_{ij} thereby decreasing the cutoff rank.■

Lemma 4: *Within a leg, a player cannot return to an unsaturated resource they have left.*

Proof. Suppose at step t, a player i changed strategies from initially unsaturated resource j to unsaturated resource j'. This means $d_{ij'}\left(n_{j'}^{t}\right) < d_{ij}\left(n_j^{t-1}\right)$. We show through contradiction that player i will not return to j at some future step $t + d$ in the leg.

Suppose player i did switch to resource j from some other resource j'' at step $t + d$. Let $t^* \in [t, t + d - 1]$ be the earliest step such that $\sigma_i^s = j''$ for all stages s in the interval $[t^*, t + d - 1]$. Note i would only switch to j at step $t + d$ if its cost decreased. That is, $d_{ij}\left(n_j^{t+d}\right) < d_{ij''}\left(n_{j''}^{t+d-1}\right)$. We have three cases:

1. $j'' = j'$
2. $j'' \neq j'$ and $\sigma_i^{t^*-1} = j'$ (i.e. player i proposed to j' at stage $t^* - 1$)
3. $j'' \neq j'$ and $\sigma_i^{t^*-1} \neq j'$

The resources appearing in the chain at each step are given in Table 28. Recall by definition, the same resource cannot appear in the chain across consecutive steps. Also, by Corollary 1, if some resource k appears in the chain at steps s_1 and s_2, we have $n_k^{s_1} = n_k^{s_2}$. Similarly, if a resource k does not appear in the chain at steps s_1 and s_2, we still have $n_k^{s_1} = n_k^{s_2}$.

Table 28. Resource appearing in the chain sequence per step, under three cases.

Step	$t-1$	t	…	t^*-1	t^*	…	$t+d-1$	$t+d$
Case 1	j	j'	…	Unknown	j'	…	j'	j
Case 2	j	j'	…	j'	j''	…	j''	j
Case 3	j	j'	…	Not j'	j''	…	j''	j

In the first case, $d_{ij''}\left(n_{j''}^{t+d-1}\right) = d_{ij'}\left(n_{j'}^{t+d-1}\right) = d_{ij'}\left(n_{j'}^{t}\right) < d_{ij}\left(n_j^{t-1}\right) = d_{ij}\left(n_j^{t+d}\right)$, contradicting that player i's cost decreased at step $t+d$. Note the second equality holds because resource j' appears in the chain sequence at both step $t+d-1$ and step t, meaning it has the same congestion at both those stages as shown in Corollary 1. The third equality holds for similar reasons with regards to resource j at steps $t-1$ and $t+d$.

In the second case, for i to have switched to j'' rather than staying at j' at step t^*, we must have $d_{ij''}\left(n_{j''}^{t^*}\right) < d_{ij'}\left(n_{j'}^{t^*-1}\right) = d_{ij'}\left(n_{j'}^{t^*}+1\right)$ (i.e. the cost must be lower). Then, $d_{ij''}\left(n_{j''}^{t+d-1}\right) = d_{ij''}\left(n_{j''}^{t^*}\right) < d_{ij'}\left(n_{j'}^{t^*-1}\right) = d_{ij'}\left(n_{j'}^{t}\right) < d_{ij}\left(n_j^{t-1}\right) = d_{ij}\left(n_j^{t+d}\right)$, resulting in the same contradiction.

In the third case, for i to have switched to j'' rather than switching to j' at step t^*, we must have $d_{ij''}\left(n_{j''}^{t^*}\right) \leq d_{ij'}\left(n_{j'}^{t^*-1}+1\right)$ (i.e. the cost cannot be higher than it would have been had it switched to j' at step t^*). Note $n_{j'}^{t^*-1}+1 = n_{j'}^{t-1}+1$ by Corollary 1, and $n_{j'}^{t-1}+1 = n_{j'}^{t}$ since player i moved to resource j' at step t. Then $d_{ij''}\left(n_{j''}^{t+d-1}\right) = d_{ij''}\left(n_{j''}^{t^*}\right) \leq d_{ij'}\left(n_{j'}^{t^*-1}+1\right) = d_{ij'}\left(n_{j'}^{t}\right) < d_{ij}\left(n_j^{t-1}\right) = d_{ij}\left(n_j^{t+d}\right)$, again resulting in the contradiction. ■

Using the previous lemmas, we can now prove the existence of an equilibrium for the player-specific singleton capacitated congestion games described in Section 5.3 when player cost functions are non-decreasing with congestion. We start proving that we can add one player to a game already at equilibrium and reach a new equilibrium in a finite number of steps. We then use induction to show we can find an equilibrium for any given game.

Proof of Theorem 1. If player P_n cannot be accommodated by any resource because all resources are saturated and P_n is not preferred over any accommodated player, match it to the first resource. The resulting strategy tuple σ defines an equilibrium as congestions and cutoff ranks and therefore costs for remaining players would not change, and player P_n would achieve its lowest possible cost of infinity.

Now consider the case where P_n can be accommodated. We aim to show the resulting chain will consist of a finite number of finitely-long legs, so the game must have an equilibrium. Specifically, Lemma 3 showed players cannot return to resources they have been displaced from. This means each saturated resource can appear at most n times in the chain, limiting the number of legs. Additionally, Lemma 4 showed within a leg, a player cannot return to an unsaturated resource they have left. Again, this means each resource can appear at most n times within a leg, limiting the length of the leg. ■

Proof of Theorem 2. We prove this theorem using induction on the number of players. When $n = 1$, we can find an equilibrium by allowing the single player to propose to its least-cost resource. That is, $\sigma_1 = \arg\min_{j \in \Sigma_1} d_{1j}(1)$. Assume the theorem holds for all $n = 1,2, \dots, k$. We consider the case where the game has $k + 1$. By the induction hypothesis, a game with k players has an equilibrium. It is enough to show we can add the final player to that at-equilibrium game and again reach an equilibrium. This is simply an application of Theorem 1. ■

D.2 Proofs for Finding a Minimum Cost Pure Equilibrium

Proof of Theorem 3. We provide a proof by a reduction from *Minimum Vertex Cover*, a well-known strongly NP-hard problem [204, 205]. Consider the graph $G = (V, E)$ where $V \coloneqq \{v_1, v_2, \dots, v_m\}$ and $E \coloneqq \{e_1, e_2, \dots, e_n\}$, respectively, denote its vertices and edges.

In the following, we construct an instance of the congestion game whose best pure equilibrium coincides with the minimum vertex cover of G. The primary idea is to consider the vertices and edges of the graph as resources and players of the game, respectively.

- $\mathcal{R} \coloneqq \{V, \bar{V}\}$ where $\bar{V} \coloneqq \{\overline{v_1}, \overline{v_2}, \dots, \overline{v_m}\}$. This means that associated with the set of vertices V, we have considered a set $\bar{V}$. All these vertices build up resources for the instance of our congestion game.
- $\mathcal{N} \coloneqq \{E, \bar{E}\}$ where $\bar{E} \coloneqq \{(v_1, \overline{v_1}), (v_2, \overline{v_2}), \dots, (v_m, \overline{v_m})\}$. This is illustrated by an example in Figure 25.
- For each $i \in \mathcal{R}$, the action space is the vertices forming the edge i. Specifically, if $(v_k, v_l) \in E$, then the player (v_k, v_l) is allowed to choose the resource v_k or v_l. Similarly, for each $(v_k, \overline{v_k}) \in \bar{E}$, the player $(v_k, \overline{v_k})$ is allowed to choose either the resource v_k or $\overline{v_k}$.

- $K_j \coloneqq n + m + 1$. This means that each resource $j \in \mathcal{R}$ may accommodate $n + m + 1$ players. Since the total number of players is $n + m$, this implies that no resource will ever be saturated under any strategy profile.
- For each $i \in \mathcal{N}$ and $j \in \mathcal{R}$, p_{ij} may be arbitrarily assigned without affecting the set of equilibria of the game. The reason is that no resource will ever be saturated for this instance of the game, so a resource never needs to rank among those players who have proposed to it.
- The players' cost function are as follows. For each $(v_k, v_l) \in E$, the player cost function is equal to zero for each possible action and congestion. More formally, for each congestion $n \in \mathbb{Z}^+$,

$$d_{(v_k,v_l),v_k}(n) = d_{(v_k,v_l),v_l}(n) = 0. \tag{D.1}$$

For each $(v_k, \overline{v_k}) \in \bar{E}$, the cost function is as follows:

$$d_{(v_k,\overline{v_k}),v_k}(n) = \begin{cases} 0, & n \leq 1 \\ 2, & n \geq 2 \end{cases} \tag{D.2}$$

$$d_{(v_k,\overline{v_k}),\overline{v_k}}(n) = 1 \ \ \forall n \in \mathbb{Z}^+. \tag{D.3}$$

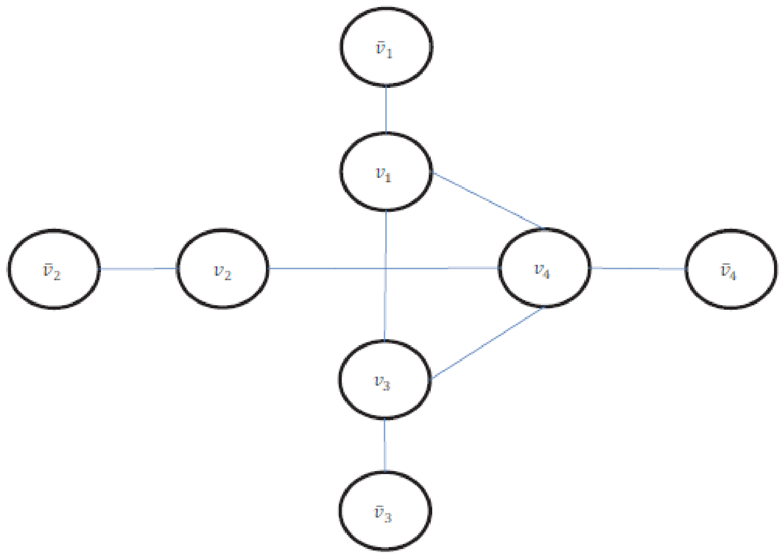


Figure 25. An example of the game instance depicting the connection between resources (vertices) and players (edges) as used in the proof of Theorem 3.

Note that this is a polynomial-time reduction of the minimum vertex cover to an instance of the congestion game. Now, we demonstrate that there is a one-to-one correspondence between each feasible solution of the minimum vertex cover and pure equilibria of this game. For this purpose, let us represent a solution of the vertex cover by $\left(x_{e_1}, \dots, x_{e_n}\right)$ where x_{e_k} denotes the assigned vertex to edge e_k in the cover. Moreover, let us represent an equilibrium of the game by the vector $\boldsymbol{\sigma} \coloneqq (\sigma_1, \dots, \sigma_n, \sigma_{n+1}, \dots, \sigma_{n+m})$. Consider the following transformation:

$$\sigma_i \coloneqq x_{e_i} \qquad \forall i \in \{1, \dots, n\} \tag{D.4}$$

$$\sigma_{n+i} \coloneqq \begin{cases} \bar{v}_i, & \text{if } \exists j \in \{1, \dots, n\}: x_{e_j} = v_i \\ x, & \text{otherwise} \end{cases} \qquad \forall i \in \{1, \dots, m\} \tag{D.5}$$

This implies that given a solution of the vertex cover problem, in its associated congestion game, each edge in E should choose the same vertex as the vertex cover solution, and each edge $(v_k, \overline{v_k}) \in \bar{E}$ should choose $\overline{v_k}$ if and only if v_k has already been chosen by some edge in E.

It can easily be shown that $\boldsymbol{\sigma}$ is an equilibrium of the game. For this purpose, note that equation (D.1) implies that all players in E satisfy the equilibrium conditions under any arbitrary selection of the vertices, including the strategy profile $\boldsymbol{\sigma}$. For each player $(v_k, \overline{v_k}) \in \bar{E}$, equations (D.2)-(D.3) implies that the equilibrium condition is satisfied if and only if $(v_k, \overline{v_k})$ chooses v_k whenever the congestion of this vertex is 1, i.e., v_k has not been chosen by any player in E, and it follows from equation (D.5) that this condition is satisfied at the strategy profile $\boldsymbol{\sigma}$, so $\boldsymbol{\sigma}$ is an equilibrium.

So far, we have shown that each solution of the vertex cover is associated with an equilibrium of the game through the transformation (D.4) and (D.5). On the other hand, given an equilibrium $\boldsymbol{\sigma}$, it is trivial to find a solution of the vertex cover by only considering the first n components of $\boldsymbol{\sigma}$, i.e., $x_{e_i} \coloneqq \sigma_i$ for each $i \in \{1, \dots, n\}$.

Now, let us consider the problem of finding a best pure equilibrium induced by the objective function $\sum_{i=1}^{n+m} f_i$ where f_i denotes the cost of player i. Note that it follows from equation (D.1) that $f_i = 0$ for each $i \in \{1, \dots, n\}$. As noted earlier, under an equilibrium $\boldsymbol{\sigma}$, each $(v_k, \overline{v_k}) \in \bar{E}$ chooses v_k whenever the congestion of this vertex is 1, and this leads to $f_{n+k} = 0$; otherwise, $(v_k, \overline{v_k}) \in \bar{E}$ chooses $\overline{v_k}$, and then $f_{n+k} = 1$. Therefore, $\sum_{i=n+1}^{n+m} f_i$ is equal to the number of edges in $\bar{E}$ which have chosen its resource in $\bar{V}$. Therefore, minimizing $\sum_{i=1}^{n+m} f_i$ is identical to minimizing the number of edges in $\bar{E}$ which have chosen its resource in $\bar{V}$. Once again we use the fact that the each $(v_k, \overline{v_k}) \in \bar{E}$ chooses $\overline{v_k}$ whenever the congestion of v_k is greater than or equal to 1, i.e., v_k has been chosen by some players in E; therefore, number of edges in $\bar{E}$ which have chosen its resource in $\bar{V}$ is the same as the number of vertices in V which have been chosen by an edge in E, which is the objective function of the minimum vertex cover problem. ■

Remark: *Note that we use an uncapacitated instance of singleton congestion game in our computational complexity proof. This also implies that the same complexity result holds if the game is non-singleton.*

Proof of Theorem 4. Note that the condition $\sum_{j \in \mathcal{R}} \mathcal{K}_j \geq n$ guarantees that each player is accommodated by some resource in an equilibrium. We show that there is a one-to-one correspondence between pure equilibria of the game and feasible points of the polyhedron (5.1a)-(5.1o).

⇒: Given an equilibrium $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_n)$, we can initially set $y_{ij} = 1$ if and only if $\sigma_i = j$; otherwise let $y_{ij} = 0$. Then set c_j, x_{ijk}, z_{jk}, and f_i by above-mentioned interpretation of the variables. We will set the value for o_{ij} and q_{ij} in the rest of this proof. We show that these values of the variables is feasible for (5.1a)-(5.1o), in the following.

It immediately follows from the definition of the variables that constraint (5.1a)-(5.1e) and (5.1h) are satisfied. Constraint (5.1g) is met since: (i) when $y_{ij} = 1$, then $c_j = k$ if and only if $x_{ijk} = 1$, and (ii) when $y_{ij} = 0$, the constraint is trivial.

Constraints (5.1i)-(5.1l) enforces that no player is better off by a unilateral deviation. Specifically, constraint (5.1k) is met since when resource j is unsaturated (i.e., $z_{jK_j} = 0$)

and $\sigma_i \neq j$, if player i decides to unilaterally deviate by switching to resource j, then she will be accommodated by the resource, and her new cost, $d_{ij}(c_j+1) = \sum_{k\in\mathcal{K}_j} d_{ij}(k) z_{j(k-1)}$, is at least as large as her cost, f_i, under strategy profile σ. Note that if $\sigma_i = j$ and resource j is unsaturated, constraint (5.1k) is met because $f_i = d_{ij}(c_j) \leq d_{ij}(c_j+1) = \sum_{k\in\mathcal{K}_j} d_{ij}(k) z_{j(k-1)}$, which holds since the cost function of each player is non-decreasing with congestion.

When resource j is saturated (i.e., $z_{jK_j} = 1$) and $\sigma_i \neq j$, if player i decides to unilaterally deviate by switching to resource j, then there are two possible cases: (i) She is accommodated by resource j, then let $o_{ij} \coloneqq 1$ and $q_{ij} \coloneqq 0$. Therefore, player i's new cost is equal to $d_{ij}(K_j)$, which is at least as large as her current cost f_i. This implies that constraint (5.1j) is met. Moreover, constraint (5.1k) is trivially met. (ii) She is not accommodated by resource j, then let $o_{ij} \coloneqq 0$ and $q_{ij} \coloneqq 1$. This implies that no player with a higher rank than player i is accommodated by resource j, and hence, constraint (5.1k) is met, and constraint (5.1j) is trivially met. Constraint (5.1l) is met since at least either $o_{ij} = 1$ or $q_{ij} = 1$. Note that when resource \$j\$ is saturated (i.e., $z_{jK_j} = 1$) and $\sigma_i = j$, we let $o_{ij} \coloneqq 1$ and $q_{ij} \coloneqq 0$. Constraint (5.1j) is met since $f_i = d_{ij}(K_j)$, constraints (5.1k) and (5.1l) are trivial.

⇐: The proof is similar to above except for reversing the direction.

■

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