Summer 8-7-2018

Quantifying Spatial Potential Access Equity in an Agent Based Simulation Model of Buprenorphine Treatment Policy in the United States

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Quantifying Spatial Potential Access Equity in an Agent Based Simulation Model of
Buprenorphine Treatment Policy in the United States

by

Alexandra Elizabeth Nielsen

A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Systems Science

Dissertation Committee:
Wayne W. Wakeland, Chair
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Portland State University
2018

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Abstract

Opioid dependence and opioid related deaths are a public health problem which the United States Centers of Disease Control have declared an epidemic. While opioid agonist therapy for opioid addiction has been accepted as the most effective treatment for opioid dependence among academics, and office based buprenorphine treatment has been available in the United States for over 10 years, OB buprenorphine faces many barriers to widespread adoption. Empirical data on the geographic distribution of physicians able to prescribe buprenorphine and the prescribing patterns of those physicians show considerable unevenness in access and utilization of treatment services.

Federal-level policies have recently been implemented to expand access to opioid agonist therapy, but the medium and long term impacts of these policy changes on individual outcomes, public health, and geographic access equity are not yet clear.

This dissertation compares two recent federal level policies on expanding access to buprenorphine treatment: raising the regulatory limit on the number of patients a provider can treat (implemented July, 2016), and extending prescribing privileges to nurse practitioners and physician assistants (implemented February, 2017), using an empirically supported Agent Based Simulation model. Policies are assessed by a novel, at-a-glance, quantitative access equity metric: the Spatial Potential Access Gini Index, in addition to year-end treatment utilization, opioid overdose deaths, and the amount of illicit medication diversion.

In the simulation, expanding access by increasing the patient limit did not result in more equitable spatial access, while extending prescribing to NPs and PAs increased both utilization and spatial access equity. This is likely due to empirically supported model assumptions that NPs and PAs providing primary care often serve in medically underserved areas including rural and remote regions. Extending prescribing to these practitioners opens up new treatment locations changing the spatial distribution of treatment opportunities. Changing patient limits does not change the overall spatial distribution of services, so spatial access equity does not change even if overall treatment supply gets better or worse.

The primary contribution of this work is the Spatial Potential Access Lorenz Curve and the Spatial Potential Access Gini Index, measures that aggregate individual-level Spatial Potential Access Scores commonly used in health care geography to map and identify areas of access disparity within a region. The equitability of Spatial Potential Access is calculated by using the Lorenz Curve, which is commonly used to characterize the distribution of wealth or income in a society, from which a Gini Index is calculated. The Spatial Potential Access Gini Index allows for direct comparison of complex quantitative information about the geographic distribution of supply and demand in a region with other regions, or in response to policies that impact supply or demand within the region. The measure has potential applications in simulation studies on the spatial allocation of services, allowing equity assessment of policy alternatives, as

well as in empirical work, allowing equity comparisons of different regions, or in hybrid studies in which policy experiments are conducted on data-rich maps.

Dedication

I dedicate this dissertation to my sons, Conrad and Conan. I'm finally putting this youngest brother to bed; now it's play time for us.

Acknowledgements

The list of people I need to thank for supporting this work is a long one. First, I need to thank Wayne Wakeland, my tireless dissertation chair. Wayne, your energy and enthusiasm have been a constant throughout my years of schooling and research, and have kept me committed to this project through dark times. I eagerly await the day we sweep away the last vestiges of hierarchy between us and I meet you as a colleague and fellow scholar. I would also like to thank my dissertation committee members, Dennis McCarty and Neal Wallace, and graduate studies representative, Matt Carlson, for patient guidance through this long process. Dennis McCarty, without you this research would never have happened. Thank you for having faith in the promise of simulation research and in me as a researcher to recommend a modeling project to analysts at JBS and SAMHSA. Out of that initial seed project grew this larger work. I also want to thank you for your mentorship over the years. I hope to live up to the promise you have seen in me. Neal Wallace, thank you for the many discussions we have had over the years and your incisive criticism. You always challenge me to think more deeply, communicate more clearly, and get to the point. Your insights into systems science methods are sharp and always valuable. You are truly one of us.

I want to thank my expert panel members for their time and insights into how the OAT system works: Melvania Briggs, Kelly Clark, Todd Korthuis, Timothy Lepak, Alane O'Connor, and Andy Saxon, I couldn't have done this without you. I also want to thank others who didn't serve on an expert panel, but whose insights into OAT helped

me formulate this model: Maraget Kotz, and Stephen Wyatt thank you for helping me understand the vital work you do. Many thanks to Timothy Lepak, Nick Reuter at Indivior, and Melinda Campopiano for sharing unpublished data.

Thank you to Bonnie Wilford, Marcia Meth, Joe Perpich, and especially Susan Hayashi at JBS, International for supporting earlier iterations of the modeling for contract work with SAMHSA. Thank you also to Melinda Compopiano at SAMHSA for financial and intellectual support of early modeling iterations.

Thank you to Peter Geissert for the many discussions about harm reduction, and for guidance on how to do statistics right. I look forward to calling you doctor, soon. To the students and professors of the Portland State Systems Science Program, your intellectual curiosity and engagement with ideas has been a source of strength. You truly are a community of learners and scholars, and I am proud to have been one of you. Thank you also to the Resource Center for Students with Children at Portland State University and the Jim Sells childcare subsidy program, for helping me support my family while meeting my academic goals, and to the Phi Kappa Phi honor society and its Dissertation Fellowship award for supporting me through the dissertation writing phase.

Finally, my deep and heartfelt gratitude goes out to my family who have always been with me providing financial, moral, intellectual, and emotional support. Wynne, Nathan, Aunt Julia, Mom, Dad, I can't say how much your support has meant to me. Your generosity is humbling. This dead parrot has finally moved on. Thank you.

Financial acknowledgement: Early modeling was supported by contract with the Substance Abuse and Mental Health Services Administration under subcontract with JBS, International. Financial support for dissertation writing was provided by a Phi Kappa Phi Dissertation Award.

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List of Abbreviations

- 2SFCA = Two-Step Floating Catchment Area
- 3SFCA = Three-Step Floating Catchment Area
- AAAP = American Association of Addiction Psychiatrists
- ABS/ABM = Agent-Based Simulation, Agent-Based Modeling
- AHRQ = Agency for Healthcare Research and Quality
- ASAM = American Society of Addiction Medicine
- CARA = Comprehensive Addiction Recovery Act
- CDC = Centers for Disease Control and Prevention
- CSAT = Center for Substance Abuse Treatment
- DATA 2000 = Drug Addiction Treatment Act of 2000
- DEA = Drug Enforcement Administration
- DSM = Diagnostic and Statistical Manual
- E2SFCA = Enhanced Two-Step Floating Catchment Area
- FDA = Food and Drug Administration
- HCV = Hepatitis C Virus
- HIV = Human Immunodeficiency Virus
- HPSA = Health Provider Shortage Area
- HRSA = Health Resources and Services Administration
- M2SFCA = Modified Two-Step Floating Catchment Area

- MAT = Medication Assisted Treatment
- MSA = Metropolitan Service Area
- MUA = Medically Underserved Area
- NIDA = National Institute on Drug Abuse
- NP = Nurse Practitioner
- NSDUH = National Survey of Drug Use and Health
- OAT = Opioid Agonist Therapy
- OB = Office Based
- ONDCP = Office of National Drug Control Policy
- OTP = Opioid Treatment Program
- OUD = Opioid Use Disorder
- PA = Physician Assistant
- POA = Prescription Opioid Analgesics
- RUCA = Rural Urban Commuting Area Codes
- SAMHSA = Substance Abuse and Mental Health Services Administration
- SD = Standard Deviation
- SPAGI = Spatial Potential Access Gini Index
- SPALC = Spatial Potential Access Lorenz Curve
- SPAR = Spatial Access Ratio
- VA = Veteran's Administration

1 Introduction

Opioid dependence and opioid related deaths are a public health problem which the United States Centers of Disease Control and Prevention (CDC) have declared an epidemic. While medication assisted therapy (OAT) for opioid addiction has been accepted as the most effective treatment for opioid dependence among academics, and office based (OB) buprenorphine treatment has been available in the United States for over 15 years, OB buprenorphine faces many barriers to widespread adoption. Policy makers at agencies and professional societies concerned with substance abuse and mental health have instituted federal-level policies that could expand access to and adoption of OB buprenorphine treatment. The CDC, the Substance Abuse and Mental Health Services Administration (SAMHSA), the National Institute on Drug Abuse (NIDA), the Health Resources and Services Administration (HRSA), and the Office of National Drug Control Policy (ONDCP) have not achieved consensus on changes in federal policy. This is not surprising because the medium and long term impacts of policy changes on individual outcomes and public health are often difficult to determine soon after implementation.

An empirically supported system-level model and policy exploration tool could give stakeholders and policy makers a big picture understanding of the current state of OB buprenorphine provision, and allow for policy exploration that reveals probable outcomes of policy changes. Models can leverage the considerable amount of research on treatment outcomes, barriers and facilitators to treatment access and provision, as

well as the lived experience of researchers, patients and practitioners and synthesize this research and experience into a high-level whole.

Empirical data on the geographic distribution of physicians able to prescribe buprenorphine and the prescribing patterns of those physicians show considerable unevenness in access and utilization of treatment services. Measuring and comparing this access inequality in the context of a simulation-based policy exploration requires a simple at-a-glance, quantitative access equality metric because of the large number of simulated scenarios that need to be compared. In this dissertation I define a metric and demonstrate its usefulness by comparing simulation outcomes of an agent-based model of buprenorphine treatment access.

1.1 Background

1.1.1 Opioid use disorder is a public health problem in the United States

The opioid class of drugs is one of the oldest drugs known to man. People have been using extracts of the opium poppy to relieve pain for thousands of years (Brownstein, 1993). Opioids also induce euphoria, and opium abuse has been recorded as early as the 16th century (Brownstein, 1993). In modern times, opioids are still used to relieve pain and still used for euphoria. We now understand that sustained abuse can lead to fundamental and long-lasting changes in brain structure and function (Leshner, 1997). While many believe that drug dependence is the result of bad choices or weak will, drug dependence is now recognized as a chronic relapsing brain disorder (Baler & Volkow, 2006; Volkow, Fowler, & Wang, 2004; Volkow & Li, 2004).

Under the American Psychiatric Association Diagnostic and Statistical Manual version IV (DSM-IV), opioid abuse and opioid dependence were regarded as two separate disorders (American Psychiatric Association & DSM-IV, 1994). The latest Diagnostic and Statistical Manual (DSM-5) combines opioid abuse and dependence into opioid use disorder (OUD), which is a spectrum of problematic use from mild to severe depending on the number of criteria met (American Psychiatric Association & others, 2013). Opioid use disorder, which encompasses both prescription opioid analgesic

(POA) use disorder and heroin use disorder, is a significant public health problem in the United States and worldwide. The number of people who have used opioids nonmedically as well as the number of people with opioid use disorders in the United States have risen dramatically since the early 1990s (See Figures 1-1 and 1-2, SAMHSA, 2014b), reaching an estimated 2.14 million in 2016 (SAMHSA 2017).

Figure 1-2: Number of people who used POA nonmedically (left plot) and heroin (right plot) in the past year. Note different scales. As the number of past year users of POA flattened, the number of past year heroin users began to rise. Source: NSDUH, SAMHSA.

Figure 1-1: Number of people with POA or heroin use disorder. Note the continued rise in POA use disorder despite the flattened trend in past year POA use above. Source: NSDUH, SAMHSA.

The problem of opioid use disorder is not restricted to cities. According to the 2012 National Survey of Drug Use and Health (NSDUH), 50% of people with opioid use disorder live in large Metropolitan Service Areas (MSAs), 35% live in small MSAs, and 15% live in non-metro areas (SAMHSA, 2013b). Negative health outcomes associated with opioid use disorder include fatal and non-fatal overdose (Chen, Hedegaard, & Warner, 2013), higher all-cause mortality (Degenhardt et al., 2009), and HCV and HIV infection risk if using intravenously (Garfein et al., 1998; Schoenbaum et al., 1989; Thorpe et al., 2002). The number of deaths involving POAs has also risen dramatically since the 1990s paralleling the rise in use and use disorder, and deaths attributed to heroin have nearly tripled since 2010 (see Figure 1-3; Centers for Disease Control and Prevention, 2015).

Figure 1-3: Opioid overdose deaths 1999-2013: Source: CDC Wonder Multiple Cause of Death, 1999-2013 Query, <http://wonder.cdc.gov/mcd.html>

1.1.2 Opioid Agonist Therapy is Effective

Pharmacotherapies, or Opioid Agonist Therapy (OAT) are highly effective treatments for opioid use disorder (i.e. POA use disorder and heroin use disorder; Mattick, Kimber, Breen, & Davoli, 2002). Pharmacotherapy for OUD has two basic types, opioid antagonist treatment, and opioid agonist treatment. Opioid antagonists (including naloxone and naltrexone) bind to opioid receptors in the brain but do not activate the receptors, effectively blocking the receptor—not allowing the brain to feel the effects of opioid drugs (Comer et al., 2002; Martin, Jasinski, & Mansky, 1973), reducing the risk of opioid overdose (Hulse et al., 2005), and reversing opioid overdoses (Kerr, Kelly, Dietze, Jolley, & Barger, 2009).

Opioid agonists bind to opioid receptors in the brain and also activate the receptors, which is why agonist treatment was previously referred to as substitution or maintenance therapy. Opioid agonist treatment reduces cravings for opioids, reduces use of illicit opioids, and allows for normal functioning (Payte, 1997). Until 2002 methadone was the only drug approved for opioid agonist treatment, and only within highly regulated Opioid Treatment Programs (OTPs) (Payte, 1997). Methadone was considered a good choice for MAT because of its high oral availability, slow onset of action and long-acting duration of action (Payte, 1997). In 2000, the Drug Abuse Treatment Act of 2000 (DATA 2000) became law, allowing doctors to use schedule III – V controlled drugs for the treatment of addiction (Carl Levin & Orrin Hatch, 2000). Methadone is a schedule II drug and cannot be used to treat addiction in private

doctors' offices. Buprenorphine, a schedule III drug approved by the FDA in 2002 for the treatment of opioid dependence, is the only opioid agonist that meets the criteria of DATA 2000. Like methadone, buprenorphine has a long duration of action which allows for daily or less than daily dosing, and a strong safety profile due to the ceiling effect on respiratory depression—the primary cause of opioid overdose deaths (Dahan et al., 2006). (A ceiling effect on respiratory depression means that higher and higher doses of buprenorphine do not result in a higher risk of respiratory depression.)

Office-based (OB) OUD treatment has many potential benefits over traditional treatment in OTPs: greater treatment accessibility especially in areas without OTPs, less stigma, greater flexibility to tailor treatment to patients' needs, and less exposure to drug dealers who may prey on those waiting to get treatment at OTPs (Fiellin & O'Connor, 2002a)(Fiellin & O'Connor, 2002). However, there are still significant barriers to the widespread adoption of OB buprenorphine treatment, and many communities lack adequate access to OB buprenorphine treatment (Rosenblatt, Andrilla, Catlin, & Larson, 2015a; Stein, Pacula, et al., 2015).

Michael Botticelli, the Director of the ONDCP through 2016; Pam Hyde, the Administrator of SAMHSA through 2015; Senators Orrin Hatch and Carl Levin, the sponsors of DATA 2000; Nora Volkow, the Director of the NIDA, and former President Barack Obama have all made public statements about the need to expand access to OB buprenorphine (ONDCP 2015; SAMHSA 2014c; Volkow, Frieden, Hyde, & Cha, 2014). The second point of the 2014 President's Plan to Reform Drug Policy states that to

reform drug policy the nation must “expand access to treatment for Americans struggling with addiction” (ONDCP 2014), and the 2015 National Drug Control Strategy stresses “integrating treatment for substance use disorders into health care and supporting recovery” (ONDCP 2015).

There are two policies within the DATA 2000 legislation that limited providers’ capacity to prescribe buprenorphine. Physicians can only prescribe to a maximum of 30 patients in the first year, and 100 or 275 patients thereafter (109th Congress, 2005; Carl Levin & Orrin Hatch, 2000; SAMHSA 2016a), and up until 2017 only physicians could prescribe buprenorphine, not other medical care providers who have prescribing authority including nurse practitioners (NPs) or physician assistants (PAs) (Fornili & Burda, 2009). Issues around access to buprenorphine including these policies are examined at length in the literature review section (Chapter 2).

1.2 Research Questions

- Question 1: What functional form should an aggregated individual-level access inequality metric have for it to be sensitive enough to detect differences in access equity in different regions or due to different policy choices?
- Question 2: How equitably distributed is access to OB buprenorphine treatment spatially in the current OB buprenorphine treatment system given regulatory caps on patient numbers, physician preferences, and geographic distribution of treatment seekers and providers?

- Question 3: To what extent would changing the DATA 2000 patient limit per physician change utilization of buprenorphine, spatial access equity, opioid overdose deaths and medication diversion?
- Question 4: To what extent would various levels of buprenorphine prescribing adoption by Nurse Practitioners and Physician Assistants change utilization of buprenorphine, spatial access equity, opioid overdose deaths, and medication diversion?

1.3 Motivation and Significance

Treatment capacity, accessibility of OB buprenorphine treatment, and gaps between treatment need and treatment capacity are complex and current national survey-based metrics do not capture this complexity. The number of buprenorphine providers, measured at the county level, serves as a proxy measure for inequality of access (Rosenblatt, Andrilla, Catlin, & Larson, 2015b; Stein, Gordon, Dick, Burns, Pacula, Farmer, & Leslie, 2015). One standardized approach for identifying communities with a shortage of waived physicians given demand was modeled after the Health Resources and Services Administration (HRSA) Health Provider Shortage Area (HPSA) metric (Dick et al., 2015). The authors defined shortage at the county level which may obscure inaccessibility due to the long travel distances required to access services in sparsely populated rural counties, and inaccessibility faced by marginalized urban residents who may not be able to travel even modest distances to access services in the counties they

live in. An individual level metric may capture this scarcity where there appears to be abundance by other metrics.

However, individual level metrics cannot be used in data models. The number and location of people requiring services is not known due to patient privacy and confidentiality concerns; therefore proxy measures must be used. In a simulation, one can generate synthetic populations based on these proxy measures and national survey data, and place synthetic people in a plausible landscape. One can then calculate how accessible services are to each individual demander based how many providers there are, the capacity of those providers, the distance to the providers, the number of other demanders, and the distance the individual is willing to travel. Aggregating all individual access measures into a single spatial access inequality index can allow for quick, quantitatively meaningful comparisons of simulated policy experiment outcomes.

1.3.1 Potential Significance

There are two distinct needs that this study addresses. First policy makers and practitioners know that buprenorphine access is uneven across the country and within the states, but this unevenness has only been captured at the county level and through proxy measures. An empirically informed agent based model can visually display the mismatch between supply of and demand for OB buprenorphine treatment and describe this mismatch quantitatively. This will give a deeper understanding of treatment capacity and access through quickly conveyed visual information, and nuanced quantitative information.

Second, a metric that aggregates map-based measures of spatial potential access could be useful to researchers who study access disparities, such as unequal access to health providers, food outlets, parks, or affordable quality childcare. Map based metrics convey detailed information, but can be difficult to use to compare access in different regions or after policy implementation. A single, aggregated metric could allow researchers to make quick comparisons. Is spatial potential access better under policy A or B? Does region C or D locate services more fairly? Spatial potential access will be defined more fully in Section 2.2.

2 Literature Review

This review of literature and data is organized into four main sections:

- Buprenorphine treatment capacity
- Measuring potential spatial access and studies on regional differences in buprenorphine access
- Two major buprenorphine policies: the patient limit, and the exclusion of non-physician prescribers in the DATA waiver system
- Simulations for exploring substance abuse policy

2.1 Opioid Agonist Therapy treatment capacity

Prior to 2002, OAT was only available in highly regulated Opioid Treatment Programs (OTPs), or in clinical trials (Fiellin & O'Connor, 2002a). In 2000, the 106th Congress passed the Drug Addiction Treatment Act of 2000 (DATA 2000) which allowed qualified physicians to prescribe schedule III – V controlled substances for the treatment of OUD for up to 30 patients per practice (Carl Levin & Orrin Hatch, 2000). Physicians could qualify for a DEA waiver under DATA 2000 by taking an 8-hour training course, by being board certified in addiction medicine or addiction psychiatry, or by having participated in a buprenorphine clinical trial (Fiellin & O'Connor, 2002a). It took an additional two years for buprenorphine to be approved by the FDA for the treatment of opioid dependence as a schedule III drug (Campbell & Lovell, 2012; Jaffe & O'Keeffe, 2003). Office-based OAT with buprenorphine began in 2002. Prior to office-based OUD

treatment with buprenorphine, only approximately 170,000 of the estimated 810,000 (21%) opioid dependent patients in the US were receiving OAT through OTPs, compared to approximately 55% opioid dependent patients during the same period in France, which had implemented a general practitioner focused, office-based buprenorphine treatment system (Fatseas & Auriacombe, 2007). While more strictly regulated than the largely unregulated French system, DATA 2000 similarly enabled office-based treatment with buprenorphine, and was intended to increase treatment capacity (Boone et al., 2004; Bridge, Fudala, Herbert, & Leiderman, 2003; Thomas et al., 2008), engage new kinds of patients in OAT (Fiellin, Rosenheck, & Kosten, 2001; Sullivan, Chawarski, O'Connor, Schottenfeld, & Fiellin, 2005), and reach patients unable to access OTPs (Egan et al., 2010; Mark, Woody, Juday, & Kleber, 2001; Rounsaville & Kosten, 2000) which were only operating in 44 out of 50 states (WESTAT & The Avisa Group, 2006) and tended to be located in urban areas.

SAMHSA maintains a record of all providers who completed buprenorphine training and obtained DEA waivers to prescribe each year since 2002. These data are publicly available and searchable on the SAMHSA website¹ (SAMHSA 2016b). The DEA maintains a list of all providers with waivers. This total number of providers with waivers has increased steadily since 2002 (see Figure 2-1). The number of providers obtaining either a new 30 patient waiver or electing to increase to the 100 patient waiver each year increased from 2002 to 2007, held steady from 2008 to 2012, and again increased from 2012 to 2016 (see Figure 2-2). The spike in 2007 was likely due to regulation change that allowed providers to treat up to 100 patients and pent up demand by providers who would have increased their patient loads in earlier years. In July, 2016,

Figure 2-1: Total number of providers waived to prescribe buprenorphine at three patient limit levels, 30, 100, and 275.

¹http://www.samhsa.gov/medication-assisted-treatment/physician-program-data/certified-physicians?field_bup_us_state_code_value=All

Figure 2-2: Number of new waived providers per year. 2016 is an underestimate because it only counts those providers who obtained waivers through July (Substance Abuse and Mental Health Services Administration, 2016a).

board certified addiction specialists could apply to further increase their patient limits to 275 patients if they met certain regulatory requirements (Federal Register, 2016). By January 2018, 4151 practitioners opted to increase their patient limit (SAMHSA 2018). Multiplying the total number of waived physicians by their certification level yields the total potential office-based buprenorphine capacity shown in Figure 2-3. This measure of total potential office-based buprenorphine capacity was used to define a treatment gap between the number of people who need opioid agonist treatment and the total capacity of the treatment system to meet that demand (Jones, Campopiano, Baldwin, & McCance-Katz, 2015).

However, this definition of potential capacity does not capture the fact that some providers who complete training and get waivers never prescribe, or are not

Figure 2-3: Total potential OB buprenorphine treatment capacity assuming every provider treats up to the maximum allowable limit of his or her DATA waiver.

currently prescribing buprenorphine. Four studies suggest that the number of physicians who do not prescribe to any patients has fallen since 2002. In a study of a nationally representative sample of addiction specialists in 2003, only 58% of respondents with waivers had prescribed buprenorphine to any patients (Kissin, McLeod, Sonnefeld, & Stanton, 2006). In early 2005, “The SAMHSA Evaluation of the Impact of the DATA Waiver Program” reported that 67% of physicians with waivers were prescribing (WESTAT & The Avisa Group, 2006). By 2008, the percentage of providers who had prescribed to patients in the last 90 day had risen to 75%², and the percentage of providers who had never prescribed buprenorphine fell to 17%² (Arfken, Johanson, di

² Calculations by the author. Arfken, et al, (2010) separates providers into those on the CSAT locator list and those not on the list, the 75% is a weighted average of the two provider populations.

Menza, & Schuster, 2010). In rural areas of Washington state, Quest, et al. (2012) found that 83% of the 24 surveyed physicians were actively prescribing buprenorphine in 2010 (Quest, Merrill, Roll, Saxon, & Rosenblatt, 2012).

Even when providers do prescribe buprenorphine, many do not prescribe up to their certification level. There have been few studies on how many patients providers typically treat, but there appears to have been an upward trend since 2002, particularly after 2007, when the patient limit was raised from 30 to 100. Gordon, et al. (2007) found that on average waived physicians at VA health facilities were prescribing to 4.3 patients in 2005 (Gordon et al., 2007). Reif, et al (2007) found that in 2005, the surveyed sample of early adopter buprenorphine prescribers wrote an average of 15.6 prescriptions a month. They also found that the mean total number of patients ever treated was 72, and the median 30, meaning that the distribution of prescribing level was skewed (Reif, Thomas, & Wallack, 2007a). Arfken, et al. (2010), found that the average number of patients per provider among providers with at least one patient rose substantially from 2004 to 2008 in a nationally representative sample of waived buprenorphine providers (see Figure 2-4; Arfken et al., 2010). This was true for both providers who chose to be on SAMHSA's Center for Substance Abuse Treatment (CSAT) locator list and for those who chose not to be on the list. In 2008, the average number of patients per provider regardless of list participation was 32.4². This average drops to 23.5 when including non-prescribers² (Arfken et al., 2010). Quest, et al (2012) found that

Figure 2-4: Mean patients per provider. Filled points represent providers on the CSAT locator list, hollow points represent providers not on the list (Arfken et al., 2010).

rural providers in Washington State treating at least one patient were treating an average of 23 patients, with the top one third of providers treating an average of 51.6 patients, the middle third treating 14.2 patients, and the lowest third treating an

average of 2 patients (Quest et al., 2012). Stacey Sigmon (2015) analyzed Vermont Medicaid claims from February through April 2014 and found that providers treated an average of 14.8 patients with a range of 1 to 76. However, as Reif and colleagues noted in 2005, she found the distribution of patients per provider was highly skewed, with 29.3% treating only one patient and 48.1% treating under 5 patients.

In the 14 years since office-based buprenorphine prescribing, substantial increases in OAT capacity have been achieved. Currently there is the potential to treat over 2.4 million people with buprenorphine under the office-based DATA 2000 waiver system. This new capacity is in addition to treatment capacity afforded through OTPs. From 2003 through 2013, though the number of OTPs has remained relatively stable, the number of patients receiving either methadone or buprenorphine at substance abuse treatment facilities rose 66% from 227,003 to 378,456 (SAMHSA 2014a). Using

the definition of “treatment gap” established by Jones, et al (2015) comparing the prevalence of opioid use disorder to total treatment capacity, the treatment gap appears to be shrinking. Jones and colleagues found that the difference between the number of people with opioid abuse or dependence and total treatment capacity was 914,000 people, or 40% of total treatment need in 2012 (Jones et al., 2015). Currently the “treatment gap” has closed; as 2,140,000 people met criteria for opioid use disorder in 2016 (most recently available data: SAMHSA 2017) and total buprenorphine treatment capacity reached 2,416,000 in 2016.

2.2 Spatial potential access: A spatially informed measure of relative shortage or surplus

Spatial accessibility is defined as the potential for geographically dispersed service demanders (e.g. people with OUD) to reach geographically dispersed opportunities (e.g. OAT slots; (Páez, Scott, & Morency, 2012). Potential access, a measure of whether people have the opportunity to use a service differs from realized access, a measure of actual service utilization. Spatial potential access measures are used to quantify regional differences in *ability*, or *opportunity* to use services and have been used to highlight regional differences in access various goods and services including: healthy food (Charreire et al., 2010; Leslie, Frankenfeld, & Makara, 2012; Ning, 2012; Ver Ploeg, Dutko, & Breneman, 2014; Walker, Keane, & Burke, 2010), day care providers (Páez et al., 2012), recreation or park facilities (Nicholls, 2001; Talen & Anselin, 1998), and health services (see, for example: Delamater, 2013; Guagliardo, 2004; Joseph & Bantock, 1982;

Khan, 1992; Knox, 1978; Li, Serban, & Swann, 2015; Lowe & Sen, 1996; W. Luo, 2004; W. Luo & Qi, 2009; McGrail & Humphreys, 2009; Ngui & Apparicio, 2011).

The simplest measure of spatial potential access is the regional availability method, also called the “container” or ratio method (W. Luo & Qi, 2009). When measuring regional availability, the region under consideration, such as a county or census tract, is pre-defined and a supply/demand ratio is calculated by summing up all supply opportunities and all demanders within that region. In the case of physicians, a physician/population ratio is generated and compared to a standard established by professional determination of physician need (Feldstein, 2012). The two measures of health provider shortage used by the Department of Health and Human Services—Health Professional Shortage Areas (HPSAs) and Medically Underserved Areas (MUAs)—are sophisticated container methods that make adjustments for need within the service regions and for resources in contiguous areas (U.S. Department of Health and Human Services, Health Resources and Services Administration, 2016b, 2016a).

There are two critiques of the regional availability method. First, the method assumes that people within the pre-defined region do not seek services outside the region. To assure that this assumption is valid, the region under consideration must be fairly large. Second, one must assume that there is little variation in access across the region considered—that access is essentially equal at all points within the container. This assumption requires that the defined regions be fairly small (W. Luo & Qi, 2009).

Geographers and demographers have been addressing these limitations for decades. The gravity model of accessibility addresses the second limitation—that access is not uniform at different distances between demanders and opportunities. In 1948, John Q. Stewart proposed formal laws of demographic gravitation, the application of the Newtonian laws of gravity to population groups. He presents the equation for physical gravitational potential V_A which a mass m at point a produces on a second mass M at point A (with gravitational constant G):

$$V_A = \frac{Gm}{d} \quad (1)$$

and then applies it to population groups. The potentials of population 1 and population 2 become:

$$V_1 = \frac{GN_2}{d}; V_2 = \frac{GN_1}{d} \quad (2)$$

where V is the population potential, N_1 and N_2 are the number of people considered, d is the distance between them, and G is a constant “left for future determination” (Stewart, 1948, p. 34). Population potential is directly proportional to the size of the population and inversely proportional to the distance from it.

Walter G. Hansen (1959) expanded Stewart’s population-over-distance population potential concept and defined a measure of population potential as the “intensity of the possibility of interaction...[or] the spatial distribution of activities about

a point, adjusted for the ability and desire of people or firms to overcome spatial separation” (W. G. Hansen, 1959, p. 73). Formally:

$${}_1S_2 = \frac{O_2}{d_{1-2}^\beta} \quad (3)$$

where ${}_1S_2$ is the measure of the accessibility in zone 1 of an activity in zone 2. O_2 is the size of the opportunity in zone 2, which could be the number of jobs, parks, people, etc. d_{1-2} is either the travel time or distance between zone 1 and 2, and β is an exponent that determines the effect of distance or travel time between the zones. The total accessibility in zone 1 to opportunity type O is the sum of the accessibility in each zone:

$$S_i = \sum_j \frac{O_j}{d_{ij}^\beta} \quad (4)$$

The addition of an exponent β to the distance function was a response to criticism that the original population potential model adhered too rigidly to the physical gravity model with an exponent of 1 on the distance term. The author contends that “it is generally agreed” that an exponential function be used for the distance decay term, and that the choice of an exponential function is empirically justified (W. G. Hansen, 1959, p. 74). Changing the exponent on the distance decay term alters how restrictive travel time or distance is for the activity in question. People are willing to travel different distances for different types of activities. For example, a person might find it reasonable to travel 40 minutes to work, but unreasonable to travel more than 15 minutes to buy groceries. Different values for the distance decay exponent reflect the

differences in people's willingness to travel. Hansen states that the value of the exponent, β , should be determined from empirical studies of people's actual travel behavior. So even though the relative accessibility measure, ${}_1S_2$, is a *potential* access measure, the exponent of the distance decay function is derived empirically from *actual* utilization data.

Hansen's claim that "it is generally agreed" that an exponential function be used for the distance decay or friction term in a relative accessibility measure may have been overstated. In D. R. Ingram's article "The Concept of Accessibility: A Search for an Operational Form" (1971), a negative exponential distance decay term was one of several operational forms for accessibility. Ingram's definition of accessibility, "the inherent characteristic (or advantage) of a place with respect to overcoming some form of spatially operating source of friction (for example, time and/or distance)" (Ingram, 1971, p. 73), is consistent with Hansen's (1959) definition. He defines relative accessibility as the degree to which two locations are connected based on their separation, and integral accessibility as the interconnection (at a given location) of all other points on a surface. Generally:

$$S_i = \sum_{j=1}^n s_{ij} \quad (5)$$

where A_i is the integral accessibility at location i , or the total accessibility of all opportunities at location i , and a_{ij} is the relative accessibility of location j at i . Unlike

Hansen, this functional form does not account for the attractiveness or the size of the activity at location j . Ingram explores various functional forms for relative accessibility, s_{ij} , including average straight line distance (a linear measure):

$$S_i = \frac{\sum_{j=1}^n d_{ij}}{n} \quad (6)$$

where locations with lower S values have greater accessibility. If we desire, instead, that larger S values imply greater accessibility, we can calculate the inverse, and the accessibility function is equivalent to Stewart's (1948) original gravity potential measure. Ingram also explores several curvilinear functions for distance decay including the reciprocal exponential function (with locations at negligible distance having accessibility scores of 100):

$$s_{ij} = 100d_{ij}^{-k} \quad (7)$$

If we substitute S_j , the size of the activity at location j for 100, this is equivalent to the accessibility measure in Hansen (1959). The reciprocal exponential function results in rapid decreases in accessibility with increasing distance. The negative exponential function:

$$s = 100e_{ij}^{-d} \quad (8)$$

results in a gentler decline of the effect of distance on accessibility. Both functions (7) and (8) are limited by the fact that they have rapid declines in accessibility at short distances, meaning that place 5 minutes away, say, would be substantially less

accessible than a place 2 minutes away. Ingram argues that the Gaussian function meets intuitive requirements of a distance decay function: that accessibility be reasonably flat near the origin, that the decline in accessibility at increasing distance be smooth, and that accessibility approach zero at large distances. He defines a modified Gaussian function:

$$s_{ij} = 100e^{-d_{ij}^2/v} \quad (9)$$

where v is a constant for the total area under consideration, and determines the width of the curve. The author offers various, somewhat arbitrary ways of determining v , including using average squared distance between all points, the radius of the smallest circle that contains all points, or empirical determination from actual trip frequency data.

These early gravity models captured an observed phenomenon in service utilization, the distance decay effect. However, they were limited because they only considered the supply side of accessibility measurement, not the demand side—consumers' competition for the opportunity, service or resource. For example: a physician in a location closely surrounded by a high number of demanders may seem highly accessible because the distances are short, but might not really be available because she has insufficient capacity to meet the demand. Qing Shen (1998) critiques the supply-side gravity models by stating that at least one of the following must be true: demand is spread uniformly across the space, or the opportunities have no capacity

limitation (Shen, 1998). If demand is spread uniformly across the space, then there will be no areas where competition or high demand strains the capacity of the resource more than any other area. If the opportunities or resources considered have no capacity limitation, such as very large public spaces, or broadcast TV signals, then competition is not a relevant concern when measuring accessibility. Medical services, however, do not meet these criteria. Demand is not uniform, and health service providers have finite capacity.

To address differences in the demand side and competition for supply, Joseph and Bantock (1982) generated a two-step method that integrates both supply and demand while considering the friction of distance between the two (Joseph & Bantock, 1982). They, and many of the authors who extended their measure, were concerned with modeling physician accessibility. So instead of using general language where suppliers are referred to as opportunities, resources and the like, they use specific language, referring to physicians and populations. They are concerned with how accessible spatially dispersed physicians are to the spatially dispersed people they purportedly serve. Like these authors, I will use the more specific physician/population language from this point forward. First the supply-side accessibility of physicians is calculated using the reciprocal exponential form of the gravity model from equation (4):

$$S_i = \sum_j \frac{O_j}{d_{ij}^\beta} \quad (10)$$

where S_i is the potential spatial accessibility of area i to physicians; O_j is a physician at location j that is within the range of area i ; d_{ij} is the distance between them; and β is the exponent on the distance function. Then the potential demand on a physician at location j is calculated:

$$D_j = \sum_i \frac{P_i}{d_{ji}^\beta} \quad (11)$$

where P_i is the size of the population in area i . Therefore, the demand, D_j , is proportional to the size of the population within the physician's catchment area, and inversely proportional to a function of the distance from that population. Combining the equations (4) and (10) yields a weighted relative accessibility measure:

$$A_i = \sum_j \frac{\left(\frac{O_j}{\left(\sum_i \frac{P_i}{d_{ij}^\beta} \right)} \right)}{d_{ij}^\beta} \quad (12)$$

or:

$$A_i = \sum_j \frac{O_j}{D_j d_{ij}^\beta}, D_j = \sum_i \frac{P_i}{d_{ij}^\beta} \quad (13)$$

Q Shen (1998) generalized equation (11) further, to allow for alternative functional forms for the distance decay function (Shen, 1998):

$$A_i = \sum_j \frac{O_j f(d_{ij})}{D_j}, \quad D_j = \sum_i P_i f(d_{ij}) \quad (14)$$

This more general form allows researchers the flexibility to calibrate the distance decay function to the actual region they are studying. By adding the potential population demand term to the original gravity model formulation, Joseph and Bantock (1982) and those that followed addressed one of the fundamental criticisms of gravity models: that they did not consider competition for available physicians by the population.

With the advent and maturity of geographic information systems (GIS), geographers became able to map physician locations precisely, to map population data at a high level of granularity, and to estimate travel distances or travel times on actual road networks. Geographers could then map potential access surfaces for areas studied, and represent differences in spatial potential access in a visually compelling way. These advances in mapping technology led to the development of the two-step floating catchment area (2SFCA) and kernel density measures of accessibility.

Luo and Wang (2003) describe the 2SFCA method in this way:

Step 1: For each physician location j , search all population locations (k) that are within a threshold travel time (d_0) from location j (that is, catchment

area of j), and compute the physician-to-population ratio, R_j , within the catchment area:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{jk} \leq d_0\}} P_k} \quad (15)$$

where P_k is the population of tract k whose centroid falls within the catchment (that is, $d_{jk} \leq d_0$), S_j is the number of physicians at location j , and d_{kj} is the travel time between k and j .

Step 2: For each population location i , search all physician locations (j) that are within the threshold travel time (d_0) from location i (that is, catchment area i), and sum up the physician-to-population ratios, R_j , at these locations:

$$A_i^F = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} \frac{S_j}{\sum_{k \in \{d_{jk} \leq d_0\}} P_k} \quad (16)$$

where A_i^F represents the accessibility at resident location i based on the two-step FCA method, R_j is the physician-to-population ratio at physician location j whose centroid falls within the catchment centered at i (that is, $d_{ij} \leq d_0$), and d_{ij} is the travel time between i and j (W. Luo & Wang, 2003, p. 872).

Computation of physician to population ratios in step one is an intuitive extension of container-based methods of calculating regional availability. However, the 2SFCA method addresses the two major criticisms of the container method. First, calculating each individual physician's physician-to-population ratio within his or her

individual catchment area in step 1 addresses the second criticism, that access is assumed to be equal over the entire region considered. In the 2SFCA method, each physician location is considered individually, so there is no need to assume uniformity. The second step of the 2SFCA method addresses the first criticism of container-based regional availability methods, that patients are assumed not to seek services outside the region. Summing the physician-to-population ratios of physicians reachable from each population location allows that patients may choose to visit any physician that is reachable. In application, authors tend to use buffer zones around the region under consideration to allow for “edge correction” of estimation of accessibility at peripheral regions (see, for example Yang, Goerge, & Mullner, 2006).

Though the steps employed calculating accessibility by the 2SFCA method and the gravity-based models are different, and may be conceptually dissimilar, it is clear that the final form of the 2SFCA accessibility equation (14), is a special form of the general gravity model equation (12) where the distance decay function is a dichotomous function, where:

$$f(d_{ij}) = \begin{cases} 1, & \text{if } d_{ij} \leq d_0; \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

Over the following decade, several authors modified either the gravity model or the 2SFCA model to address limitations in each. The dichotomous function in the 2SFCA was criticized as too rigid in assuming that a person was as willing or able to travel short distances as long distances (W. Luo & Qi, 2009), so alternatives were proposed. Luo and

Qi (2009) recognized the criticism of assumed uniformity of access across catchment areas, but also criticized gravity models as overemphasizing the distance decay term, resulting in concentric rings of access around physicians and excessive smoothing of the accessibility surface. To address both limitations, Luo and Qi (2009) created the enhanced two-step floating catchment area E2SFCA by applying weights to three travel zones (z) to allow for distance decay effects. The weights are calculated from the Gaussian function as follows:

$$w_{ij} = f(d_{ij}) = f(z) = e^{-(z-1)^2/\beta} \quad (18)$$

Beta must be determined empirically or through calibration or sensitivity testing methods. Graphically, the difference between the 2SFCA and E2SFCA can be seen in Figure 2-5.

Figure 2-5: Weights, or values of the distance decay function in the 2SFCA and E2SFCA (Delamater, 2013)

Several modified forms of the 2SFCA method emerged over the years as researchers found limitations in the E2SFCA when applying the method. In the simplest modifications, different forms were proposed for the distance decay function

(Schuurman, BÉRubé, & Crooks, 2010), in others, steps were added to allow for variable sized catchment areas (W. Luo & Whippo, 2012), or to add a selection weighting term to account for competition among facilities (Wan, Zou, & Sternberg, 2012). Luo (2014) proposed integrating the Huff model of selection probability for demand into the 2SFCA method. In this case the physician-to-population ratio would be modified by the probability that a person at a given location would select a given physician in their catchment area over another based on the distances to each (J. Luo, 2014). Delamater's (2013) modified M2SFCA adjusted the number of beds available (the supply) based on distance to the population, multiplying the supply term by the distance function twice, arguing that inaccessible beds do not "count" as much as highly accessible beds (Delamater, 2013). McGrail and Humphreys (2009) modified the 2SFCA to include a distance decay term and a capping function that does not allow access at fringe rural populations to be dominated by demand from outer metropolitan areas (McGrail & Humphreys, 2009). Ngui and Apparicio (2011) modified the 2SFCA using carried centrophraphic analysis and density analysis to adjust the supply side for their "optimized" 2SFCA (Ngui & Apparicio, 2011).

All of these gravity-based models or 2SFCA methods generate quantitative measures of relative accessibility for population locations within a given area, which can be used to generate maps that qualitatively demonstrate disparities in accessibility using heat mapping. However, additional steps are required to quantify disparities in accessibility at each location. Wan and colleagues (2012) created the spatial access ratio

(SPAR), which is a ratio of the accessibility index of each location and the mean accessibility index of the entire area. A SPAR of greater than 1 indicates greater accessibility than the overall mean. In defining an optimization problem in which a new facility would be located to minimize the inequality in potential spatial access, Wang and Tang (2013) simply define this inequality as:

$$v_i = (A_i - a)^2 \quad (19)$$

where v_i is the deviation from the average accessibility, and a is a constant equal to the total supply to total demand ratio for the entire area (Wang & Tang, 2013). In other words, the constant, a , is equal to the population weighted average accessibility of the entire region. This property of all (standard, unmodified) gravity models was proven by Shen in 1998 (Shen, 1998). Simply aggregating the accessibility scores of all locations yields the regional availability ratio of supply to demand with the entire area under consideration as the “container.” This does not characterize the access disparity in the area being studied. To date, there does not appear to be a single metric that quantifies the disparity in access in a region. A single metric could allow for quick comparisons of policy implications in what-if exploratory studies of areas that have already been mapped using a gravity model or 2SFCA method, or for comparisons of access disparity in different regions that have been mapped using the same methods. In Chapter 3 I propose a method of aggregating access disparity, and in Chapter 4, I test its usefulness in a spatial agent based model of OUD treatment accessibility.

2.2.1 Spatial disparity in access to buprenorphine treatment

Regional disparities in access to buprenorphine treatment exist and have been measured by several authors. In general, authors assess regional differences in access either by measuring regional or spatial differences in realized access (utilization) or in potential access through the regional availability “container” method.

Hansen, et al. (2013, 2016) analyzed differences in buprenorphine and methadone utilization in New York City residential zip codes and “social areas,” residential zip codes aggregated into areas based on race/ethnicity and income variables (H. B. Hansen et al., 2013; H. Hansen, Siegel, Wanderling, & DiRocco, 2016). In both papers, the authors found that buprenorphine treatment rates, defined as the number of people receiving buprenorphine per 10,000 residents in the area, was highest (in 2007) and rose most quickly (2004 – 2013) in social areas that were predominantly white and well off. By aggregating the zip codes into social areas, the authors chose not to highlight regional differences in buprenorphine utilization, but rather demographic differences in utilization as extracted from zip-code level data.

Schmitt, Phibbs, and Piette (2003) found that inpatient substance abuse treatment patients who live farther from their source of mental health care were less likely to receive aftercare, and that those who did receive aftercare received a lower volume of care (Schmitt, Phibbs, & Piette, 2003). The authors use their finding of a distance decay effect on utilization to support the statement that “lack of geographic

access (distance) is a barrier to outpatient mental health care following inpatient substance abuse treatment” (Schmitt et al., 2003, p. 1183).

Beardsley, et al., (2002) found a strong distance decay effect on retention in outpatient drug treatment at very short distances. Clients who traveled one mile or less to a treatment center in an urban area were 50% more likely to complete treatment than clients who traveled more than a mile, and clients who traveled over 4 miles were likely to remain in treatment for a shorter time than those that traveled less than a mile (Beardsley, Wish, Fitzelle, O’Grady, & Arria, 2003). Similarly, Brian Lockwood (2012) found that among juveniles attending court mandated treatment programs in Philadelphia, every increase of 3 miles to treatment nearly doubles odds of dropout (Lockwood, 2012). These suggests that there is a steep drop in treatment accessibility at short distances for urban residents. In each case, the authors did not measure geographic access directly, but this work does provide the type of empirical support on the effect of distance on utilization to inform the selection of a weighting scheme or distance decay function.

Several authors noted differences in potential access using the regional availability container or ratio methods. Kvamme, et al. (2013) compared the distribution of buprenorphine waived physicians, and potential buprenorphine treatment slots (number of physicians x waiver level) to the distribution of population in Washington State (Kvamme, Catlin, Banta-Green, Roll, & Rosenblatt, 2013a). They found that the population to provider and population to treatment slot ratios differed based

on urbanity as measured by RUCA codes, with the lowest ratios in small rural areas, and the highest ratios in isolated rural areas. While this appears to be a regional availability analysis, it is not. The authors used RUCA codes associated with the zip codes of physicians' practice locations to differentiate practices by urban/rural designation, and calculated population to physician ratios of each type of region, not the specific regions themselves. To illustrate, the population to treatment slot ratio in small rural areas of the state is the lowest, at 279:1, indicating the best access. However, if all 21 of these rural buprenorphine providers happened to practice in the southeastern corner of the state, people in the northwestern corner of the state might have no access to providers despite also living in a small rural area.

Robenblatt, et al. (2015) conducted a similar county-level analysis on the number and distribution of DATA waived physicians using the US Department of Agriculture Urban Influence Codes to differentiate counties by urbanity level (Rosenblatt et al., 2015a). Like Kvamme, et al. (2013), they aggregated counties by urbanity level, and presented a high-level analysis of accessibility, for the most part. Counties in metropolitan areas had the highest physician to 100,000 population ratio, 6.3, while rural areas had the poorest, 3.1. They note that 82.5% of rural areas counties have no waived providers. Also, like Kvamme, et al (2013), their main findings on the differences in provider ratios by urbanity is not a regional availability analysis. However, they do map all counties according to whether they have any buprenorphine providers at all, exposing large disparities in regional access to providers, which is, in effect, a

simple regional availability analysis. However, like all container analyses, even this simple map can be criticized for the assumption that all people within counties with at least one provider have equal access to that provider, and that people in areas with no providers will not seek services outside of the county.

Hirschak and Murphy (2016) analyzed differences in the number of opioid agonist treatment centers and DATA waived physicians per 10,000 residents aged 16-84 in Washington State zip codes based on urban-rural classification and whether the land was designated American Indian reservation/trust land (Hirschak & Murphy, 2016). They calculated, but did not report, physician to 10,000 resident ratios for every zip code, as the independent variable of a regression model on the association with rurality and AI reservation status, and found no relationship.

Stein and colleagues (2015) calculated the number of DATA waived physicians per 100,000 residents at the county level from 2008 to 2011 to predict the effects of state policies and county characteristics on the physician/population ratio (Stein, Gordon, Dick, Burns, Pacula, Farmer, Leslie, et al., 2015). Like Hirschak and Murphy (2016), they calculated this provider to population ratio, but did not report it at the county level because this was an intermediate step in generating the models for their study. They did report some trends in county level disparities in this availability metric. In 2008, 51% of counties had no buprenorphine providers, which dropped to 43% in 2011. They reported that the distribution of providers per 100,000 residents was highly skewed, “with a mean of 3.3 (sd = 6.6) in 2008 and 4.82 (sd = 8.2) in 2011, with only 5%

of counties having more than 13 waived physicians per 100,000 residents in 2008 and 17.6 per 100,000 residents in 2011” (Stein, Gordon, Dick, Burns, Pacula, Farmer, Leslie, et al., 2015, p. 106).

In the only article specifically addressing spatial potential access, Dick and colleagues (2015) created a methadone, buprenorphine, and overall treatment shortage area metrics using a methodology similar to that used to calculate HPSAs (Dick et al., 2015). They defined a treatment shortage county as a county that either had 0 providers, had a provider to population ratio that fell in the lowest 10%, or a provider to population ratio that fell in the lowest 20% and high need for treatment. High need was determined by proxies of need: the number of opioid overdose deaths, heroin prices, and demographic characteristics. They reported that the number of people residing in treatment shortage counties declined from about 49% to 10%, largely due to the dramatic increase in buprenorphine waived physicians over that time period. They go on to report that the increases in potential access were not uniform across all metropolitan status types, with small and medium non-metropolitan counties seeing the smallest increases in potential access, and large non-metropolitan counties seeing the greatest increases in potential access. Nor were these gains uniformly distributed across the country. By 2011, large areas in the Midwest remained treatment shortage areas.

2.3 Two buprenorphine policies and their impacts on treatment capacity

DATA 2000 established the regulatory framework to allow buprenorphine prescribing for the treatment of opioid use disorder in office-based settings.

Buprenorphine prescribing for OUD differs from prescription of all other medications in two respects: prescribers are limited in the number of patients to whom they can prescribe, and nurse practitioners and physician assistants were not allowed to prescribe buprenorphine even when they had the prescribing authority for other controlled substances (until the passage of the Comprehensive Addiction Recovery Act in 2017).

2.3.1 The history of the patient limit policy

A limit on the number of patients to whom a provider could prescribe was a part of office-based OAT policy from the outset. The Controlled Substances Act (CSA) of 1970 allowed for dispensing, but not prescribing, of narcotic drugs for maintenance treatment or detoxification treatment and imposed strict regulatory requirements on dispensing providers (91st United States Congress, 1970). The first draft of legislation to allow for office-based buprenorphine prescribing, the Drug Maintenance and Detoxification Act of 1995, sought an exemption to the regulatory requirements of the CSA when physicians treated 20 or fewer patients with a Schedule V drug (buprenorphine was in Schedule V at the time due to its safety profile and perceived limited abuse potential) (Jaffe & O’Keeffe, 2003). When DATA 2000 was signed into law in 2000, prescribing was limited to 30 patients per practice (Carl Levin & Orrin Hatch,

2000). In 2005, congress passed a law to allow 30 patients per physician, rather than per medical practice (109th Congress, 2005).

In studies that surveyed physicians on buprenorphine use, the 30 patient limit was often cited as a barrier limiting patient access to treatment (Barry et al., 2008; Join Together, 2003; Kissin et al., 2006; WESTAT & The Avisa Group, 2006). In December of 2006, congress again amended the CSA, this time to allow physicians to treat up to 100 patients at one time (109th Congress, 2006), and in 2007 the DEA finalized the rule change that allowed waived physicians to apply for a patient limit increase after one year (Drug Enforcement Administration, 2008). Finally, in 2016, SAMHSA finalized a regulatory rule change, without a preceding act of Congress, to allow certain board certified addiction specialists to increase their patient limit to 275 (SAMHSA 2016a).

2.3.2 The intent of the patient limit policy

No authors explicitly stated the reasoning behind the original 20 or 30 patient limit, but much can be inferred from OAT policy papers published around the time that DATA 2000 became law and buprenorphine prescribing began. Two themes for why policy-makers may have chosen to limit patient numbers emerged from this literature: integrating addiction treatment into mainstream or primary medical care—as opposed to higher volume specialty care settings, and reducing the risk of diversion.

2.3.2.1 Integrating addiction medicine into mainstream or primary medical care

In a primary care addiction treatment model, in which a provider would treat a patient's addiction as part of that patient's routine medical care, many providers would each treat few patients. This was the case in France around the time that DATA 2000 became law. In 1995, in response to a heroin crisis, France allowed all physicians to prescribe buprenorphine for the treatment of opioid use disorder without requiring any special certification or education. Bell, et al. (2002) wrote that 29% of French General Practitioners (GPs) were prescribing to 1 patient (6% of patients) and that 12% were prescribing to 12 or more (50% of total patients; Bell, Dru, Fischer, Levit, & Sarfraz, 2002). In 1999, in a study of one French region, 20% of GPs were prescribing buprenorphine, 0.8% had 50 or more patients, while 84% had fewer than 6 patients (Auriacombe, Fatséas, Dubernet, Daulouede, & Tignol, 2004). Several studies through 2002 showed that the "large majority of buprenorphine prescribers in France [were] office-based general practitioners" (Auriacombe et al., 2004, p. S18). This GP focused system was able to engage 50% of problem heroin users in OAT, and likely contributed to a dramatic reduction in opioid overdose deaths at the time (79% reduction from 1994 to 1999; Auriacombe et al., 2004).

In the United States, interest in integrating OAT into primary care pre-dated DATA 2000 and buprenorphine FDA approval. In the 1980s and 90s, there were several successful studies of "medical maintenance programs," or office based methadone treatment for stable methadone patients (Fiellin, O'Connor, et al., 2001; Merrill, 2002;

Novick et al., 1988; Schwartz, Brooner, Montoya, Currens, & Hayes, 1999; Senay et al., 1993). Because of these successful studies and the French experience, by the time DATA 2000 became law, authors were calling for broadening the OAT prescriber base through primary care methadone or buprenorphine treatment (Rounsaville & Kosten, 2000), for the reintegration of “methadone maintenance and other addiction pharmacotherapies into [office-based] medical practice” (Merrill, 2002, p. 1), for “the much needed medicalization or opioid agonist pharmacotherapy” (Kreek & Vocci, 2002, p. 102) , and for the expanded role of the primary care physician in “optimizing health of opioid dependent patients” (Krantz & Mehler, 2004, p. 1).

Buprenorphine prescribing under DATA 2000 was originally envisioned as a system in which opioid agonist treatment was integrated into the normal course of medical treatment. The manufacturer of buprenorphine, Reckitt Benckiser, needed buprenorphine “to reach the mainstream practice of medicine” (Jaffe & O’Keeffe, 2003) in order to make the investment in the FDA approval of buprenorphine worthwhile. SAMHSA generated a Treatment Improvement Protocol (TIP) to support DATA 2000 prescribers with limited experience with addiction treatment. The TIP authors wrote of the vision of OB buprenorphine treatment, “Office-based treatment with buprenorphine promises to bring opioid addiction care into the mainstream of medical practice”, and “The promise of DATA 2000 is to help destigmatize opioid addiction treatment and to enable qualified physicians to manage opioid addiction *in their own practices*” (emphasis mine; Boone et al., 2004, p. xv and 2-3). Feillin and O’Connor (2002) wrote

“the current initiatives are designed to meet the dual objectives of treatment expansion and involvement of physicians in the care of opioid-dependent patients....increasing the participation of the medical community in the treatment of opioid dependent patients” (Fiellin & O’Connor, 2002b).

The original vision of DATA 2000 conveyed by researchers at the time was a primary-care based addiction treatment system as a supplement to OUD treatment in specialty addiction treatment settings, in which addiction treatment was integrated into mainstream medical practices (Ling & Smith, 2002). With the example of the French GP-based system and the promise of a similar primary care based system, one could see how a 30-patient limit might have seemed like a non-issue from an access standpoint.

2.3.2.2 Reducing the risk of diversion

In crafting the law that would create the envisioned diffuse, primary care based system, the early policy makers had to balance access with against the risk of diversion. In the French system at the time, access was paramount, and diversion did occur (Auriacombe et al., 2004). Auriacombe et al. (2004) wrote of the largely unregulated French system that “a lack of regulation could increase the occurrence of...diversion to non-registered patients and thus limit the overall benefit of this medication” (Auriacombe et al., 2004, p. S18). In the United States, the addiction treatment system in place before DATA 2000 was highly regulated to prevent methadone diversion (Bridge et al., 2003; Campbell & Lovell, 2012; Jaffe & O’Keeffe, 2003; Merrill, 2002). In the balancing concerns about access against diversion, diversion concerns appeared to be

paramount, as “limiting diversion dominated discussion of methadone within the domestic drug control apparatus in the early 1970s” (Campbell & Lovell, 2012).

By the late 1990s, treatment access was once again a major concern as opioid overdose deaths were on the rise. Buprenorphine was seen as a desirable product for office based treatment because it appeared to have lower potential for diversion and misuse than methadone (Bridge et al., 2003; Fiellin et al., 2002), especially when combined with naloxone, an abuse deterrent formulation that discourages medication injection. Even with a lower potential for diversion and abuse due to its pharmacological properties, there were continuing concerns about medication diversion. Jaffe and O’Keefe (2003) that “The FDA was concerned that the system could get out of hand unless limits were place on the number of doctors and patients who could initially participate in the system” (Jaffe & O’Keefe, 2003, p. S8). A congressional aide interviewed by Fornili and Burda (2009) remembered that there was opposition to DATA 2000 from legislators concerned about “potential diversion of any opioid medication” (Fornili & Burda, 2009). This concern may have contributed to the inclusion of a patient limit in the legislation.

2.3.3 The effects of and reaction to the patient limit policy

In the early days after DATA 2000, uptake of office-based treatment was low (Netherland et al., 2009). As predicted, the early adopters tended to be addiction specialists (West et al., 2004). According to SAMHSA’s evaluation of the DATA waiver program, by 2005 44% of waived providers were addiction specialists (WESTAT & The

Avisa Group, 2006), and 80% of all waived physicians were prescribing to zero or very few patients, leaving 20% of waived physicians to treat the majority of patients seeking buprenorphine treatment (Albright, Ciaverelli, Essex, Tkacz, & Ruetsch, 2010). Similarly, a 2005 national survey of all psychiatrists found that 86% were not comfortable with prescribing buprenorphine (West et al., 2004). And in a non-representative survey of psychiatrists in 4 cities also conducted in 2005, only 13% of non-addiction specialist psychiatrists had received waiver training and 9% had prescribed buprenorphine (Thomas et al., 2008).

In these early days, patient counts tended to be low or even zero, but distributions of patient counts were skewed, indicating that while most providers were treating few patients, a few were treating a lot of patients (Albright et al., 2010; Fiellin, 2007; Reif, Thomas, & Wallack, 2007b; WESTAT & The Avisa Group, 2006). These few were likely the early adopting addiction specialists. Many providers at the time were frustrated by the patient limit policy and were vocal in opposition to it. Physicians were frustrated with two aspects of the patient limit—the limit on patients per practice, and the limit itself. The limit on the number of patients per practice did not differentiate between large medical practices that could have hundreds or thousands of providers, and single solo practices (Schackman, Merrill, McCarty, Levi, & Lubinski, 2006; WESTAT & The Avisa Group, 2006). Providers in large medical groups, or in groups that specialized in addictions were particularly frustrated by the 30 patient limit for medical groups (WESTAT & The Avisa Group, 2006). The 30 patient limit was cited as barrier to

access to buprenorphine in several physician surveys (Barry et al., 2008; Join Together, 2003; Thomas et al., 2008). Addiction specialists who responded to open ended survey questions in the SAMHSA evaluation report were eager to convey to SAMHSA that the 30-patient limit hampered their ability to provide care to patients who need treatment. Many stated that they maintained waitlists and turned patients away. Some called for the limit to be raised, others for it to be abolished for specialists (WESTAT & The Avisa Group, 2006). The American Society of Addiction Medicine wrote in its public policy statement that “arbitrary caps on the number of patients who can be treated by a physician....that are not supported by medical evidence, should not be imposed by law, regulation or health insurance practices” (American Society of Addiction Medicine, 2006, p. 2).

After changes to the patient limit policy in 2005 and 2007, the patient limit was still cited as a constraint on physician capacity and a barrier to access (Green et al., 2014; Molfenter, Sherbeck, Zehner, & Starr, 2015; Stein, Pacula, et al., 2015), and several providers have reported demand that exceeds their 100-patient limit (ASAM staff, 2015; Molfenter et al., 2015).

2.3.4 Post-hoc policy analysis of patient limit changes

To date there have been two post-hoc policy analysis studies of lifting the patient limit from 30 to 100. Stein and colleagues found that the amount of buprenorphine dispensed and the number of waived providers increased in general from 2004 to 2011, but that buprenorphine dispensing increased most from providers

with 100-patient waivers. They estimated 24 to 45 additional patients received treatment per 100-patient provider in urban areas and 57 additional patients received treatment per 100-patient provider in rural areas (Stein, Pacula, et al., 2015). The authors noted that many of the physicians waived at the 30-patient level were prescribing to few or no patients. The same research group published a study on pharmacy retail transactions and found that among those that prescribed, the majority, 69%, prescribed to 30 or fewer patients (Stein BD et al., 2016). Similarly, Hefei Wen (2016) found that “the availability of 100-patient waived physicians was strongly associated with increase in Medicaid prescriptions for and spending on buprenorphine MAT,” but did not find a significant association between prescribing and the availability of 30-patient waived physicians (Hefei Wen, 2016). These studies suggest that though most providers are prescribing to a small number of patients and were unaffected by the cap change policy, increasing capacity did afford greater access to treatment through the smaller proportion of providers who elected to increase their limits, and that this increase in access occurred in both rural and urban areas.

2.3.5 Exclusion of Nurse Practitioners and Physician Assistants as eligible DATA 2000 prescribers until 2016

A provision of the Comprehensive Addiction Recovery Act (CARA) passed in 2016 enabled Nurse Practitioners (NPs) and Physician Assistants (PAs) to prescribe buprenorphine for the treatment of OUD. The original language of DATA 2000 explicitly stated that “qualified physicians may prescribe” schedule III, IV and V controlled

substances for the treatment of opioid use disorder. It is not clear whether NPs and PAs were excluded from the waiver program due to oversight or design (Fornili & Burda, 2009). Senator Levin, one of the original sponsors of DATA 2000 and an advocate for expansion of buprenorphine treatment expansion was in favor of NP buprenorphine prescribing in 2014 (“Congress and SAMHSA look at ways to expand buprenorphine,” 2014), so it is unlikely that he had intended that they be excluded when the law was originally written. Whatever the original intent, up until passage of CARA, NPs and PAs could not prescribe buprenorphine for the treatment of OUD.

Advocates for extending prescribing authority to NPs and PAs note that NPs and PAs could expand OAT capacity to vulnerable populations because NPs and PAs working in primary care often serve in Health Provider Shortage Areas (HPSAs) or Medically Underserved Areas (MUAs), in safety-net settings, or as front line health care workers in rural areas (Fornili & Burda-Cohee, 2006; O’Connor, 2011; Strobbe & Hobbins, 2012).

Three studies have been conducted on NP/PA attitudes toward buprenorphine prescribing. Roose, et al. (2008) found that 48% of PAs and NPs surveyed at HIV educational conferences expressed interest in prescribing buprenorphine and that PAs and NPs (pooled) were more likely than infectious disease physicians to be interested in prescribing (aOR 2.89; Roose, Kunins, Sohler, Elam, & Cunningham, 2008). The authors note the limitations of their study: small sample size and possibility of selection bias—NPs and PAs at HIV conferences may be more likely to show interest in buprenorphine prescribing than those who don’t go to conferences. They should be commended in not

making general claims about NP and PA interest from this small sample of NPs and PAs that work in HIV settings. However, authors of policy and advocacy papers have not always been so careful. This study is widely cited as proof of a general claim that NPs and PAs are interested in prescribing buprenorphine. Additionally, the odds ratio in the study is a little suspect because physicians who were already prescribing buprenorphine to their patients were excluded from the analysis. PAs and NPs who *can't* prescribe buprenorphine are compared to physicians who have already had the chance to prescribe buprenorphine and have chosen not to.

In a study of all PAs in Kansas to which only 25% responded, Spiser and Dumolt (2011) found that 53% of respondents believe legislation should be changed to allow PAs to prescribe buprenorphine, while 32% are unsure. 29% of primary care PAs were interested in becoming certified if the legislation would allow, while 15% were unsure. 50% believed there was a need for more certified buprenorphine prescribers in their communities, while 29% were unsure. 65% of primary care PAs reported having to turn patient away or recommend another location for opioid addiction treatment. Average distance from their practice to the nearest certified provider site was 28.87 miles. Of those who practiced in rural or frontier communities, the average distance was 42.6 miles, with more than one response of 150 miles (Spiser & Dumolt, 2011).

The biggest issue with this study is selection bias: the PAs who are interested in buprenorphine may also be interested in filling in the survey, and the ones who didn't respond might not have because they are not interested in buprenorphine. However, it

does provide another data point (if not a perfect one) on interest in buprenorphine prescribing by a group of non-physician providers. The average distance metrics also provide a good picture of how patients are currently being affected by the physician-only legislation, and how extending prescribing to this group could benefit geographically isolated patients.

In her dissertation on advanced practice nurses' perspectives on DATA 2000, Dorothy Were (2014) reports on a survey of a convenience sample of 96 NPs in 32 states. 64% of those surveyed felt a subspecialty in addiction medicine should be required for buprenorphine prescribing. 65% believe that NPs should be authorized to prescribe buprenorphine, and 24% thought that maybe they should. 99% said NPs should go through the same training as physicians for buprenorphine prescribing (Were, 2014). The use of a convenience sample limits the conclusions that can be drawn from the study since NPs interested in prescribing buprenorphine may have been more likely to complete the survey, potentially biasing the results. Also, recruitment via social media likely resulted in a young sample, while the median age of NPs is fairly high (American Association of Nurse Practitioners, 2016). Further, the author's interpretation of survey results may have been overzealous. She used survey results to support a broad assertion not gathered from survey. Responding that NPs *should* be allowed to prescribe buprenorphine was interpreted as representing the surveyed NPs' personal interest in prescribing buprenorphine, while it may instead indicate that NPs believe that they should have the same prescribing authority as physicians regardless of actual interest.

These studies, while limited by their use of convenience samples, do show that some NPs and PAs are interested in buprenorphine prescribing. In fact, some NPs who work in practices with physicians prescribing buprenorphine have already completed waiver training (O'Connor, 2011). Because NPs and PAs often work with marginalized communities or people in rural communities, it may be that extending prescribing authority to these types of providers will alleviate some of the regional disparities in access.

With the passage of the Comprehensive Addiction Recovery Act (see McCarty, Priest, & Korthuis, 2018), nurse practitioners and physician assistants may now prescribe buprenorphine for the treatment of opioid use disorder after completing 25 hours of training (compared to 8 hours for physicians) which some providers have identified as a barrier to adoption by NPs and PAs.

2.4 Simulation for substance abuse policy analysis

Researchers have been generating substance abuse policy simulations since the 1970s. While this is not a comprehensive list of all substance abuse policy simulations, several examples are shown in Table 2-1, categorized by substance and methodology.

Table 2-1: Dynamic policy models of substance use grouped by substance and modeling methodology.

Topic	Modeling Methodologies				
	System Dynamics/ Differential or Difference Equations	Markov/ State Transition	Monte Carlo Simulation/ Discrete Event Simulation	Microsimulation	Agent Based Simulation
Alcohol	(H. D. Holder & Bloese, 1987) (H. Holder, 1998)	(Mortimer & Segal, 2005) (Chisholm, Rehm, Van Ommeren, & Monteiro, 2004) (Barbosa et al., 2010)			(Garrison & Babcock, 2009) (Giabbanelli & Crutzen, 2012)
Tobacco	(Levy, Chaloupka, Gitchell, Mendez, & Warner, 2002)			(Levy & Friend, 2001) (Levy et al., 2002) (Levy, Friend, Holder, & Carmona, 2001) (Tomintz, 2009)	
Heroin/Opioids	(Levin, Roberts, & Hirsch, 1975) (White & Comiskey, 2007) (Nyabadza & Hove-Musekwa, 2010)	(Barnett, 2009) (Schackman, Leff, Polsky, Moore, & Fiellin, 2012)	(Zarkin, Dunlap, Hicks, & Mamo, 2005) (Zarkin et al., 2011)		(Perez et al., 2006) (Hoffer, Bobashev, & Morris, 2012) (Heard, Bobashev, & Morris, 2014)

	(Wakeland et al., 2013) (Wakeland, Nielsen, & Geissert, 2015)				
Cocaine	(Homer, 1993a) (Homer, 1993b) (Behrens, Caulkins, Tragler, Haunschmied, & Feichtinger, 1999)	(Sohler Everingham, Peter Rydell, & Caulkins, 1995) (Jonathan P. Caulkins, Rydell, Everingham, Chiesa, & Bushway, 1999) (Jonathan P. Caulkins, Behrens, Knoll, Tragler, & Zuba, 2004)			
Other	Methamphetamines (Nyabadza & Hove-Musekwa, 2010)	Injection drug users (Peterson, Willard, Altmann, Gatewood, & Davidson, 1990) Drug use trajectories (J. P. Caulkins, Dietze, & Ritter, 2007)	Injection drug users (Peterson et al., 1990)		Drug use in general (Galea, Hall, & Kaplan, 2009) Injection drug users (Gutfraind et al., 2015) Recreational poly drug use (Lamy, Bossomaier, & Perez, 2015)

2.4.1 Model typologies for policy analysis

As simulation is increasingly used for policy analysis, methodologists have developed simulation classification schemes and recommendations for best practices. Boero and Squazzoni (2005) defined three basic agent based simulation (ABS) model typologies and prescribe appropriate levels of empirical embeddedness for each (Boero & Squazzoni, 2005). Simulations may be theoretical abstractions, typifications, or case-based models. Theoretical abstraction models aim to explain or explore a “wide range of general phenomena with no direct reference to reality” (Boero & Squazzoni, 2005, p. 4), such as the SugarScape models which explore economic concepts including wealth disparity and trade in a simple stylized artificial world (Epstein & Axtell, 1997). Case-based models simulate a specific event or phenomenon such as the rapid disappearance of the Anisazi people in around 1300 modeled in the Artificial Anisazi Project (Dean et al., 2000). Typification models target a class of empirical phenomena that share certain properties, but not a single, specific case. Theoretical abstractions require no empirical data, and case-based models aim to replicate a phenomenon as faithfully as possible and require as much empirical support as is available. Typification models make use of empirical data to specify, calibrate and validate models, but aim at a more generalizable understanding of studied phenomena. The buprenorphine treatment capacity model in this research is a typification model. The purpose of the model is not to explain or understand access to buprenorphine in a given region at a specific time, but rather how policy could impact treatment access for people who live in different kinds of

communities based on typical provider and patient preferences. The choice of a typification model rather than a case-based model for policy analysis may allow for more generalizable policy recommendations, as outlined in Yücel and van Daalen (2009).

Yücel and van Daalen (2009) propose a conceptual framework for policy analysis simulations, specifically, based on the objective of the simulation (Yücel & van Daalen, 2009). They delineate six general model objectives:

1. To research and analyze
2. To design and recommend
3. To advise strategically
4. To mediate
5. To democratize
6. To clarify values and arguments

The buprenorphine policy model in this research is type 2, intended to design and recommend policies that increase buprenorphine access and reduce geographic access inequality. As an “advisory model” the buprenorphine policy simulation “focus[es] on a particular problem context, rather than representing [the] dynamic phenomenon in general” (Yücel & van Daalen, 2009, p. 5). They go on to recommend best practices for advisory models beyond standard modeling practices, including boundary assessment, basis assessment, and representation assessment. I will include

specifics on how these assessments will be used here as the concepts are defined, rather than in chapter 4, where I propose the actual tests.

Boundary assessment is the evaluation of the selection of what is left out of the model, or what can be modeled as an exogenous input. In advisory models decisions on boundary selection, these decisions must be defensible in reference to the particular problem context of the policy. In the case of the buprenorphine policy model, the policy problem is one of provider capacity and access, not treatment adequacy, quality, or patient quality of life. As such, the model excludes rich modeling of relationships among potential patients, motivations to seek treatment, or medical decisions by providers. Further, the incidence of OUD and treatment seeking are exogenous constants because they change slowly compared to the time horizon in the model.

Basis assessment is the extent to which a model should be based on empirical data, theory or the knowledge of experts. The buprenorphine policy model is a typification model that makes heavy use of empirical data. Because the model is a typification, broad, survey-based empirical data is sufficient, where a case-based model might require specific, high fidelity geographic data (such as tract-level census data, or geo-coded provider locations). Also, because the model is a typification, the fact that the model is ad hoc rather than strictly theory-based is not problematic (Boero & Squazzoni, 2005). The highest quality, most generalizable data was sought to empirically support model parameters, and the opinion of a wide array of expert stakeholders with different policy perspectives was sought to guide the specification of model structure.

Experts included addiction specialist physicians, a primary care physician, a nurse practitioner, a physician assistant, a patient advocate in OUD recovery. Providers serve a variety of patient populations including rural residents, urban residents, pregnant women with OUD, and veterans; practice in a variety of settings including primary care clinics, OB clinics, university hospitals, addiction treatment centers, VHA clinics; and live and practice in different regions of the country including the Northeast, the Northwest, Appalachia, and the Mid-Atlantic.

Representation assessment includes standard assessments of validity as well as whether the model represents the behaviors and structures of the modeled system sufficiently to build confidence in policy recommendations. A model should replicate both the underlying agent level processes (structures) the overall behavior of the system for advising on policies to be meaningful. Though “models heavily dependent on the participators’ depiction of the system are naturally validated and already approved by the participants/problem owners,” as the buprenorphine policy model will be, standard validation tests should also be used (Yücel & van Daalen, 2009, p. 13). To develop appropriate model structures while simultaneously replicating the overall behavior of the buprenorphine treatment system, I will use Grimm and Railsback’s (2012) “pattern oriented modeling” approach (Grimm & Railsback, 2012), in which I will attempt to fit multiple quantitative and qualitative patterns at both the agent and system levels.

The literature reviewed in Chapter 2 reviewed the limited access to opioid agonist therapy in the US, outlined historical approaches to assessing variation in spatial access, described the unique limits imposed on buprenorphine prescribing, and discussed prior simulation models used to assess policies related to treatment for substance use disorders. The stage is now set to address the methods used in the analysis of potential changes in policies controlling buprenorphine prescribing.

3 Methods

This research uses Agent-Based Simulation (ABS), a modeling methodology in which heterogeneous agents act and interact in a dynamic environment according to individual rules of behavior. Population level outcomes of interest are generated by local interactions of agents acting in their own interest—in this case: providers interacting with people with OUD seeking treatment, and people with OUD interacting with providers and peers.

Empirically-based simulation models have been used to model state alcohol and traffic policies, social influence on BMI, drinking behavior, and health behavior and drug use (see Table 2-1). There are many advantages of using Agent-Based Models (ABMs) as policy analysis tools. ABMs allow for the exploration of policy options *in silico*, without putting people at risk, at lower cost, and often in less time than empirical studies. ABMs are not aggregate population-based models, but rather individual-based models which allow for exploration of the effects of individual heterogeneity including spatial heterogeneity. As in real target systems, population level dynamics arise from the interactions of these heterogeneous agents within the modeled environment. In this study, issues of buprenorphine treatment capacity arise due to the interactions between people with OUD entering treatment and their prescribers, and due to the simulated geography which these actors inhabit. This simulation method was selected specifically because of an apparent mismatch between simply-calculated buprenorphine treatment capacity numbers (the sum of waived doctors times the three patient limit

levels) and the actual experience of providers: some of whom treat very few patients, and others who maintain waitlists and routinely turn patients away.

It should be noted that in some research studies an ABM is the result of research, and in others, an ABM is a research method. The latter is the case in this research. The ABM developed is used to research policy options in the context of future uncertainty, and to assess the usefulness and functional form of the proposed aggregate geographic accessibility metric. As such, the model is described in this methods chapter, while the results of metric exploration and policy analysis experiments are described in Chapter 4.

The model was implemented in NetLogo 6.0.2 (Wilenski & others, 1999).

3.1 Model development

Simulation modeling is often a participatory and iterative process. Subject matter experts are involved throughout the model development process, from conceptualization of the system to validating that the model represents the actual system. As initial, simple models expand to include more detail in order to explore more outcomes or to assess a new set of policy questions, the modeling process is repeated. This iterative process is outlined in Figure 3-1, below.

Figure 3-1: The model development process is iterative, and a single model may require many cycles through the process.

The model used to assess the research questions in this thesis is the fourth iteration of a modeling process focused on addressing the question of buprenorphine capacity. Early model iterations included simple simulated geographies and were presented at SAMSHA's 2014 Buprenorphine Summit (iteration 1: SAMHSA 2014c), at the American Association for the Treatment of Opioid Dependence (AATOD) annual conference in 2015 (iteration 2: Alexandra Nielsen, 2015), and submitted to an academic journal (iteration 3). In the third iteration, model geography was based on a real map, and the scope of the model expanded to include: 1) a greater number of relevant outcomes, 2) more detail on patients seeking treatment, 3) people not seeking treatment as agents, 4) methadone treatment offered at Opioid Treatment Programs (OTPs), 5) children and pregnant women, and 6) more policy options. Model revision followed each dissemination activity in response to reviewer comments and critique. In

the fourth modeling iteration, the model was streamlined and several outcomes and populations were removed. For example, because child buprenorphine poisonings are a significant public health concern, children and this outcome were included in iteration 3, to increase applicability, but removed in iteration 4, to address more targeted dissertation research questions.

Each step of the modeling process detailed in Figure 3-1 is detailed below:

3.1.1 Conceptualize the system

I sought understanding of the target system to be modeled through extensive literature search and through interviews with experts in OB buprenorphine treatment. Prior to initial modeling, I interviewed two addiction medicine specialists who had experience developing the eight-hour training course for DATA 2000 waiver certification, Dr. Margaret Kotz, and Dr. Stephen Wyatt (Kraus et al., 2011). In order to involve a broader base of stakeholders, I empaneled a diverse group of experts to guide model conceptualization and specification. Expert panel members consulted during model development for iterations 2 through 4 are listed below. I interviewed each panel member at least twice using an unstructured format, and asked specific questions via email as they arose in the modeling process. Dr. Alane O'Connor and Dr. Andrew Saxon were also consulted to assess iteration 4 face validity.

3.1.1.1 Expert Panel Members

- Dr. Todd Korthuis—Oregon Health and Science University, General internal medicine, HIV research program director—Primary Care Provider in Oregon
- Timothy Lepak—president National Alliance of Advocates for Buprenorphine Treatment—Patient Advocate
- Melvania Briggs, PA-C—Academic coordinator for the Duke University Physician Assistant Program. Co-Principal Investigator of a NIDA funded Buprenorphine Clinical Trial for a community based mental health organization and Duke University Medical Center—Physician Assistant in North Carolina
- Dr. Kelly Clark—Chief Medical Officer of CleanSlate Addiction Treatment Centers, president of the American Society of Addiction Medicine (ASAM)—Addiction Medicine specialty provider in Kentucky and Pennsylvania
- Dr. Andrew Saxon—Center of Excellence in Substance Abuse Treatment and Education, VA Puget Sound Health Care System, Director Addiction Psychiatry Residency Program, University of Washington, associated with the American Association of Addiction Psychiatrists (AAAP)—Addiction Psychiatry provider in Washington
- Dr. Alane B. O'Connor, DNP, FNP—Maine Dartmouth family Medicine Residency Faculty Adjunct Instructor, author of NP buprenorphine health

policy article, investigator of clinical trials of buprenorphine use in pregnancy—Family Practice Nurse Practitioner in Maine

3.1.2 Build a model

The operational model was developed in NetLogo 6.0.2, an ABS tool. I used the pattern oriented modeling technique (Grimm & Railsback, 2012), in which a model is developed to fit several quantitative and qualitative patterns. The Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2010) was employed to convert the understanding of the system into an operational model. The model is documented in Section 3.2 using the ODD protocol, which is the gold standard for model reporting and replicability.

3.1.3 Add data to the model

Modeling best practice requires that all aspects of the system that are considered important in model conceptualization be included in an operational model whether or not high quality data are available to support them (Caro, Briggs, Siebert, & Kuntz, 2012). When possible, I obtained empirical support for model parameters from peer-reviewed published literature through both comprehensive and targeted literature searches. I obtained empirical support for model parameters for which high quality data were not available from smaller studies that are not necessarily generalizable, “grey” literature, expert opinion, and through the process of model calibration.

3.1.4 Test the Model

For models to serve as credible proxies for the target system, models should be calibrated, verified, and validated to the degree possible. The model should also be tested for sensitivity to specific parameter values and critical assumptions about model structure. I calibrated the iteration 4 model manually to reproduce historical trends in opioid overdose deaths and the number of unique buprenorphine recipients for a given year. I conducted model verification—testing that the model performs as expected—throughout the iterative modeling process, as model code was developed and as new data added to the model. The model was assessed for face validity by two panel experts, Dr. O'Connor and Dr. Saxon, and externally validated by comparing model-generated annual opioid overdose deaths and number of unique buprenorphine recipients against data that was not used in model calibration. I conducted one-way sensitivity testing by varying each model parameter by 30%. I tested the model's sensitivity to the geography selected by conducting baseline model runs with 10 different maps. I tested sensitivity to assumptions about provider preferences for patient loads by running the model under several alternative assumptions about providers' patient load preferences.

In general, model testing built confidence that the model is a sufficiently faithful representation of the world to be able to consider the results of policy experiments to be meaningful. Calibration can show that a model is capable of generating known behavior, verification shows that the operational model matches the conceptual model developed with subject matter experts, and validation can show that the model is

capable of generating real world behavior in a way that conforms to experts' understanding of the target system. Sensitivity testing builds confidence by showing the degree to which model performance is dependent on assumptions and on parameter values which may or may not have strong theoretical or empirical support. While none of these tests can prove that a model is "right," they do build confidence that a model may be useful for its intended purpose.

Model testing specifics and results are reported in Section 3.4.

3.1.5 Run Experiments

I conducted policy experiments by systematically changing the values of policy variables and observing model outcome values after a year of modeled time. Because the model contains several random variables, each experiment was repeated 35 times to establish the possible range of outcomes. One-way ANOVA power analysis indicated that with 35 replications, one could detect medium to large effects ($f = 0.30$), with an alpha of 0.05, beta of 0.1, and 5 variable levels. Fewer replications would risk low power, or inability to detect differences in outcome variables that are present in simulation data. Policy experiments and results are detailed further in Section 3.7 and Section 5.

I also conducted spatial potential access metric exploration experiments using alternative formulations of the aggregated spatial disparity metric to assess the relative

sensitivity and usefulness of each formulation. The process is further detailed in Section 3.6, results detailed in Section 4.

3.2 Model specification

Model specification is detailed below using the ODD (Overview, Design concepts, and Details) protocol for ABS models (Grimm et al., 2010). The ODD protocol is a standardized description protocol that facilitates rigorous formulation of ABS models, and allows for reproducibility of such models. Model overview is outlined in three sections: purpose; entities, state variables and scales; and process overview and scheduling. Major ABS design concepts are described in the design concepts section, and details are provided in the initialization, and input data sections. Full model code is attached as an appendix to support model replicability. Embedding a full model description using the ODD protocol in a dissertation results in some redundancy, but I include all sections for rigorous adherence to the reporting standard.

3.2.1 Purpose

The purpose of this model is to represent OB buprenorphine treatment capacity in the United States, and to assess policy options that impact treatment capacity. Specifically: Is OUD agonist treatment capacity sufficient to meet patient pharmacotherapy treatment demand, given: regulatory limits on patient numbers, barriers to provision of treatment, geographic dispersion of people with opioid use disorder, and geographic concentration of providers? Is treatment capacity equitably

distributed spatially? The simulation explores two policy areas to increase OB buprenorphine access:

- How does changing the patient limits affect treatment access, access equity, and medication diversion?
- How does extending buprenorphine prescribing authority to NPs and PAs affect treatment access, access equity, and diversion?

My research also explores the usefulness of the proposed aggregate spatial accessibility metric.

3.2.2 Entities, state variables, scales, and environment

There are four types of entities in the model: people with opioid dependence, OAT treatment providers, OTPs, and spatial units.

Agents with OUD, “agents” are characterized by the following state variables, or attributes:

Table 3-1: Attributes of agents with OUD

Attribute	Range	Units
Is the agent seeking OAT?	True/False	Boolean (yes, no)
Is the agent receiving methadone?	True/False	Boolean
Number of weeks receiving OB BUP	[0, length of simulation)	weeks
Has the agent relapsed? (defined as no longer seeking treatment, not engaged in	True/False	Boolean

treatment, or not completed treatment)		
Is the agent stably abstinent from non-medical opioids, (including reduced use)?	True/False	Boolean
Chance that agent will never achieve stable abstinence (or reduced use)	50%	--
Length of time in treatment required to attain stable abstinence (or reduced use)	[10, ~400)	weeks
Distance willing to travel for treatment	(0, ~150)	miles
Length of time will wait for treatment before relapsing	[1, ~10)	weeks
Length of time currently waiting for treatment	[0, ~10)	weeks
Is the agent currently on a waitlist?	True/False	Boolean
Is the agent too far from a provider?	True/False	Boolean
Provider the agent would like to establish with	provider agent	provider agent
Group of referred or nearby providers	unsorted list of provider agents	list
Sorted list of referred or nearby providers	list of provider agents sorted by distance from agent	list
Has the agent purchased buprenorphine from an illicit source?	True/False	Boolean
Source of illicit buprenorphine	"friend" or "street"	list
Has the agent sold/given away treatment buprenorphine	True/False	Boolean
Reason for diverting	"can't afford treatment", "wanted money", "friend asked"	list

Dose of buprenorphine needed	[8, 32]	mg per day
Weeks of buprenorphine medication in the agent's possession	[0, 4]	weeks
Insurance held by agent	"public", "private", "none"	--
Coinsurance—percentage paid for treatment	[0, 100%]	percentage
Poverty level of agent	[1,3]	Indicator of income relative to the poverty level. 1 is below 100% of poverty level, 2 is below 200% of poverty level, etc.
Income	(0, ~\$3000)	\$ per month
Monthly treatment out-of-pocket payment	[0, ~\$1300)	\$ per month
Monthly medication cost	[0, \$480)	\$ per month
Can the agent afford his/her treatment?	True/False	Boolean
Sex	Male/Female	--
At the end of the current year, did the agent receive any OAT treatment?	True/False	Boolean
At the end of the current year, did the agent receive OB BUP?	True/False	Boolean
At the end of the current year, did the agent never receive OB BUP?	True/False	Boolean
At the end of the current year, did the agent attempt to get OB BUP even once?	True/False	Boolean
weighted sum of provider to agent ratios	[0, upper patient limit * number providers]	dimensionless

For model simplicity, some of these states are mutually exclusive. For example: an agent cannot be receiving OB BUP and also seeking OAT treatment.

Provider agents, “providers” are characterized by the following attributes:

Table 3-2: Attributes of provider agents

Attribute	Range	Units
Number of years the provider has had a waiver	[0, 15]	years
Other waived providers that a provider might refer a patient to	list of provider agents	list
Population density of the provider’s practice location (depending on provider type)	(0, ~15,000)	people/mi ²
Provider type	“doctor,” “NP,” “PA,” “methadone only doctor”	--
Does the provider work at an OTP?	True/False	Boolean
Does the provider have an addiction medicine specialty?	True/False	Boolean
Does the provider have a high waiver (100 patients at baseline, in 2013)?	True/False	Boolean
Is the provider on the SAMHSA searchable list?	True/False	Boolean
Is the provider currently prescribing?	True/False	Boolean
If the provider has a low waiver, will he or she then get a high waiver?	True/False	Boolean
Number of patients the provider is willing to treat under ideal circumstances	[0, ~2500)	people
Number of patients the provider is able to treat with patient limits	[0, upper patient limit levels] determined by policy experiment	people
Number of patients a methadone prescriber can treat with methadone	[0, ~650)	people

Number of patients a methadone prescriber is currently treating with methadone	[0, ~650)	people
Total capacity for all OAT treatment types by OTP doctors	[0, ~650 + upper patient limit levels)	people
Does a methadone provider have a no-pay option?	True/False	Boolean
Does the provider offer telemedicine BUP treatment?	True/False	Boolean
Types of insurance the provider accepts	"Public," "Private," "None"	Combinations are allowed
Cost of a typical BUP office visit before insurance	(60, ~\$800)	\$/month
Physician to agent ratio in physician's catchment area	(0, upper patient limit level]	dimensionless

Opioid Treatment Programs, OTPs are characterized by the following attributes

Table 3-3: Attributes of OTPs

Attribute	Range	Units
OTP type	Private for profit, Private non-profit, Government, Veteran's Health Administration	--
Types of insurance the OTP accepts	"Public," "Private," "None"	based on OTP type, one OTP may accept some, one or all types
Does the OTP have a no-pay option?	True/False	Boolean
Does the OTP provide buprenorphine?	True/False	Boolean
Providers that work at the OTP	List of providers	list
Methadone spots at the OTP	(~5, ~1300)	people
Methadone recipients at the OTP	(~5, ~1300) depending on the number of spots at the OTP	people

Spatial Units: The spatial units are 1 square mile grid cells that are characterized by population density, the amount of "street" buprenorphine available for purchase in that square mile, and whether the 1 square mile cell is in a "medically underserved area (MUA)."

Scales: Time is measured in weeks; 52 weeks constitutes a year, and the model was run for one year. Each spatial unit represents one square mile, and the total modeled environment is 150 units by 150 units, representing 22,500 square miles.

Environment: The modeled environment contains a gradient of population densities, with more dense clusters representing cities and less dense areas

representing rural regions. The population density of the modeled environment was derived from actual population density maps of 150 x 150 mile regions of the United States.

Policy: Policy variables are as follows: the patient limit for providers waived for greater than one year (patients), and the percentage of NPs and PAs who obtain DATA 2000 waivers (percentage).

3.2.3 Process overview and scheduling

The process overview and scheduling section outlines which entities do what, and in what order things happen. In general, this describes what happens when we “run the model.”

In one time step, first, the environment does its process, then agents not in treatment or seeking treatment do their processes. Next the agents seeking treatment or in treatment do their processes, and finally, providers do their processes. These four sets of processes are outlined in pseudo-code below:

Environment process:

```
Environment patches (1 mile grid cells) with diverted
    buprenorphine diffuse a fraction of the street buprenorphine
    to neighboring patches
```

Out of treatment or not seeking treatment Agent processes:

A number of people develop opioid use disorder, and initialize
state variables as non-treatment-seeking agents

A fraction of people not in treatment die of overdose and are
removed from the model

Treatment seeking or in-treatment agent processes:

A fraction of patients in treatment die and free up a treatment
spot

Agents who have been waiting for treatment longer than their wait
threshold relapse, become non-treatment-seeking agents,
update state variables

Patients in methadone treatment either:

Quit treatment: relapse, become non-treatment-seeking
agents, update state variables

Continue treatment: update state variables

Patients in buprenorphine treatment either:

Quit treatment: relapse, become non-treatment-seeking
agents, possibly die due to post-treatment relapse,
update state variables

Complete treatment: free up treatment spot, update state
variables

Continue treatment:

Get medication:

If it has been 4 weeks since the last office
visit or this is the first office visit,
get 4 weeks of buprenorphine medication

Set monthly out-of-pocket treatment and
medication costs based on: insurance,
whether it is an initial or follow up
visit, and provider charges

Set affordability variable based on out-of-
pocket costs and income

Divert medication:

A fraction of patients who need money or can't
afford treatment divert a fraction of
their medication to the "street":

Subtract medication from myself, add medication
to the environment

Set diversion flag variable to true

Use medication: decrement the amount of medication by
1 weeks' worth

Update state variables

Patients on waitlists start treatment if possible:

If the closest provider IS NOT within the distance the
patient is willing to travel try to get diverted
buprenorphine:

Ask nearby people, "friends" in treatment for
medication directly. If obtained: update
diversion variables of self and friend, DO NOT
increment time waiting variable

If not obtained from friends, look for "street"
buprenorphine in the environment patches in the
neighborhood. If obtained: update diversion
variable of self, update amount of buprenorphine

in the local environment, DO NOT increment time
waiting variable

If couldn' t get diverted buprenorphine, increment
time waiting variable, update state variables

If the closest provider IS within the distance the patient
is willing to travel, check capacity of provider

If the provider does not have a spot, get a list of
other providers who may have spots

If either a buprenorphine or methadone provider on the
referral list has a spot, start treatment, take
treatment spot, update state variables

If no providers have spots, try to get diverted
buprenorphine (as above)

If can' t get diverted buprenorphine, increment weeks
waiting, update state variables

Patients NOT on waitlists start treatment if possible (same as
waitlisted patient code), except that if no providers have
capacity, become waitlisted

A number of non-treatment-seeking agents become treatment-seeking agents and start seeking treatment, update state variables

There are a few scheduling issues that merit mention: a patient could quit treatment and begin seeking treatment again in the same time step. This represents leaving treatment for a period of time shorter than a week. Patients cannot start seeking treatment and get treatment in the same time period with this schedule. And finally, patients seeking treatment will attempt to enter treatment before using diverted buprenorphine to avoid relapse.

Provider Processes:

Age all providers by one week:

If a provider's time providing buprenorphine is now > 1 year
and the provider wants to have a higher patient limit,
change to higher patient limit, update state variables

Add more providers and initialize new providers

It should be noted that providers update their patient limit levels and that new providers are added after the patient processes in a given week. So, a provider will get more patients due to a limit change in the time step after the limit level variable changes.

3.2.4 Design concepts

ABS models tend to incorporate the design concepts below to some degree. This model is a more top down, probabilistic ABS model than many ABS models and as such does not fully employ some of the design concepts. Learning and prediction (by agents within the model) are not employed.

3.2.4.1 Emergence

The model is a top down, probabilistic model, so much of the dynamics are “built in” rather than emergent. However, the heterogeneous geography, placement of waived providers, and patients’ willingness to travel do result in the emergence of groups of unserved individuals even in more urban locations with many providers. These emergent groups do not arise out of the actions and interaction of agents, but more due to a confluence of many random properties of geography, treatment seekers and physician siting.

3.2.4.2 Adaptation

Again, as a top-down, probabilistic model the proposed model treats adaptation only lightly. Patients seek to establish treatment with the closest provider, and if this fails, seek to establish with referred providers, failing that, they will use diverted buprenorphine or wait. This could be construed as adaptive behavior in treatment seeking. Use of diverted buprenorphine could be construed as an adaptive behavior in prolonging treatment seeking through self-medication. Patients in treatment may be in treatment long enough to reach stable abstinence or reduced opioid use. Once this

threshold is reached, a patient no longer uses a provider's OAT treatment spot. This could be construed as an adaptive behavior in recovery. Patients who cannot afford their treatment or who need money will divert some of their medicine to the street (presumably for money). This is an adaptive behavior in treatment retention.

3.2.4.3 Objectives

Treatment-seeking agents in the model want to get into treatment. Most people with opioid dependence do not want to enter treatment, their implied objective is to use opioids. As in actual treatment, attrition out of treatment is high, but retention in treatment and possibly reaching stable abstinence or reduced opioid use is also an objective of agents. While "success" per se is not modeled from the agent perspective, from the model observer perspective, an agent in treatment or stably abstinent is considered "successful."

Providers in the model want to provide treatment but only up to patient limit levels or to the level that they are comfortable.

3.2.4.4 Sensing

Treatment-seeking agents do not have complete information on all providers within the radius they are willing to travel, but they are assumed to know the closest provider. They are able to query whether a provider has an open treatment spot and act according to this information. Agents are also aware of their own internal states,

such as how long they have been waiting for treatment, or how long they have been in treatment.

Providers know how many patients they have, what the patient limits are, and how many patients they are willing to treat. They also know how long they have been waived. Providers know that patients have left treatment. If a provider is in a densely populated area, a provider has complete information on all providers within a given radius. If a provider is in a rural area, the provider may only know the closest provider. For this model purpose—determining capacity and access, it is not necessary for providers to know patient details.

3.2.4.5 Interaction

Interaction between agents is simple, and much of it is indirect. Treatment-seeking agents and providers interact when patients take up provider treatment spots. This results in indirect interaction among treatment-seeking agents. Indirect interaction occurs when a treatment spot is occupied and a potential patient is denied treatment, or when a treatment spot opens up and another patient can receive treatment.

3.2.4.6 Stochasticity

Stochasticity is the driving force behind this model. Providers and OTPs are placed on the map using a random process. A statistical distribution is fit to the actual population densities of the zip codes of waived physicians and OTPs. Modeled providers select the density of their own practice location by drawing from this

probability distribution and matching their practice location population density to a close population density on the map. The location of agents with OUD is also randomly selected based on the percentage of NSDUH respondents with dependence in different metro area types. The proportion of large MSA, small MSA, and non-MSA are fixed at initialization, but the actual location of agents with OUD on the map is random. This is because the actual locations of people with dependence is protected information, and not known to modelers. The distance a patient is willing to travel for treatment is determined by 10 empirical probability distributions based on population density of patient zip code obtained from the NAABT patient locator data file (www.naabt.org), with a greater proportion of rural residents willing to travel large distances to receive treatment. Treatment retention is treated probabilistically based on retention in treatment studies.

To model capacity and access, I have chosen to fit certain variables to empirically observed distributions to be both general and empirically grounded, specifically willingness to travel based on urban/rural designation. I have also chosen to simulate decisions as probabilities based on aggregate survey and study data because it is simple and more nuanced decision making logic is likely not necessary to address the research aims.

3.2.4.7 Collectives

While different agent types are aggregated into collectives for observation (see below), agents act as individuals and do not interact with groups of agents. For

example: there are no professional societies of providers that share a common desired cap level.

3.2.4.8 Observation

Observation refers to what data are collected from the model. The following metrics are recorded at the end of a model year:

- Total population in the modeled environment
- Number of people who received BUP treatment in the past year per 100,000 population
- Number of people who received ANY OAT treatment in the past year per 100,000 population
- Milligrams of diverted buprenorphine in the region
- The number of opioid overdose deaths in the past year per 100,000 population
- Spatial Potential Access Gini Indices (see Section 3.5 for derivation of these measures)

3.3 Data

3.3.1 Initialization

Initialization varies from one simulation run to the next as described above in Section 3.3.1. Initialization consists of 4 steps: geography, OTPs, providers, and agents with OUD are each initialized in turn.

Geography is initialized by importing population density maps into the simulation environment and by assigning densities to 1 square mile “patches” accordingly. Similarly, a map of medically underserved areas (MUAs) is imported and overlaid on the population map to determine for which patches the “medically underserved area” variable is “true.” MUAs maps are generated by the HRSA to identify regions which have a shortage of primary care health services and are publicly available for GIS analysis (Health Resources and Services Administration, 2018). Figure 3-2 shows the initial population density and MUA maps. The model is initialized with nine other sets of maps to explore the effect of geographic variation on outcomes and measures. This is described in Section 3.4.4.3.

Figure 3-2: Population density (left) and Medically Underserved Area (right) maps. Blue-grey regions represent MUAs.

OTPs are initialized with the following random and calculated parameters:

Table 3-4: OTP initial parameter values and empirical support

Parameter	Value	Support	Comment
Number of OTPs	1368 * total model population / US population	SAMHSA Opioid Treatment Program Directory (Division of Pharmacologic Therapies, 2015)	The number of OTPs is scaled to the size of the model geography
Location of OTPs	Random: Lognormal distribution (mean 9050 sd 32900) for density of OTP location	SAMHSA Opioid Treatment Program Directory	The lognormal distribution is the best fit to the actual densities of OTP locations on the OTP directory. Model OTPs select a population density from the distribution and then are sited on a patch with a similar population density.
VA			
accepts cash	64%	2011 OTP Survey (SAMHSA 2013a)	
accepts private insurance	91%	2011 OTP Survey	
accepts public insurance	35%	2011 OTP Survey	
have a no-pay option	94%	2011 OTP Survey	
offer buprenorphine	94%	2011 OTP Survey	
methadone spots	Mean 103 sd 89	2011 OTP Survey	
number of physicians	Random: 1 or 2	2011 OTP Survey	
Government OTP			
accepts cash	92%	2011 OTP Survey	
accepts private insurance	49%	2011 OTP Survey	

accepts public insurance	71%	2011 OTP Survey
have a no-pay option	70%	2011 OTP Survey
offer buprenorphine	35%	2011 OTP Survey
methadone spots	Mean 362 sd 469	2011 OTP Survey
number of physicians	2	2011 OTP Survey
<hr/> Private Non-profit <hr/>		
accepts cash	96%	2011 OTP Survey
accepts private insurance	58%	2011 OTP Survey
accepts public insurance	92%	2011 OTP Survey
have a no-pay option	44%	2011 OTP Survey
offer buprenorphine	44%	2011 OTP Survey
methadone spots	Mean 235 sd 213	2011 OTP Survey
number of physicians	Random: 1 or 2	2011 OTP Survey
<hr/> Private For-Profit <hr/>		
accepts cash	100%	2011 OTP Survey
accepts private insurance	33%	2011 OTP Survey
accepts public insurance	46%	2011 OTP Survey
have a no-pay option	8%	2011 OTP Survey
offer buprenorphine	48%	2011 OTP Survey
methadone spots	Mean 255 sd 204	2011 OTP Survey
number of physicians	Random: 1 or 2	2011 OTP Survey

Providers are initialized with the following random and calculated parameters:

Table 3-5: Provider initial parameter values and empirical support

Parameter	Value	Support	Comment
Number of years the physician provider has had a waiver	Random: Uniform distribution [0, 15]	SAMHSA list of all waived physicians, obtained 2014 ³	Uniform distribution best fits data
Population density of physician practice location (for geographic placement)	Random: Lognormal mean 9460 sd 46300 for physicians with high waiver; lognormal mean 5570 sd 19600 for physicians with low waiver	SAMHSA list of all waived physicians, obtained 2014	Lognormal is best fit to actual population density of waived physicians' zip codes.
Location and population density of NP or PA practice	30% in Medically Underserved Areas (MUAs), 25% of those in "isolated small rural" areas with density < 20. Otherwise with a BUP physician.	Cross sectional analysis of administrative and survey of primary care providers (Grumbach, Hart, Mertz, Coffman, & Palazzo, 2003), 13 state survey of a random sample of rural physicians, NPs and PAs (Doescher, Andrilla, Skillman, Morgan, & Kaplan, 2014)	Between 26% and 42% NPs and PAs in Washington and California practice in HPSAs. HPSAs may be rural or urban in the model and in the US. Co-locating NPs and PAs not in HPSA/MUAs with other BUP providers was suggested by the PA expert.
Theoretical patient capacity	Random: 30 + random exponential mean 220 for providers who are	Calibrated to: Healthcare Analytics Retail Data ⁴ and (Stein BD et al., 2016).	See Section 3.4.5: Recalibration. Calibrated to fit total number of unique

³ A full de-identified list of providers with a DATA 2000 waivers was provided directly by SAMHSA in 2014.

⁴ Data obtained from a representative of Reckitt Benckiser in personal communication.

	<p>prescribing, non-specialists, have or will get a high waiver; Normal(20, 7) for providers who are prescribing, non-specialists, don't have or want a high waiver, 30 + random exponential mean 250 for providers who are addiction specialists.</p>	<p>Supported by expert opinion.</p>	<p>buprenorphine recipients per year, and so that physicians' actual patient census numbers approximate mean, median, IQR of Stein, et al (2016). With some specialists willing to treat very large numbers, and other willing to treat fewer than 100. Experts supported that specialists with good infrastructure could treat a very large number of patients, and that primary care providers are unlikely to treat very many. Providers willing to treat more than the high patient limit, are forced to treat a maximum of 100 or 275, depending on model year</p>
Patient capacity with current patient limits	<p>Range[0, high patient limit], theoretical capacity truncated at patient limit</p>		
Percentage of physicians that do not prescribe	<p>7%</p>	<p>Upper limit established from a national survey of buprenorphine providers 2004 - 2008 (Arfken et al., 2010), calibrated to fit (Stein BD et al., 2016)</p>	

Number of physicians	Calculated: 22631 / model population in 2013; 22218 in 2014; 25504 in 2015; 29961 in 2016	SAMHSA list of all waived physicians	Converted to doctors/person and multiplied by the model population
Number of NPs	71% * 220,000 * model population/US population	2013 NP survey: 71% of 220000 NPs are in adult primary care or psychiatric fields (American Association of Nurse Practitioners, 2013).	192000 NPs in 2013, with approximately 14,000 graduates per year gives 220,000.
Number of PAs	26.5% * 101318 * model population/US population	2013 PA survey: 26.5% of 101318 PAs are in adult primary care or psychiatric fields (American Academy of Physician Assistants, 2014).	
Insurance types accepted by all providers	90% cash 77% private 60% public 21% cash only	Small survey of physicians (Wisniewski, Dlugosz, & Blondell, 2013)	Model parameters are set so that the resulting distribution of insurance accepted fits the empirical data. NP and PAs are assumed to take the same insurance as physicians.
Cost of physician office visit	Random normal (mean \$150 sd \$150), redrawn for visit costs less than \$60.	Expert opinion of buprenorphine treatment patient advocate, and patient advocate website (Timothy P. Lepak, 2014)	Initial visit is double the maintenance office visit. Costs vary considerably from provider to provider and region to region. The random function

allows for a large
range of visit costs.

Cost of NP or PA office visit	70% * cost of physician office visit	Assumed. Primary care NPs are often reimbursed at a lower rate than primary care physicians by managed care payers (Hansen- Turton, Ware, Bond, Doria, & Cunningham, 2013).
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Agents with OUD are initialized with the following random and calculated parameters:

Table 3-6: Agent initial parameters and empirical support

Parameter	Value	Support	Comment
Number of people with opioid use disorder	3556000 * model population / US population in 2013; 3400000 in 2014; 3418000 in 2015; 3538000 in 2016	2013, 2014, 2015, and 2016 NSDUH (SAMHSA 2014b) and ONDCP “What Americans Spend on Drugs” (ONDCP 2012)	Opioid use disorder is defined as opioid abuse or dependence per the NSDUH definitions. The number of people who primarily use opioid analgesics is estimated from the NSDUH, while heroin use is estimated from the ONDCP document since many heroin users are hidden from the NSDUH survey.
Percentage of patients that are female	30%	2013 NSDUH	Assumed to be the same proportion as people with OUD.
Distance willing to travel for treatment	drawn from empirical distributions of patient willingness to travel based on zip code (presented in Appendix B)	National Alliance of Advocates for Buprenorphine Treatment (NAABT) treatment locator data	Dataset is not publicly available.
Number of patients at baseline (seeking treatment or in treatment)	35% of total OUD population	2013 NSDUH, Calibrated to: Healthcare	Using the highest estimate of receiving treatment in the NSDUH, “received

Percentage of patients in treatment at baseline	60% in 2013 70% in 2014 80% in 2015	Analytics Retail Data ⁵ Calibrated to: Healthcare Analytics Retail Data ⁵	treatment in past year.” Calibrated to reproduce estimated number of unique recipients of BUP.
Number of weeks in treatment for those initialized in treatment	Random: exponential mean 10	Assumed	
Stable abstinence threshold (time to achieve abstinence or reduced opioid use after opioid agonist therapy)	Random: normal distribution (200, 200), redrawn for weeks < 10.	Assumed	
Geographic distribution of patients	Random: 49.9% areas with population density > 1000, 35.5% in areas with population density between 35 and 1000, 14.5% areas with population density less than 35 with 48% of rural residents in areas with population density > 35	SAMHSA, 2012 NSDUH, (Kvamme, Catlin, Banta-Green, Roll, & Rosenblatt, 2013b)	To protect privacy, NSDUH only reports if a respondent lives in a large MSA, small MSA, or non-MSA. We assume that this roughly maps onto population density. Kvamme reported that in Washington, 52% of rural residents live in small towns while 48% live in remote areas.
Willing to wait threshold	random-exponential mean 4 weeks	Harm reduction expert opinion	A random-exponential distribution with a mean of 4 results in a median willingness to wait of about 2.5 weeks.

⁵ Data obtained from a representative of Reckitt Benckiser in personal communication.

			Agents with waiting times less than 1 week will seek treatment in the given week, but will relapse if they cannot immediately access treatment.
Number of weeks waiting	0	All initialized to 0 weeks waiting for simplicity	
Percentage of patients who divert because they need or want money	14 % of people below 200% of the poverty line per year	Calibrated to fit buprenorphine patient survey (Genie L. Bailey, Monique Ziebro, Timothy P. Lepak, Richard G. Soper, & Michael M. Miller, 2015).	Setting the parameter to 14% results in approximately 29% of patients listing “needed money” as a reason for diversion
Percentage of patients who can’t afford treatment who divert medication	54% of people who can’t afford treatment per year	Calibrated to fit buprenorphine patient survey (Genie L. Bailey et al., 2015).	Setting the parameter to 54% results in approximately 47% of patients listing “I needed it to afford my treatment” as a reason for diversion
Percentage of patients who say yes when a friend requests diverted buprenorphine	35% per year	Calibrated to fit buprenorphine patient survey (Genie L. Bailey et al., 2015).	Setting the parameter to 35% resulted in approximately 38% of patients listing “I was pressured to divert by a friend or because someone else needed it more than I did” as

			a reason for diversion
Amount of medication diverted to the "street"	1, 2, or 3 days' worth out of a week selected at random	Assumed	
Poverty level of people with OUD	30% are below the poverty level, 26% are below 200% of the poverty level, 44% are above 200% of the poverty level	2011-2013 NSDUH analysis of full data set	
Insurance of people in poverty	47% have public insurance, 20% have private insurance, 33% have no insurance	2011-2013 NSDUH analysis of full data set	Insurance types for people with opioid abuse or dependence calculated based on poverty level.
Insurance of people to 200% of poverty level	30% have public insurance, 34% have private insurance, 36% have no insurance	2011-2013 NSDUH analysis of full data set	
Insurance of people above 200% of poverty level	11% have public insurance, 72% have private insurance, 17% have no insurance	2011-2013 NSDUH analysis of full data set	
Coinsurance	0 for public insurance, 50 – 70% for private insurance, 100% for no insurance	Assumed	Medication coinsurance and office visit coinsurance were assumed equal for simplicity
Buprenorphine dose	18% 8 mg, 63% 16 mg, 15% 24 mg, 4% 32 mg	2011 OTP survey	The SAMHSA OTP survey gives ranges of doses. For simplicity, doses were rounded up

to the highest dose
in the range

Figure 3-3: Graphical display of the simulation after model initialization. Maroon squares represent OTPs; large red triangles are OB BUP providers; small triangles represent people seeking OAT.

3.3.2 Input data

Input data are those empirical data that are used when the model is running to update the state of the model. The geography, population density and OTP values are static. Provider and agent variables are updated with the following input data:

Table 3-7: Input data for updating provider and patient variables

Parameter	value	support	comment
Number of new providers obtaining waivers	2500* (total model population / total US population) per year	SAMHSA list of number of waived physicians by state 2007-2015	Data show near linear growth in providers since 2007
Buprenorphine treatment retention	76% week 1, 64% week 2, 50% in week 6, mean days in treatment 214	Randomized controlled trial of buprenorphine retention (Bell, Trinh, Butler, Randall, & Rubin, 2009)	The model was configured to simulate a closed cohort to reproduce the retention in treatment from this closed cohort study as a verification test
Methadone treatment retention	74% retained at 6 months, 50% at a year	Multisite randomized controlled trial (Hser et al., 2014)	
Crude mortality rate: in treatment	3/1000 patient years	Randomized controlled trial, cohort study, of buprenorphine retention and mortality (Bell et al., 2009)	
Crude mortality rate: stable abstinence	3/1000 patient years	Assumed	assumed equal to in-treatment mortality

Crude mortality rate: people taking diverted BUP	3/1000 patient years	Assumed	Assumed equal to in-treatment mortality
Crude mortality rate: not in treatment	8/1000 patient years in 2013, 10.5/1000 patient years in 2014, 12/1000 patient years in 2015	Calibrated to fit national opioid related deaths data: CDC Wonder Multiple Cause of Death Database for opioid and heroin deaths (NIDA, 2017)	See Section 3.4.5: Recalibration
Crude mortality rate: relapsing out of treatment	8/1000 patient years	Randomized controlled trial, cohort study, of buprenorphine retention and mortality (Bell et al., 2009)	
Rate of growth of people with opioid use disorder	10%	2002-2012 NSDUH Surveys	Fit to rate of increase of prevalence of opioid use disorder
Incidence of treatment seeking	40% of people with OUD including multiple attempts by one person	2013 NSDUH	Calibrated to fit the unique recipients of BUP per year.

3.3.3 Outcome variables

Policies were assessed by their impact on the following outcome variables at year end: Population adjusted unique recipients of buprenorphine, opioid overdose deaths, and milligrams of diverted buprenorphine. Population adjusted unique recipients of buprenorphine was normalized to the model population: total buprenorphine recipients/model population * 100,000. This outcome variable will be

referred to as Unique BUP recipients, for short. Access equity was assessed using the Spatial Potential Access Gini Indices.

3.4 Model Testing

3.4.1 Calibration

To establish the baseline model scenario, I initialized the model the model with 2013 data and calibrated to fit two outcome variables: unique buprenorphine recipients and opioid overdose deaths; a pattern of buprenorphine diversion assessed by patient survey; and a pattern of buprenorphine prescribing based on pharmacy survey. Values and data sources for these calibration targets are detailed in Table 3-8.

Prior to final model calibration, I conducted sensitivity analysis to highlight tunable parameters. I didn't calibrate or validate against the medication diversion outcome directly because the quantity of diverted buprenorphine in the US is not known. While there are several surveillance systems that can estimate trends in diversion including NFLIS (US Drug Enforcement Administration, Office of Diversion Control, 2013), or the RADARS system (see, for example: Dart et al., 2015), these rely on proxy measures such as calls to poison centers or seizures by law enforcement, and don't generate estimates of total quantity diverted.

I chose to calibrate the model against the provider patient census pattern reported by Stein, et al (2016) because provider preferences for patient loads are not

Table 3-8: Calibration targets and data sources

Parameter	National value	Support
2013 unique buprenorphine recipients	1,300,824	Healthcare Analytics Retail Data ⁶
2013 opioid overdose deaths	24,492	CDC Wonder Multiple Cause of Death Database for opioid and heroin deaths (NIDA, 2017)
Diversion by patients to non-patients	9% of patients (47% to afford treatment) (29% needed money) (38% friend wanted or needed)	Buprenorphine patient survey (Genie L. Bailey et al., 2015)
Use of non-prescribed BUP	27% have used non-prescribed BUP	Buprenorphine patient survey
Provider patient census	Median 13, IQR 5-36; 22% had 1-3 patients 49% had 4-30 patients 20% had 31-75 patients 9% had more than 75	Analysis of Symphony Health Solutions' Integrated Dataverse retail pharmacy transactions (Stein BD et al., 2016)

known empirically, and these preferences play an important role in model dynamics. It was difficult for the model to generate a large enough number of unique buprenorphine recipients while tuning provider preferences for patient loads to fit the provider census pattern. Even when attempting to fit the prescribing pattern loosely, allowing a greater percentage of providers to have higher patient census levels than recorded in Stein's group's analysis, the number of unique buprenorphine recipients was 7-10% low. It is worth noting that Stein reported that regression analysis showed an increase in prescribing levels in later years, though they did not report specifics on the census in

⁶ Data obtained from a representative of Reckitt Benckiser in personal communication.

later years. As discussed in Section 3.4.5, I found it necessary to calibrate the model further after validation tests.

3.4.2 Face Validation

I reached out to all expert panel members via email for face validation interviews, received four responses, and conducted interviews with two panel members: Dr. Alane O'Connor, and Dr. Andrew Saxon. Interviews were two hours long, and covered boundary, basis, and representation assessment (see Section 2.4.1), as well as critical model assumptions, policies, and future conditions that should be considered in policy analysis.

At the outset of the interview, I introduced Drs. O'Connor and Saxon to the research questions, to the basic structure of the spatial ABS capacity model, and explained that the purpose of the interview was to check assumptions about model scope (boundary assessment), assumptions that informed the use of data (basis assessment), and model logic that drives key dynamics (representation assessment), and to share early findings prior to final external validation.

In general, the experts were comfortable with the boundary of the model, agreeing that a model that is narrowly investigating questions of capacity might not need rich details on patient experience, for example. They were both interested in the spatial dimension of the model since they both had experience working with rural communities. As to basis assessment, they seemed comfortable with populating a real

map with people with OUD and providers placed plausibly according to population density and the NSDUH survey. However, this may have stemmed more from a lack of familiarity with ABS methods and a reluctance to “red flag” something unfamiliar. They agreed that there was a large variance in the patient loads of providers, which was reported by Stein, et al (2016) and suggested several reasons that some providers choose to serve different numbers of patients. Dr. O’Connor’s practice experience did not conform to the data used for patient retention, which was several years old. In her experience, by the time patients are admitted to her program, they are heavily invested in treatment and are better retained, and suggested that retention in the model may be overly conservative.

Regarding key model logic, both agreed that diversion was likely primarily not for recreational purposes but for self-treatment, or to maintain active opioid use when preferred drugs might not be available. This supports model assumptions about reasons for diversion, which has implications for diversion outcomes of policies that expand access. They also agreed that many people self-treat with buprenorphine while waiting to start formal treatment, sometimes for years. On the other hand, both also questioned the validity of the assumption that people with OUD select providers on the SAMSHA searchable list. Dr. O’Connor asserted that word of mouth was a much more likely source of information on potential providers, especially in rural areas.

Interviews concluded with open questions about the impact of policies implemented since modeling began in 2014, including the patient limit expansion policy

and NP/PA prescribing policy, and what unforeseen circumstances may have had outsized impact on their practices and patients. Dr. O'Connor had already obtained her DATA 2000 waiver by the time the interview took place. The model was originally intended to test very modest penetration of NP and PA prescribing, at the 3-5% level, mirroring the uptake among primary care physicians. Dr. O'Connor expects much higher uptake by NPs, and suggested testing the impact of uptake among 50-70% of primary care NPs in states with high NP autonomy. She also expects that initially patients will be shifted from overloaded specialty providers to less distant NPs resulting in a reallocation of treatment without apparent expansion until those specialist spots are backfilled and word of mouth brings new patients to NP prescribers.

Both providers were not surprised that early model experiments with the patient limit policy didn't produce large gains in the number of people who receive buprenorphine in a given year, though Dr. Saxon was dismayed by it. In Dr. O'Connor's experience, while some providers, such as those who run intensive outpatient recovery programs, may have expanded their practices dramatically after increasing their patient limit, many may have elected to expand to 275 patients as a safety valve just in case they approach the 100 patient limit. Dr. Saxon also explained that even addiction medicine specialists may be reluctant to build their practices around buprenorphine prescribing, preferring a more diverse patient mix in part because practice barriers such as high paperwork burden and low reimbursement remain.

I closed by asking what surprised them in 2014-2017 and what to look out for when modeling future policy. The emergence of synthetic fentanyl as a street drug was completely unanticipated and resulted in increased opioid deaths. State policies squeezing down on prescription opioid diversion and the resultant uptick in heroin use wasn't totally unanticipated, but it did drive up overdoses and would not have been captured in a policy model that doesn't differentiate between opioids, including this one. I was made aware of a major change in insurance that could have a large impact on access to treatment. A person with an extremely high deductible insurance plan may be insured on paper, but that insurance wouldn't pay for treatment, leaving that person effectively uninsured and paying out of pocket, making treatment unaffordable.

3.4.3 External Validation

I performed external validation by initializing the model in week 1 of 2013, 2014, 2015, and 2016, and running the model for 52 weeks thirty times for each model year. I also initialized the model in 2013 and 2014 and ran for 104 weeks (two years) thirty times for each model year. I scaled up the model-generated number of unique buprenorphine recipients and opioid overdose deaths to the total national population, by dividing by model population and multiplying by the national population for that year. I generated 95% confidence intervals around the simulation means and compared these model ranges to the real world target values. The number of opioid overdose deaths in 2016 was not available at the time of writing. Results are shown in Table 3-9.

Table 3-9: External validation results, simulation compared with data for 2013, 2014, and 2015.

One year runs Model year	Simulation		Data	
	Unique BUP recipients: mean [95% CI]	Opioid overdose deaths: mean [95% CI]	Unique BUP recipients (% deviation from mean)	Opioid OD deaths (% deviation from mean)
2013	1178147 [1155141, 1201152]	23819 [23050, 24589]	1300824 (9.43%)	24492 (2.74%)
2014	1065499 [1045661, 1085337]	20574 [20006, 21143]	1294715 (17.7%)	28647 (28.18%)
2015	1166551 [1147081, 1186021]	20931 [20452, 21411]	1387815 (15.9%)	33091 (36.75%)
2016	1242834 [1220505, 1265164]	21375 [20802, 21948]	1380616 (9.9%)	Not reported
Two year runs Model year				
2013-2014	1132527 [1103229, 1161825]	25257 [24562, 26153]	1294715 (12.5%)	28547 (11.5%)
2014-2015	1087457 [1062895, 1112020]	21736 [21080, 22392]	1387815 (21.6%)	33091 (34.3%)

The 7-10% under-calculation of total unique buprenorphine recipients at the end of calibration resulted in a systematic low estimate of total unique buprenorphine recipients in each modeled year. This was compounded by a change in the estimation method for the starting number of people with OUD in each modeled year. The model was calibrated to an initial population with OUD of 3,895,621 in 2013, rather than an estimate of 3,556,000 using the estimation method for 2014 forward. The fit to 2014

year end data when starting the model in 2013 and running for two years was likely better than when the model was initialized in 2014 and run for one year because of the higher starting population with OUD in 2013.

Opioid overdose deaths in 2013 were calibrated to fall within the 95% confidence interval of simulated overdose deaths. However, the fit 2014 onward was poor. This is unsurprising given that the opioid overdose death rate was held fixed in the model. The introduction of synthetic fentanyl and the shift in use of diverted prescription opioids to counterfeit prescription pills and heroin reported by Dr. O'Connor likely increased the risk of opioid overdose despite an apparent level trend in people with prescription OUD recorded in the NSDUH at that time.

3.4.4 Sensitivity Analysis

Sensitivity analysis consisted of three processes: one-way sensitivity analysis, structural sensitivity analysis to the provider patient load preference assumption, and structural sensitivity analysis to the map selected for simulation.

3.4.4.1 One-way sensitivity analysis

Holding all other parameter values fixed, I systematically increased and decreased each parameter value by 30% and recorded the impact on model outcome variables: unique BUP recipients, opioid overdose deaths, and diverted buprenorphine. I report the percentage difference of the means of 30 replications of these outcome variables from baseline level means and present results as tornado diagrams on each

outcome variable to highlight the sensitivity of model outcomes to changes in particular parameters (Eschenbach, 1992). If confidence intervals on the mean for outcome levels of tested parameters overlapped with the baseline mean, the difference in the mean is not detectable due to random variation in the model. These parameters are in not included in the diagrams.

The number of buprenorphine recipients was sensitive to three treatment seeking parameters, and three provider specific parameters, as shown in Table 3-10. The number of buprenorphine recipients was sensitive to the incidence of treatment seeking—the percentage of people with OUD who would seek treatment in the model year starting the year uninterested in treatment, and the initial percentage of people with OUD who start the year in treatment or seeking treatment, but only when these parameters were reduced. Increasing these parameter values did not significantly increase the number of buprenorphine recipients at year end. The relative percentage of people with OUD who start the model year in or seeking treatment who

Table 3-10: Tornado diagram of sensitivity analysis on the number of unique buprenorphine recipients. In general, an increase (or decrease) in the parameter value resulted in an increase (or decrease) in the number of buprenorphine recipients, with the exception of the number of OTPs (), for which a 30% increase in the number of OTPs resulted in a 5% decrease in unique recipients of BUP*

	Unique BUP recipients: percentage difference from baseline											
+/-30% change in paramter value	25-30%	20-25%	15-20%	10-15%	5-10%	0-5%	0-5%	5-10%	10-15%	15-20%	20-25%	25-30%
incidence of treatment seeking					-10%							
initial % people with OUD in/seeking tx					-8%							
% providers = specialist high-cap					-6%							
initial % seeking vs in tx					-5%		4%					
number of OTPs *						-5%						
% providers accept private insurance						-4%						

are assigned into treatment increases buprenorphine recipients when increased, and decreases it when decreased.

Decreasing the percentage of providers who are addiction medicine specialists with high waivers and replacing those providers with an equal number of non-specialists who have low waivers resulted in a 6% decrease in buprenorphine recipients. Even though the percentage of specialist providers was only reduced from 12% to 9% of all providers, providers of this type were initialized with preferences for the highest number of patients (often over 100) and were replaced by providers with the lowest preference levels (around 10).

Increasing the number of OTPs in the model decreased the number of buprenorphine recipients significantly, but did not affect the number of people who received any OAT. Conversely, decreasing the number of OTPs by 30% did result in a 7% decrease in OAT treatment overall, while having no detectable effect on the number of people receiving buprenorphine. This suggests that increasing OTPs results in a treatment substitution effect in the model.

The amount of diversion in the model was sensitive to three types of parameters (see Table 3-11): diversion-specific parameters, poverty and affordability parameters, treatment seeking parameters, and two parameters that didn't fall into those categories: number OTPs, and % patients with 16 mg BUP daily dose.

Table 3-11: Tornado diagram of sensitivity analysis on the amount of buprenorphine diverted to non-patients. An increase (or decrease) in the parameter value resulted in an increase (or decrease) in the amount of diversion, with the exception of parameters marked with an (*).

	Diverted buprenorphine: percentage difference from baseline											
	25-30%	20-25%	15-20%	10-15%	5-10%	0-5%	0-5%	5-10%	10-15%	15-20%	20-25%	25-30%
+/-30% change in paramter value												
% patients who divert b/c "can't afford tx"				-16%					12%			
incidence of treatment seeking				-14%					15%			
% patient income for tx = "unaffordable"*				-11%					13%			
weeks can wait for tx before relapse				-12%					12%			
% patients who will divert when asked				-12%				9%				
% patients with 16 mg BUP daily dose*					-10%			10%				
% people with OUD w/ income < poverty level (\$)*					-9%			10%				
% patients who dirvert b/c "want money"					-6%			10%				
initial % people with OUD in/seeking tx								10%				
% people with OUD w/ income 2x poverty					-8%			7%				
number OTPs*					-6%			7%				
base BUP cost per month per mg								5%				
mean cost of treatment visit					-5%							

Not surprisingly, increasing the percentage of patients who divert medication for various reasons resulted in large increases in diversion. This is due to model logic that does not require that an increase in one reason for diversion be offset by a decrease in another reason. A person may divert medication both because she can't afford treatment and because she wants money. Increasing the weeks a person is willing to wait to begin treatment before relapsing increases diversion because of the way the demand for diverted buprenorphine is coded. People who are waiting for treatment will ask friends in treatment to divert, and will stop asking for diverted medication when they stop self-treatment and treatment seeking and resume regular opioid use. So in the model, relatively quick abandonment of treatment seeking results in less diversion demand.

Incidence of treatment seeking increases demand for diverted buprenorphine as people self-treat with diverted buprenorphine while waiting for formal treatment spots to open. Decreasing incidence of treatment seeking also likely reduces the supply of diverted buprenorphine since it also decreases the unique number of buprenorphine recipients.

Changes to poverty parameters affect diversion because most of the reasons for diversion are due to poverty. People with incomes below two times the poverty level might divert because they can't afford treatment or need money. In the model, people whose incomes are above those levels will not divert due to affordability or money issues. The cost of treatment and medication did affect diversion because they impact affordability logic. A patient who pays less for treatment is less likely to find treatment unaffordable, and hedge the cost of treatment by selling medication.

Changes in the number of OTPs affects diversion from the supply side, by changing the relative proportion of people receiving methadone versus BUP for OAT.

Finally, the amount of diverted buprenorphine decreases when the percentage of people who require 16 mg per day of buprenorphine increases because of how required dosages are set. Increasing the number of people who require 16 mg doses squeezes down on the number of people getting 32 mg per day, followed by 24 mg per day, while decreasing the number of people who need 16 mg per day increases the number of people who need 8 mg per day. When diverting medication in the model,

people give up a fraction of what they receive. So if most people get less medication, less is diverted per diversion occasion.

The number of opioid overdose deaths was only affected by changes in the crude mortality rate for people not in treatment, and the change was approximately 1:1. A 30% increase in the mortality rate resulted in 27% more overdose deaths overall, and a 30% decrease resulted in a 28% decrease. That no other parameter impacted opioid overdoses is likely due to the fact in the model, the vast majority of people with OUD are not in treatment.

3.4.4.2 Structural sensitivity analysis: provider preferences

The baseline model was run with provider preferences tuned to roughly match the provider census reported in Stein, et al (2016) and the number of unique buprenorphine recipients (Stein BD et al., 2016). I assumed that providers have a maximum patient number above which they would not accept new patients, no matter the patient limit. For some providers this maximum lay above the patient limit level, for other, it lay below the limit. In baseline runs, an individual provider's maximum was drawn from a random distribution based on provider type. These baseline distributions are reported in Table 3-5 as "Theoretical Patient Capacity."

I conducted one-way sensitivity analysis by provider type with three different sets of parameters for determining the patient maximum for each provider: a low uniform random distribution, a high uniform random distribution, and a fixed constant

at the patient limit for the waiver type held (30 or 100, in 2013). I conducted a five-way analysis by setting patient preferences to the maximum waiver level (30 or 100) for all provider types. Sensitivity analysis parameter values are shown in Table 3-12.

Table 3-12: Distributions for provider preference sensitivity analysis

	Baseline distribution	Alternative random distribution (low)	Alternative random distribution (high)	Fixed constant
Specialist, low waiver	30 + exponential (250)	Uniform[0, 150]	Uniform[0, 1000]	100
Specialist, high waiver	30 + exponential (250)	Uniform[0, 150]	Uniform[0, 1000]	100
Non-specialist, high waiver, on SAMSHA list	30 + exponential (120)	Uniform[0, 100]	Uniform[0, 1000]	100
Non-specialist, low waiver, on SAMHSA list, will get high waiver	20 + exponential (40)	Uniform[0, 100]	Uniform[0, 200]	100
Non-specialist, low waiver, on SAMHSA list, will NOT get high waiver	Normal (3.5, 7), redraw for values below 0	Uniform[0, 10]	Uniform[0, 30]	30
Non-specialist, low waiver, not on SAMHSA list	Normal (3.5, 7), redraw for values below 0	Uniform[0, 10]	Uniform[0, 30]	30

Changing provider preference did not result in significant differences from baseline in medication diversion or opioid overdose deaths. However, there were significant changes in the number of buprenorphine recipients, as shown in Table 3-13. Only parameter settings with detectable differences are shown, and differences are expressed as percentage difference in means.

Table 3-13: Impact of changing assumptions about provider preferences on total number of buprenorphine recipients after a year.

Parameter setting	Percentage difference between mean and baseline
All parameters to maximum level for waiver type	+21%
Fixed Constant (100) Non-specialist, high waiver, on list	+11%
Fixed Constant (30) Non-specialist, low waiver, not on list	+10.9%
Random, Low (uniform[0, 100]) Non-specialist, high wavier, on list	-10%
Random, High (uniform[0, 1000]) Non-specialist, high waiver, on list	+9.8%
Random, Low (uniform[0, 150]) Specialist, high wavier	-5.1%
Random, High (uniform[0, 30]) Non-specialist, low waiver, not on list	+4.3%

In the model, if all providers are willing to treat up to the regulatory limit depending on demand, the number of people who receive buprenorphine at year end increases by around 21%. The greatest impact comes from changes in preferences of non-specialists, each of which increase utilization by around 10% alone. This is likely because these two groups represent 20% and 48% of buprenorphine providers respectively, and because the maximum number of patients treated by non-specialists with low waivers was held very low at baseline.

3.4.4.3 Structural sensitivity analysis: model map

To test the model's sensitivity to the selected geography, I generated 9 additional population density maps based on the 2010 United States Census merged with HRSA Medically Underserved Area maps using the QGIS GIS mapping software (QGIS, 2017). The population density maps are shown in Figure 3-4 and the underlying MUA maps are shown in Figure 3-5. I selected the maps from a wide array of regions in the US including the North East, South East, Midwest, Mountain West and California, and include highly urbanized regions (such as Figure 3-4, bottom middle), and rural regions (such as Figure 3-4, bottom left). Models were run 30 times each for one year, initialized at the start of 2013, and buprenorphine recipients, opioid overdose deaths and diversion outcome variables were compared against baseline model runs. I normalized diversion and opioid overdose death outcome variables to the population size to allow for direct comparison. The buprenorphine recipients outcome variables for each set of runs was also compared against 2013 unique buprenorphine recipient data.

There were no significant differences in opioid overdose deaths when using different starting maps. Regions 1, 3 and 6 had significantly fewer buprenorphine recipients than the baseline Region 0 (Figure 3-4 top left, top right and middle right, respectively), with mean values 12%, 6% and 7% lower than the mean number of recipients per 100,000 population. Regions 1, 3, 5, and 7 (Figure 3-4 top left, top right, middle middle, bottom left) had significantly lower diversion (mg per 100,000 population) than the baseline region, with mean values 14%, 10%, 7% and 15% lower.

Regions 4 and 8 (Figure 3-4 middle left, bottom middle) had significantly higher diversion (mg per 100,000 population) than the baseline region, with mean values 7% and 6% higher. In general, more densely populated regions had higher diversion than less densely populated regions despite normalization, and may signal a systematic bias in how demand for diverted buprenorphine is modeled in remote and urban areas.

The number of unique buprenorphine recipients at year end was low for all regions. Model confidence intervals did not cover the actual year-end value adjusted for model population in any region. Inadequate calibration to the year-end target in the baseline region reported in Section 3.4.3 resulted in the use of poorly calibrated parameter values in all regional model runs.

Figure 3-4: Alternative population density maps for geographic sensitivity testing. Population density is measured in people per square mile. Maps are numbered sequentially left to right, top to bottom.

Figure 3-5: Additional Medically Underserved Areas (MUA) maps for geographic sensitivity analysis. Darker regions are MUAs. Maps correspond to population density maps in Figure 3-4.

3.4.5 Recalibration

The original research plan called for calibration on 2013 data, external validation on 2014-2015 data, and sensitivity analysis followed immediately by policy experimentation. Rather than perform policy experiments on a model that failed tests of external validity, I chose to iterate and use all available data for model calibration and to perform policy experiments on a better calibrated, though non-validated model. Failure to validate large simulation models or poor results on tests of model fit tend to be a challenge when striving to simulate complex social systems.

To recalibrate the model, I made three choices—

1. to initialize the model in 2013 with the number of people with opioid dependence calculated the same way as the 2014 and 2015 populations,
2. to tune provider preference parameters to privilege fit to total unique buprenorphine recipients over fit to provider patient census in Stein, et al (2016),
3. to use a non-stationary opioid overdose death rate (the death rate changes over time).

I chose to recalculate the initial population with OUD in 2013 because calculating the population in a different way resulted in an apparent decrease in people with OUD from 2013 to 2014 due to a modeling artifact. I removed this spurious effect by calculating the population the same way for all model years. The modeling artifact was

introduced in the first place because of the considerable lag between early modeling efforts in iterations 1-3 of the model and validation efforts on model iteration 4.

I chose to recalibrate the model by tuning provider preference variables because these variables have considerable leverage over the unique buprenorphine recipients outcome measure as shown in structural sensitivity analysis (see Section 3.4.4.2).

Further, Stein's regression model on 2009-2011 patient census data showed that patient census levels were rising even in 2011 (Stein BD et al., 2016).

Lastly, to fit trends in opioid overdose deaths in 2013-2015, I chose to parameterize the model with a non-stationary opioid overdose mortality rate. It may have been possible for a non-stationary opioid overdose mortality rate to have arisen endogenously by introducing considerable model complexity. I could have chosen to model people's shift from prescription opioids to heroin, from oral to injection drug use, and other transitions from lower risk to higher risk behaviors, but I would likely still have had to introduce exogenous factors that drove up overdose mortality, such as changes to price and purity of heroin and the introduction of synthetic fentanyl (see Section 3.4.2, Face Validation). Rather than introduce this complexity, which I felt would have little relevance to capacity and access equity research questions, I chose the simpler option of a time-varying opioid overdose mortality rate.

The following parameters were tuned to fit the number of unique buprenorphine recipients in 2013, 2014 and 2015: theoretical patient capacity for non-

specialists with a high waiver and for non-specialists with a low waiver not on the SAMHSA searchable list, and percentage of patients in treatment at baseline each year. Table 3-14 shows all post-recalibration parameter values including crude mortality rates. The initialization data and input data parameterizations reported in Sections 3.3.1 and 3.3.2 record parameter settings after calibration and recalibration was complete.

Table 3-14: Parameter values changed during recalibration and the final values of these parameters.

Theoretical patient capacity	
Non-specialist, high waiver, on SAMSHA list	30 + random exponential(220) patients
Non-specialist, low waiver, not on SAMHSA list	random normal(20, 7) patients
Percentage of patients in treatment at baseline	
2013	60%
2014	70%
2015	80%
Opioid overdose crude mortality rate (not in treatment)	
2013	8/1000 patient years
2014	10.5/1000 patient years
2015	12/1000 patients years

3.5 Spatial Potential Access Aggregate Measure

To generate an aggregate access equity metric for OAT in the simulation model, I took advantage of the following simulation properties:

- the simulation generates plausibly sited synthetic individual demanders with opioid use disorder along with plausibly sited sources of OAT supply—providers with limited treatment capacity
- each demander has an empirically informed distance he or she is willing to travel to get OAT based on the population density of his or her location.

Using these model properties, I modified the two-step floating catchment area (2SFCA) method (see Equations 13 and 14) in the following manner. Substantive differences from Luo and Wang (2003) are italicized.

Step 1: For each *provider j*, search all *individuals (i)* that are within *i's willingness to travel distance (d_{i0})* from the location *j* (that is, the *individualized catchment area of j*), and compute the *weighted provider capacity-to-population, R_j* , within the catchment area:

$$R_j = \frac{S_j}{\sum_{i \in \{d_{ji} \leq d_{i0}\}} w_{ji} i} \quad (20)$$

where S_j is the capacity of provider *j* (the number of patients that *j* is willing to treat given patient limits and preference), d_{ji} is the Euclidean distance between *i* and *j*. The weight, w_{ji} , is calculated by various distance decay functions described in Section 3.5.1, below.

Step 2: For each *individual, i*, search all provider locations (*j*) that are within the threshold *willingness to travel distance (d_{i0})* of *i* (that is, the *reachable*

provider region of i), and sum up the *weighted provider-capacity-to-population ratios*, R_j , at these locations:

$$A_i^F = \sum_{j \in \{d_{ji} \leq d_{i0}\}} w_{ji} R_j = \sum_{j \in \{d_{ji} \leq d_{i0}\}} \frac{w_{ji} S_j}{\sum_{k \in \{d_{ji} \leq d_{i0}\}} w_{ji}} \quad (21)$$

where A_i^F represents the *potential access of individual i* , R_j is the *OAT treatment capacity of provider j , who is within the reachable provider region of i (that is $d_{jk} < d_{i0}$)*. The weight, w_{jk} is the same distance weight as used in step 1. (Modified from W. Luo & Qi, 2009, p. 1102; W. Luo & Wang, 2003, p. 872)

Changing the numerator of the first step to total provider capacity, and the demand from populations at census tract centroids to individuals preserves an important property of the 2SFCA method. The population weighted average of the accessibility values of a system will equal the provider-population ratio of that system (Shen, 1998). Put another way, if you multiply the accessibility values of the population units by their population and sum, you get the total supply in the system (Delamater, 2013). In the individualized version, each population unit is one person, so the sum of the individuals' potential accessibility scores equals the total capacity in the considered region:

$$\sum_i A_i^F = \sum_j S_j \quad (22)$$

This property allows us to consider one individual agent's potential accessibility score as its fraction of the total supply. As such, we can quantify the equitability of the distribution of accessibility using the Lorenz curve and Gini coefficient (Gini, 1912; Lorenz, 1905).

The Lorenz curve and Gini coefficient (or Gini Index) are usually used to quantify unequal distributions of wealth or income in an economy. A Lorenz curve is constructed with the x axis representing the cumulative proportion of the population, and the y axis representing cumulative proportion of wealth or income. The population is indexed in increasing order of wealth or income. The x value of the function is equal to the cumulative fraction of the population, and the y value of the function is equal to the cumulative fraction of total wealth or income. If wealth is distributed perfectly, with each person having a proportional share, the function becomes the straight line $y = x$. If one person has all the wealth or income and everyone else has none, the function is a stepwise curve with $y = 0$ for $x < 1$ and $y = 1$ for $x = 1$. In all other cases, the curve is

Index is 0, because the area A is 0. In the case in which one person has all the wealth, the Gini Index is 1 because $A+B = A$. The US Central Intelligence Agency publishes Gini Indices for household income in The World Fact Book (Central Intelligence Agency, 2018). Lethoso and South Africa have the most unequal distribution of income at Gini Index = 63.2 and 62.5 respectively, and Slovakia and Finland have among the most equal distribution of income at Gini Index = 23.7 and 21.5, respectively. The United States' Gini Index is ranked 41st highest out of 156 nations at 45.0. The Gini Index of income

Figure 3-6: Typical Lorenz curve with the line of perfect equality in black. The Gini coefficient summarizes the unequal distribution represented by the curve in an index given by the ratio $A/(A+B)$.

distribution does not give any information on individuals' actual income, or the total income in the system. Income in the United States is distributed about as equally as income in Cameroon (ranked 42nd out of 156, Gini Index = 44.6), but per capita income differs by an order of magnitude (\$58,030 in the US, and \$3,250 in Cameroon, 2018).

I use the same general method to generate a Lorenz Curve and Gini Index for spatial potential access—the Spatial Potential Access Lorenz Curve (SPALC) and the Spatial Potential Access Gini Index (SPAGI). The x axis represents the cumulative fraction of the total population of demanders, and the y-axis the fraction of the total OAT supply in the system. Agents are indexed in increasing order of spatial potential accessibility scores, A_i^F , and the y value is calculated by dividing the spatial potential accessibility score by the sum of all spatial potential accessibility score, which is equivalent to the total amount of supply in the system: $\frac{A_i^F}{\sum_j S_j}$. The area of region

between the resultant Spatial Potential Access Lorenz Curve (SPALC), and the line of perfect equality of access is the Spatial Potential Accessibility Gini Index, or SPAGI for short.

Like the Lorenz Curve and Gini Index for income does not give information of the adequacy of income to meet peoples' needs, neither does the SPAGI give information on the adequacy of OAT supply to meet treatment demand, only the equitability of the distribution of that supply based on location and travel preferences. Adding treatment supply to the system could cause the SPAGI to increase, decrease, or stay about the same depending on the location of that supply.

Figure 3-7: Eight demanders equidistant to one provider. In the left figure, the provider has excess capacity, and in the right figure, the provider has inadequate supply.

Figure 3-7 shows an idealized case. In both the left and right figure, using a dichotomous weighting scheme with $d_{ij} < d_{i0}$, SPAGI = 0. In the Capacity = 16 case,

$$R_j = \frac{16}{8} = 2$$

$$A_i^F = 2 \forall i$$

$$\frac{A_i^F}{\sum_j S_j} = \frac{2}{16} \forall i$$

Each demander has a 1/8 proportional share of the 16 units of supply, and therefore the area of the region between the curve and the line of perfect equality is 0.

In the Capacity = 4 case,

$$R_j = \frac{4}{8} = 0.5$$

$$A_i^F = 0.5 \forall i$$

$$\frac{A_i^F}{\sum_j S_j} = \frac{0.5}{4} \forall i$$

And again, each demander has a proportional share of the 4 units of supply, and again SPAGI is 0.

3.5.1 Weighting schemes for the Spatial Potential Access Gini Index (SPAGI)

As emphasized in Section 2.2, the distance decay weights 2SFCA models can take on various forms. I tested the range, sensitivity, and differences among five different weighting schemes: dichotomous 2SFCA at an individual's stated willingness to travel distance, inverse logistic distance decay, Gaussian distance decay, exponential distance

decay, and at three cut off distances (10, 30 and 60 miles) per the E2SFCA method in equation (18). All weights are calculated based on Euclidean distances because the simulation model maps do not include road systems, or actual geo-located individuals, and because travel times and straight line distances are highly correlated (Phibbs & Luft, 1995).

3.5.1.1 Dichotomous weighting

When using the dichotomous weighting scheme, (hereafter designated “2SFCA”), an individual regards all providers within his or her willingness to travel distance as equally reachable and all those outside that distance as unreachable. Provider catchment areas are determined by whether that provider is reachable by the patient. Individuals in the model have heterogeneous distances they are willing to travel, so one demander at a given location may be *inside* a provider’s catchment area, while another demander at the *same* location may be *outside* that provider’s catchment area. The individualized dichotomous measure becomes:

$$f(d_{ij}) = \begin{cases} 1, & \text{if } d_{ij} \leq d_{i0}; \\ 0, & \text{otherwise} \end{cases} \quad (23)$$

where d_{ij} is the distance between the provider j and individual i , and d_o , the population-wide catchment cutoff distance is replaced by d_{i0} , an individualized cutoff value.

3.5.1.2 Continuous distance decay functions: Inverse Logistic, Gaussian, and Exponential decay

The three continuous distance decay functions are also based on individuals' willingness to travel distances. In these weighting schemes providers within the willingness to travel radii of demanders are reachable, but not equally desirable. Those that are near are assigned high weights, and those that are further, but still within the willing-to-travel radius are assigned low weights. Providers outside the willing-to-travel radius are unreachable and are assigned a weight of 0. The inverse logistic weight (designated "Logistic" hereafter) is calculated as follows:

$$f(d_{ij}) = \begin{cases} 1 - \frac{1}{1 + e^{\frac{-10}{d_{i0}}(d_{ij} - \frac{d_{i0}}{1.5})}}, & \text{if } d_{ij} \leq d_{i0}; \\ 0, & \text{otherwise} \end{cases} \quad (24)$$

where, d_{ij} is the distance between the provider j and individual i , and d_{i0} is individual i 's willing-to-travel distance, and the constants -10 and 1.5 tune the shape of the curve.

The Gaussian weight function (designated "Gaussian") is calculated as follows:

$$f(d_{ij}) = \begin{cases} e^{-\frac{d_{ij}^2}{0.3d_{i0}^2}}, & \text{if } d_{ij} \leq d_{i0}; \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

where d_{ij} and d_{i0} are defined as previously, and the constant, 0.3, is used to tune the shape of the curve.

The exponential weight function (designated “exponential”) is calculated as follows:

$$f(d_{ij}) = \begin{cases} e^{-\frac{d_{ij}}{0.3d_{i0}}}, & \text{if } d_{ij} \leq d_{i0}; \\ 0, & \text{otherwise} \end{cases} \quad (26)$$

where d_{ij} and d_{i0} are defined as previously, and the constant, 0.3, is used to tune the shape of the curve.

The tuning parameters were selected so that each curve would have a weight of .0357 at the maximum travel distance, and a weight of 1 if the provider and demander were within a mile. The four curves are shown below for an individual with a maximum travel distance of 60 miles.

Figure 3-8: The dichotomous and continuous distance decay functions for 60 mile travel willingness. The orange curve is inverse logistic, which penalizes small deviations from collocation less than the other continuous measures: blue for Gaussian and green for exponential. The red region is reachable under the dichotomous scheme, and the region to the right of 60 miles is unreachable under all weighting functions.

3.5.1.3 Enhanced Two-Step Floating Catchment Area (E2SFCA) weighting zones

For the final measure, I chose the three weighting zones proposed by Luo and Qi (2009). Any distance less than 10 miles is assigned weight 1, 10 to 30 miles 0.6, and 30 to 60 miles 0.123 per the Gaussian function in equation (18). Any provider outside of 60 miles is unreachable.

This weighting function differs from the others because it is not based on individuals' stated willingness to travel or their geographic placement. City dwellers are assumed equally willing to travel 50 miles as country residents.

3.6 Exploratory Analysis Experiments

Because the Spatial Access Gini Index (SPAGI) is a novel metric, I needed to understand more about its applicable range in idealized as well as plausible scenarios before using the measure to compare research scenarios. To answer Research Question 1—What functional form should an aggregated individual-level access inequality metric have for it to be sensitive enough to detect differences in access equity in different regions and/or due to different policy choices?—I performed simple scenario exploration exercises and tests, as detailed in Section 3.6.1.

3.6.1 Exploring the Spatial Potential Access Gini Index (SPAGI) with six test scenarios

To explore the range and applicability of SPAGI with the five different weighting functions, I generated six test cases. In five of the six cases, I explored the effect of

different geographies, using the ten maps generated for spatial sensitivity analysis (see Section 3.4.4.3). The six cases are as follows:

- “Baseline”—Placement of people with OUD and providers according to model assumptions (see Section 3.3.2).
- “Random”—Initial placement as “Baseline” (to generate willingness to travel distances in people with OUD and patient capacity for providers), reassignment to random locations.
- “Baseline Double”—Placement as “Baseline,” but all providers at double baseline capacity.
- “Hotspots”—Placement as “Baseline” with the addition of small regions of high demand with the following characteristics:
 - “Rural hotspot”—an additional 20% of the population in a 625 square mile rural region have OUD.
 - “Rural hotspot, low transport”—as “Rural hotspot,” but with willingness to travel restricted to 10+uniform(20) miles.
 - “Urban hotspot”—an additional 10% of the population in a 225 square mile urban region have OUD.
- “High capacity provider closure”—Placement as “Baseline” with 1-5 of the highest capacity providers removed from the model, simulating the sudden closure of one or more high capacity providers.

- “Rural provider closure”—Placement as “Baseline” with 1-5 of the most remote providers removed from the model, simulating the sudden closure of one or more rural/remote providers.

The “Hotspot” scenarios were only explored on the baseline map, all others were repeated on all 10 simulation maps.

I conducted the following analyses on the six scenarios:

3.6.1.1 Full Range of SPAGI

For each weighting scheme (2SFCA, E2SFCA, Logistic, Gaussian, Exponential—referred to as “weight” for short), I combined the datasets for each map and graphed the full range of the Spatial Potential Access Gini Index (SPAGI) for plausible allocation geographies.

3.6.1.2 Allocation Exploration

For each region and weight, I tested the difference in the SPAGI with respect to two population allocation scenarios, “Random,” and “Baseline.” This tested the ability of the SPAGI to detect large differences in the spatial allocation of populations of the same size. This tests the basic question: Does spatial allocation matter when calculating SPAGI, or just population sizes?

3.6.1.3 Exploration of Regional Differences

For each region, I plotted all five SPAGI measures and tested the differences among the measures to see if the measures are different for each other, and if they are systematically different from each other across all ten regions.

Additionally, for each measure, I also plotted and tested the difference in the SPAGI dependent variable with the region as the dependent variable. This tests whether SPAGI can detect differences between regions with different spatial features and plausible population allocations.

3.6.1.4 Double Capacity Exploration

For each map and each weight, I tested the difference in the SPAGI between the “Baseline” scenario and “Baseline Double” scenario. This tests whether the SPAGI necessarily tracks with supply expansions. Colloquially: is more always more equal, as measured by SPAGI?

3.6.1.5 Hotspot Exploration

For each weight, I tested the difference in the SPAGI for each hotspot scenario. This tests whether SPAGI can detect unusual concentrated demand within a broader region.

3.6.1.6 Supply Shock Exploration

For each map and each weight, I tested the difference in the SPAGI for one to five high-capacity provider closures, and for up to five of the remotest providers. This

tests whether SPAGI can detect the effect on access equity of the loss of individual providers.

To test the response of the five parameterizations of the SPAGI in these scenarios, I had intended to perform one-way ANOVA tests (or t-tests in the Allocation and Double Capacity analyses). However, when checking that the analyses met criteria for ANOVA, I found that the SPAGI often fails the Shapiro-Wilk normality test of residuals, and one-way linear models of the SPAGI often fail the Bartlett test of homoscedasticity. Because I could not assume homogeneity of variance or normality of residuals, I opted to use the Kruskal-Wallis test as a non-parametric alternative to ANOVA, Dunn tests for post-hoc pairwise comparisons. For the Allocation Exploration and Double Capacity Exploration experiments I used the modified two-sample-t confidence interval procedure, also called the Welch confidence interval approach, set out in *Simulation Modeling and Analysis* (2005), a gold standard text on the construction and analysis of simulation models with random inputs and outputs (Law, 2013).

3.7 Policy Analysis Experiments

Because the model is complex and SPAGI is a novel measure, I kept policy research experiments simple.

3.7.1 Model Baseline including Spatial Potential Access Gini Indices

Research Question 2—How equitably distributed is access to OB buprenorphine treatment in the current OB buprenorphine treatment system given: regulatory caps on

patient numbers, physician preferences, and geographic distribution of treatment seekers and providers?—was answered simply by calculating SPAGI measures on the fully calibrated and tested baseline scenario in addition to generating other baseline outcome measures. No tests were performed to answer this question; the outcome variables including SPAGI measures serve as a baseline foundation for comparing changes in outcomes including spatial potential access in the policy analysis. Because outcome measures are the results of a random process, I report 95% confidence intervals on all model outcomes.

3.7.2 Patient Limit Change Experiments

To answer Research Question 3—To what extent would changing the current DATA 2000 patient limit per physician change utilization of buprenorphine, equality of access, opioid overdose deaths and medication diversion?—I set patient limit levels to 100, 275 (baseline), 500 and 4000, initialized the model in 2016, and ran it 35 times at each patient limit level. The SPAGI measures were calculated at the end of the year. Because the patient limit has already been expanded to 275, this is the baseline scenario, and a patient limit of 100 represents a policy roll-back to the previous patient limit prior to 2016. I chose to use patient limit level of 4000 as a proxy for the complete removal of the patient limit because this exceeded the maximum unlimited patient capacity of modeled providers.

To test the impact of different patient limits on outcome variables including SPAGI measures, I used ANOVA tests where heteroscedasticity was absent and residuals

were normally distributed, Welch one-way tests with Games-Howell post hoc tests where heteroscedasticity was present and residuals were normally distributed, and Kruskal-Wallis non-parametric tests with Dunn post hoc tests where both assumptions were not valid.

3.7.3 NP and PA Buprenorphine Adoption Experiments

To answer Research Question 4—To what extent would various levels of buprenorphine prescribing adoption by Nurse Practitioners and Physician Assistants change utilization of buprenorphine, equality of access, opioid overdose deaths, and medication diversion?—I set the percentage of NPs and PAs who prescribe buprenorphine to 0, 5, 10, 20 and 30 percent, initialized the model in 2016, and ran it 35 times at each patient limit level. The SPAGI measures were calculated at the end of the year. Because patient limit regulations were changed in July 2016, the patient limit for physicians was held to 100 for the first 26 week of the modeled year, and expanded to 275 in week 27.

To test the impact of different levels of NP PA buprenorphine adoption on outcome variables including SPAGI measures, I conducted ANOVA tests when assumptions were met, and Welch one-way test or Kruskal Wallis rank sum tests when assumptions were not valid, along with post hoc tests as described in Section 3.7.2.

4 Exploratory Analysis Results

In Chapter Four I report the results of exploratory analyses of the Spatial Potential Access Gini Indices and the Spatial Potential Access Lorenz Curves. Because this section reports on my efforts to understand what these novel measures mean when used in practice, the tone in Chapter 4 is more conjectural and inquisitive than in Chapter 5, when the measures are used to make inferences on the spatial equity impacts of policy. Also, rather than wait to discuss the implications of the SPAGI exploration experiments in the discussion section after they are used for policy analysis, I have chosen to dig deeper into the exploratory analysis of the measures in Chapter 4. In Chapter 5, I return to the more traditional format, in which I present results with little commentary in Chapter 5, followed by discussion in Chapter 6

In this Chapter, some of the SPAGI exploration exercises required testing of five measures on ten maps, generating fifty separate analyses. In these cases, I present a single case which shows a typical result, and any non-typical cases.

4.1 Descriptive Statistics of 10 Regions

Table 4-1 includes a brief list of descriptive statistics about the regions and the accompanying map. Mean and standard deviation of 35 replications are reported for random inputs.

Table 4-1: Descriptive statistics of 10 regions used for exploratory analysis.

Region 0
Total population (people)	2,666,164(19520)	
Proportion of population living in a MUA (dml)	0.157 (0.002)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.638 (0.0028)	
Average population density (people/mi ²)	124.32 (0.91)	
Total number of providers at initialization (people)	255.5 (3.02)	
Proportion of providers with high waiver (dml)	0.316(0.022)*	
Total number of people with OUD at initialization (people)	29,194 (213.7)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	11	
Region 1
Total population (people)	1,088,659 (4162)	
Proportion of population living in a MUA (dml)	0.33 (0.0015)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.041 (0.0023)	
Average population density (people/mi ²)	54.9 (0.21)	
Total number of providers at initialization (people)	103.5 (2.03)	
Proportion of providers with high waiver (dml)	0.315 (0.05)*	
Total number of people with OUD at initialization (people)	11,920 (45.6)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	4	

*value fixed prior to simulation

Region 2		
Total population (people)	3,435,904 (10160)
Proportion of population living in a MUA (dml)	0.22 (0.0011)	
Proportion of population living in an urban area with population density > 1000 people /mi² (dml)	0.30 (0.0024)	
Average population density (people/mi²)	152.7 (0.45)	
Total number of providers at initialization (people)	328.6 (3.49)	
Proportion of providers with high waiver (dml)	0.303 (0.02)*	
Total number of people with OUD at initialization (people)	37,623 (111.2)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	14	
Region 3		
Total population (people)	1,185,966 (5912)
Proportion of population living in a MUA (dml)	0.749 (0.0026)	
Proportion of population living in an urban area with population density > 1000 people /mi² (dml)	0.179 (0.004)	
Average population density (people/mi²)	52.7 (0.26)	
Total number of providers at initialization (people)	113.6 (2.03)	
Proportion of providers with high waiver (dml)	0.303 (0.035)	
Total number of people with OUD at initialization (people)	12,986 (64.7)*	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	4.8 (0.4)	
*value fixed prior to simulation		

*value fixed prior to simulation

Region 4		
Total population (people)	5,319,913 (23025)
Proportion of population living in a MUA (dml)	0.25 (0.0013)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.69 (0.0018)	
Average population density (people/mi ²)	237.1 (1.03)	
Total number of providers at initialization (people)	509.3 (3.5)	
Proportion of providers with high waiver (dml)	0.31 (0.017)*	
Total number of people with OUD at initialization (people)	58,253 (252.1)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	22	
Region 5		
Total population (people)	1,062,685 (7522)
Proportion of population living in a MUA (dml)	0.22 (0.0024)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.469 (0.003)	
Average population density (people/mi ²)	47.69 (0.33)	
Total number of providers at initialization (people)	100.9 (1.8)	
Proportion of providers with high waiver (dml)	0.32 (0.035)*	
Total number of people with OUD at initialization (people)	11,636 (82.3)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	4	

*value fixed prior to simulation

Region 6		
Total population (people)	732,390 (4303)
Proportion of population living in a MUA (dml)	0.24 (0.0018)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.15 (0.004)	
Average population density (people/mi ²)	32.6 (0.19)	
Total number of providers at initialization (people)	69.8 (1.52)	
Proportion of providers with high waiver (dml)	0.30 (0.05)*	
Total number of people with OUD at initialization (people)	8,019 (47.2)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	3	
Region 7		
Total population (people)	248,524 (2681)
Proportion of population living in a MUA (dml)	0.92 (.001)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.209 (0.008)	
Average population density (people/mi ²)	11.1 (0.11)	
Total number of providers at initialization (people)	23.6 (1.04)	
Proportion of providers with high waiver (dml)	0.319 (0.102)*	
Total number of people with OUD at initialization (people)	2720 (29.3)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	1	

*value fixed prior to simulation

Region 8		
Total population (people)	6,920,384 (22035)
Proportion of population living in a MUA (dml)	0.14 (.001)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.71 (.001)	
Average population density (people/mi ²)	315.5 (1.0)	
Total number of providers at initialization (people)	663.8 (5.3)	
Proportion of providers with high waiver (dml)	0.31 (0.20)*	
Total number of people with OUD at initialization (people)	75,778 (241.2)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	29	
Region 9		
Total population (people)	2,524,241 (12268)
Proportion of population living in a MUA (dml)	0.23 (0.0017)	
Proportion of population living in an urban area with population density > 1000 people /mi ² (dml)	0.702 (0.002)	
Average population density (people/mi ²)	114.4 (0.54)	
Total number of providers at initialization (people)	242.5 (3.3)	
Proportion of providers with high waiver (dml)	0.31 (0.027)*	
Total number of people with OUD at initialization (people)	27,640 (134.2)	
People with OUD per 100,000 population (1/100000)	1095*	
Total number OTPs (number)	10	

*value fixed prior to simulation

4.2 Full Range of Five Weighted SPAGI

The full range of each of the five is shown in Figure 4-1. The three SPAGI with continuous weighting have similar medians and ranges as shown in Table 4-2. E2SFCA weighting has consistently lower SPAGI values, and 2SFCA has the largest potential

Figure 4-1: Box plots of the full range of each SPAGI measure over all regions. Plots left to right: 2SFCA, E2SFCA, Exponential, Gaussian, Logistic.

range of values. E2SFCA SPAGI is much lower than the other measures because access is not discounted by individuals' ability to travel. Providers that are up to 60 miles away are considered reachable but distant for urban residents by E2SFCA, are unreachable by most urban residents by the other measures since many urban residents are willing to travel only 5 or 10 miles. 2SFCA SPAGI tends to be lower than the other willingness-weighted measures because all reachable providers are assigned a weight of 1, while

the other willingness-weighted measures discount more distant providers that are still reachable.

Because E2SFCA is different from the other measures, in experiments that follow, I will discuss E2SFCA results first followed by willingness-weighted SPAGI results, noting any substantive differences among the willingness weighted measures.

Table 4-2: Median, IQR and full range of each SPAGI measure.

Measure	Median	IQR	Range
2SFCA	0.447	0.102	[0.137, 0.563]
E2SFCA	0.29	0.079	[0.180, 0.459]
Exponential	0.503	0.101	[0.328, 0.603]
Gaussian	0.495	0.118	[0.278, 0.602]
Logistic	0.512	0.124	[0.269, 0.621]

4.3 Allocation Exploration

Does spatial allocation matter when calculating SPAGI in a region? For each SPAGI measure and each region, can SPAGI detect a difference between the random allocation of the region-appropriate number of people with OUD and treatment providers, “Random,” and a plausible allocation of the same number of people and treatment providers, “Baseline?” The null hypothesis is that the simulation mean for 35 replications at “Random” and “Baseline” are equal, and was tested using the Welch Confidence Interval Approach (see Section 3.6.1 for specifics on how the populations were allocated randomly). I ran 50 tests: the 5 SPAGI measures for 10 regions. Mean differences in confidence intervals did differ significantly from zero in 48 out of 50 tests

at $p < 0.001$. Differences between E2SFCA SPAGI for “Random” and “Baseline” allocation could not be detected in region 5 or 6.

4.3.1 E2SFCA Typical Results

Region 4 results are typical, and are featured in Figure 4-2. Typically, where a significant difference was detected in E2SFCA SPAGI, “Random” allocation resulted in substantially better E2SFCA SPAGI scores than “Baseline” allocation, as shown for region 4 in Figure 4-2a. In region 4, under the “Random” allocation rule almost all people are within 10 miles of a provider. For the remaining tiny fraction of the population the closest provider is between 10 and 30 miles. Further, “Random” allocation means the catchment areas of each provider has about the same number of individuals, so the population denominator of the treatment supply to population ratio is about the same for all providers. Further, when populations are large, each person can reach a large number of providers, diluting the impact of high treatment capacity of individual providers. Deviation from perfect equality is due to chance placing slightly more providers near some demanders, to the variation in provider capacity, or due to edge effects. These effects combined result in near perfect spatial access equity when populations are large. When populations are smaller, each person can reach fewer providers variation in the capacity of individual providers becomes more important, resulting in more heterogeneity in access. However, when population density is greater than 50 people/mi², E2SFCA SPAGI scores are still higher than “Baseline” allocation.

4.3.2 Willingness-weighted Typical Results

“Baseline” allocation resulted in substantially better willingness-weighted SPAGI than “Random” allocation in all region. The box plots for 2SFCA, Logistic, Gaussian and Exponential SPAGI for region 4 shown in Figure 4-2(b-e) are typical. By random allocation, people with large willingness to travel radii aren’t relegated to provider-scarce regions rural regions, so they have a disproportionately large share of the spatial potential access pie. Further, people who are willing to travel very short distances are not concentrated in regions of denser provider locations, so providers are more likely to be unreachable. Slow growth at the low access end of the Spatial Potential Access Lorenz Curve coupled with as steep rise at the high access end of the curve results in high inequality as measured by SPAGI.

Figure 4-2: Region 4 boxplots comparing SPAGI of the two population allocation scenarios using 5 different weights. The willingness-weighted measures show the same trend, and are grouped to the right in plots (b-e), while E2SFCA shows the opposite trend and is high

4.3.3 E2SFCA Atypical Results

Region 5, 6, and 7 results for E2SFCA are not typical. These regions have small populations (47 people/mi², 32 people/mi², and 11 people/mi², respectively). In region 5 and 6, no difference could be detected between “Random” and “Baseline” allocation. In region 7, the most sparsely populated region, “Random” allocation resulted in worse E2SFCA SPAGI, as shown in the boxplot in Figure 4-3. At low population levels, each individual may only be able to reach one or two providers, making the effect of the treatment capacity much more important when calculating equity. If one person can reach a provider with 20 treatment spots, and another person can reach an OTP which has 2 providers who can treat 150 people each, their access is not equal, despite the fact that the providers have about the same number of people in their catchment areas.

Figure 4-3: Region 7 E2SFCA does not have the characteristic pattern of lower E2SFCA SPAGI for “Random” allocation.

4.3.4 Implications of Allocation Exploration

This set of simple, stylized tests show that the Spatial Potential Allocation Gini Indices can detect differences from random spatial allocation. It is encouraging that the

differences between “Baseline” population allocation and “Random” allocation are much larger than the random run to run variation inherent in spatial agent based models. As a first test of a spatial potential access equity measures, this is encouraging. Failure to detect a difference between totally random allocation of supply and demand and geographically plausible allocation of supply and demand would mean that the measures are aspatial. Rejecting the null hypotheses in most cases means that, yes, spatial allocation does matter when calculating SPAGI.

The analysis also highlights that SPAGI results that appear to be typical may not generalize to regions with particularly low population density.

The attempt to understand the regional differences between regions where “Random” allocation resulted in higher E2SFCA SPAGI than “Baseline” allocation highlighted the importance of considering the capacity of reachable providers, distance from those providers, and the number of reachable providers. With “Random” allocation, provider catchment areas contained about the same number of people, so differences in competition for supply did not need to be considered. Even without competition and willingness to travel, understanding the source of a regional difference in the metric required careful consideration of three pieces of information. SPAGI compresses a lot of information about individual differences in spatial potential access into a single measure. Understanding SPAGI results requires the unpacking of that compressed information.

4.4 Exploration of Differences among SPAGI Measures in a Given Region

Are the five SPAGI measures different, and are they different from each other in the same way in all regions? For each region, are there detectable differences in medians of the 5 SPAGI measures as measured by Kruskal-Wallis rank sum tests? The null hypothesis is that all medians are equal, and rejection of the null hypothesis implies that at least one of the SPAGI measures gives different information about the region. Figures 4-4 through 4-8 show maps of each region, the allocation of people with OUD and providers in that region, and a boxplot of SPAGI by weighting scheme. In all regions differences in medians were detected at $p < 0.0001$. Post hoc tests showed that in all cases E2SFCA is different from all other measures. Typically, 2SFCA is different from the other willingness-weighted SPAGI measures, and typically differences could not be detected among the Logistic, Gaussian and Exponential SPAGI measures.

4.4.1 Typical Results

All regions but region 7 show the same general trend: E2SFCA SPAGI is far lower than the other measures, and 2SFCA SPAGI is lower than the other willingness weighted measures. The reasons for this were discussed in Section 4.2. Regions with lower population density have larger run-to-run SPAGI variation, so in some cases differences between 2SFCA SPAGI and the other willingness measures could not be detected, as in regions 1, 3 and 6.

Figure 4-4: Regions 0 and 1. Left, regional map; center, providers (red), OTPs (maroon), and people with OUD (black); right, Box plots of SPAGI by weight

Figure 4-5: Regions 2 and 3. Left, regional map; center, providers (red), OTPs (maroon), and people with OUD (black); right, Box plots of SPAGI by weight

Figure 4-6: Regions 4 and 5. Left, regional map; center, providers (red), OTPs (maroon), and people with OUD (black); right, Box plots of SPAGI by weight

Figure 4-7: Regions 6 and 7. Left, regional map; center, providers (red), OTPs (maroon), and people with OUD (black); right, Box plots of SPAGI by weight

Figure 4-8: Regions 8 and 9. Left, regional map; center, providers (red), OTPs (maroon), and people with OUD (black); right, Box plots of SPAGI by weight

4.4.2 Atypical Results

In region 7, 2SFCA has the lowest SPAGI. To understand why the trend is different in region 7, I inspected the map shown in Figure 4-7(bottom), and the Spatial Potential Access Curves (SPALCs) shown in Figure 4-9.

Figure 4-9: Spatial Potential Access Lorenz Curves for region 7. The 2SFCA weighting scheme results in the lowest SPAGI in this region only.

Lower SPAGI means supply is more equitably allocated among demanders. In region 7, the majority of people live in one small urban center or in rural areas. The small number of suppliers are also located in the urban centers where people are not willing to travel far. Virtually everyone else is willing to travel large distances to the two more densely populated zones. The few people in small towns can't access any provider, so the SPAGI curves are horizontal near the origin. Then, by 2SFCA, providers are far, but reachable for almost everyone else, hence the steep, linear curve. With the E2SFCA providers who are between 30 and 60 miles away are less preferable, so the curve is more bowed out.

However, at this very low population level, the SPAGI are sensitive to the actual allocation of the small number of providers, which is why several simulations resulted in outlier SPAGI values. Counterintuitively, when a provider is allocated to a small town in

the west, as in Figure 4-10, the SPAGI values go down. Inspection of the curves gives a clue as to why. It is easiest seen in the 2SFCA curve. The curve is still flat near the origin, rises linearly until about the 80% mark, and then rises dramatically. So the increase in inequality is not to more people having *worse* access, which would be indicated by a longer flat region near the origin, but instead by some people having much *better* access, indicated by the steep rise near the right axis.

Figure 4-10: Region 7 map and Spatial Potential Access Lorenz Curves (SPALCs) with random allocation of a provider to the small town in the west.

4.4.3 Implications of Exploring Differences among SPAGI measures in a Given Region

The SPAGI measures are different. E2SFCA SPAGI is consistently much lower than the other measures because it does not include ability to travel in its calculation of individual spatial potential access. 2SFCA is typically slightly lower than the other willingness-weighted measures because there is no distance decay discounting of reachable providers. The Logistic, Gaussian and Exponential willingness-weighted SPAGI are the most complex measures because they include both ability to travel and a distance decay weighting within the willingness to travel radius. The subtle differences in the weighting curves typically do not result in detectable differences in SPAGI.

The fact that results were again atypical in the lowest density region 7 highlights the need for special consideration in measuring Spatial Potential Access in low density regions. Analysis of an outlier simulation run in region 7 highlighted an important aspect of SPAGI—Spatial Potential Access Equity can get worse because a small, select group of individuals gets particularly good access. If we say that supply within a region is a pie, SPAGI calculates whether everybody is getting a fair and proportional piece of the pie. If a lucky few get large slices, there is less to go around for everyone else. Changes in equity are zero sum.

4.5 Exploration of Regional Differences: Comparing the Ten Regions for Each SPAGI Measure

Can SPAGI detect differences between regions with different spatial features and plausible population allocations? For each SPAGI measure, I tested for differences in

SPAGI medians using Kruskal-Wallis rank sum tests. The null hypothesis is that medians are indistinguishable, and rejection of the null hypothesis would mean that SPAGI can detect differences in Spatial Potential Access equity based on regional differences.

Figure 4-11 shows a plot of population density and boxplots of each of the 5 SPAGI measures. The population density plot is included for comparison. Kruskal-Wallis rank sum tests for each measure were significant at $p < 0.001$, and the results of Dunn post-hoc pairwise comparison test are shown in Table 4-3. In general, as was found when comparing the five SPAGI measures within each region, the trends across regions for the four measures based on willingness to travel were very similar. Figure 4-11 shows similar trends in the box plots, though note the slightly different y-axis scaling. Table 4-3 shows that most differences detected by one continuous measure were detected by all of the continuous measures. When detecting differences among these particular simulations, the Gaussian weighed SPAGI was the most discriminating of the continuous measures, but all measures performed about the same. All differences detected by the willingness-to-travel based measures were in the same direction: no region appeared less equitable than another by one measure, and more equitable than another by another, as indicated by the (+) and (-) notation in Table 4-3. 2SFCA detected differences in spatial potential access between some regions not detected by the continuous measures in some pairwise comparisons.

E2SFCA SPAGI is different from the other measures both in magnitude, as shown in Section 4.2 but also in whether it detects differences between regions, and the

direction of the differences. Even when E2SFCA and another measure both detect differences in spatial potential access between two regions, the direction of the difference may not be the same, as indicated by opposite signs (+/-) in Table 4-3. For example, SPAGI is higher for region 8 than 1 by all willingness-weighted measures (here 8 appears to have less equitable allocation than region 1), but lower by E2SFCA. This same reverse trend was seen in the simple allocation exploration in Section 4.3.

Figure 4-11: SPAGI measures by region (right column), and population density by region (left). Differences among all plots but E2SFCA are small. E2SFCA has a substantially different trend

Table 4-3: Results of Dunn post-hoc pairwise comparison tests for each SPAGI, comparing the 10 regions. Kruskal-Wallis rank sum tests were significant, $p < 0.001$. (+/-) indicate that SPAGI was higher (+) or lower (-) in the second region than the first.

Regions	2SFCA p-value; +/-	Logistic p-value; +/-	Gaussian p-value; +/-	Exponential p-value; +/-	E2SFCA p-value; +/-
1 vs 0	n.s.	n.s.	n.s.	n.s.	<0.001; +
2 vs 0	<0.001; +	<0.001; +	<0.001; +	<0.001; +	<0.001; +
3 vs 0	n.s.	n.s.	n.s.	n.s.	<0.001; +
4 vs 0	<0.01; +	<0.001; +	<0.001; +	<0.001; +	n.s.
5 vs 0	n.s.	<0.05; -	n.s.	n.s.	n.s.
6 vs 0	n.s.	n.s.	n.s.	n.s.	n.s.
7 vs 0	<0.001; -	<0.001; -	<0.001; -	<0.001; -	n.s.
8 vs 0	<0.001; +	<0.001; +	<0.001; +	<0.001; +	n.s.
9 vs 0	n.s.	n.s.	n.s.	n.s.	n.s.
2 vs 1	n.s.	<0.001; +	<0.001; +	<0.001; +	n.s.
3 vs 1	<0.01; -	n.s.	n.s.	n.s.	n.s.
4 vs 1	n.s.	<0.01; +	<0.01; +	<0.001; +	n.s.
5 vs 1	<0.001; -	<0.01; -	<0.01; -	n.s.	<0.001; -
6 vs 1	<0.001; -	<0.01; -	<0.05; -	n.s.	n.s.
7 vs 1	<0.001; -	<0.001; -	<0.001; -	<0.001; -	<0.001; -
8 vs 1	<0.01; +	<0.001; +	<0.001; +	<0.001; +	<0.001; -
9 vs 1	n.s.	n.s.	n.s.	n.s.	<0.01; -
3 vs 2	<0.001; -	<0.001; -	<0.001; -	<0.001; -	n.s.
4 vs 2	n.s.	n.s.	n.s.	n.s.	n.s.
5 vs 2	<0.001; -	<0.001; -	<0.001; -	<0.001; -	<0.001; -
6 vs 2	<0.001; -	<0.001; -	<0.001; -	<0.001; -	n.s.
7 vs 2	<0.001; -	<0.001; -	<0.001; -	<0.001; -	<0.001; -
8 vs 2	n.s.	n.s.	n.s.	n.s.	<0.001; -
9 vs 2	<0.001; -	n.s.	n.s.	n.s.	<0.001; -
4 vs 3	<0.001; +	<0.001; +	<0.001; +	<0.001; +	n.s.
5 vs 3	n.s.	n.s.	n.s.	n.s.	<0.001; -
6 vs 3	n.s.	n.s.	n.s.	n.s.	n.s.
7 vs 3	<0.01; -	n.s.	<0.05; -	<0.05; -	<0.001; -
8 vs 3	<0.001; +	<0.001; +	<0.001; +	<0.001; +	<0.001; -
9 vs 3	n.s.	<0.01; +	<0.01; +	<0.01; +	<0.01; -
5 vs 4	<0.001; -	<0.001; -	<0.001; -	<0.001; -	n.s.
6 vs 4	<0.001; -	<0.001; -	<0.001; -	<0.001; -	n.s.
7 vs 4	<0.001; -	<0.001; -	<0.001; -	<0.001; -	<0.001; -
8 vs 4	n.s.	n.s.	n.s.	n.s.	<0.001; -
9 vs 4	<0.05; -	n.s.	n.s.	n.s.	n.s.
6 vs 5	n.s.	n.s.	n.s.	n.s.	n.s.
7 vs 5	n.s.	n.s.	n.s.	n.s.	n.s.
8 vs 5	<0.001; +	<0.001; +	<0.001; +	<0.001; +	n.s.
9 vs 5	<0.05; +	<0.001; +	<0.001; +	<0.001; +	n.s.
7 vs 6	n.s.	n.s.	n.s.	n.s.	<0.001; -
8 vs 6	<0.001; +	<0.001; +	<0.001; +	<0.001; +	<0.001; -

9 vs 6	n.s.	<0.001; +	<0.001; +	<0.001; +	n.s.
8 vs 7	<0.001; +	<0.001; +	<0.001; +	<0.001; +	n.s.
9 vs 7	<0.001; +	<0.001; +	<0.001; +	<0.001; +	<0.01, +
9 vs 8	<0.001; -	n.s.	<0.05; -	n.s.	n.s.

A.1.1 E2SFCA SPAGI Results

Because E2SFCA SPAGI is not based on individuals' willingness to travel, two people in the same location will always have the same Spatial Potential Accessibility Score, entirely determined by distance to providers, the treatment capacity of those providers, and the overall demand on those providers. To explore the differences between regions using E2SFCA, I first used the Dunn pairwise comparisons from the Kruskal-Wallis rank sum test post hoc procedure to identify differences in Spatial Potential Access equity as measured by SPAGI, compared Spatial Potential Access Lorenz Curves (SPALC) and summaries of the information conveyed by the curves, which I call SPALC decile summaries, and finally, generated and compared heat maps of individual Spatial Potential Accessibility Scores.

Among other significant differences detected reported in Table 4-3, regions 1, 2 and 3 have higher spatial inequity than most other regions (0, 5, 7, 8, and 9), though they cannot be distinguished from each other or regions 4 and 6. For illustration, I am analyzing region 3.

I found that region 3 SPAGI was significantly higher than regions 0, 5, 7, 8 and 9. E2SFCA SPALCs and decile summaries for the curves are presented in Figures 4-12 and 4-13. Often Lorenz curves are interpreted by stating what fraction of the population owns

a given percentage of the total, for example: 80% of the population owns 20% of a nation's wealth. In this case, I report which fraction of the population lays claim to a given percentage of total potential access in the system, subtracting out all groups who have lower access. Each SPALC and SPAGI in Figures 4-12 and 4-13 are generated by a single model run. I am comparing them to better understand why significant differences were detected over multiple runs, though different runs do produce different curves and accompanying indices.

In all cases, a disproportionately large percentage of the population are in the bottom decile of access. In this particular model run of region 3, 27% of the population shares 10% of the capacity, weighted by distance, and each of the top 4 deciles have about 4% to 5% of the population in each. This near-linear increase indicates that there is relative access equity among the 20% of people with the best access, but that this 20% of the population have the highest 10% of Spatial Potential Access Scores. In the case of E2SFCA weighting this means they either fall within the 10 mile catchment area of high capacity providers, that they live where many catchment areas overlap, or that their reachable providers have low demand from others or combinations of these factors.

When compared to region 3, region 0 has about same fraction of the population in the lowest access decile, but a more even distribution of access in the remainder of the population. Regions 9 shows the same trend: a disproportionate fraction of the

population has very poor access, but there is near equality in all deciles above the first, indicating near equal access for all but the worst off. Regions 5 and 7 show the same

Region 3

gini-E2SFCA

0.3462

SPALC decile	Population at decile
1 st decile	27.0%
2 nd decile	16.0%
3 rd decile	11.9%
4 th decile	10.1%
5 th decile	9.6%
6 th decile	6.8%
7 th decile	4.7%
8 th decile	4.6%
9 th decile	4.4%
10 th decile	4.4%

Region 0

gini-E2SFCA

0.2912

SPALC decile	Population at decile
1 st decile	28.5%
2 nd decile	13.6%
3 rd decile	10.4%
4 th decile	8.3%
5 th decile	7.2%
6 th decile	6.7%
7 th decile	6.5%
8 th decile	6.3%
9 th decile	6.1%
10 th decile	5.8%

Region 5

gini-E2SFCA

0.2387

SPALC decile	Population at decile
1 st decile	22.2%
2 nd decile	12.8%
3 rd decile	11.6%
4 th decile	9.7%
5 th decile	8.8%
6 th decile	8.3%
7 th decile	7.8%
8 th decile	7.6%
9 th decile	6.7%
10 th decile	4.0%

Figure 4-12: Along with following Figure (4-13), SPALC and SPALC decile summary for region 3 and the 5 regions with significantly different SPAGI—regions 0, 5, 7, 8, and 9. SPALC and summaries are from 1 model run.

Region 7

gini-E2SFCA

0.2239

SPALC decile	Population at decile
1 st decile	24.3%
2 nd decile	11.3%
3 rd decile	9.1%
4 th decile	8.6%
5 th decile	8.6%
6 th decile	8.6%
7 th decile	8.6%
8 th decile	8.4%
9 th decile	8.2%
10 th decile	3.8%

Region 8

gini-E2SFCA

0.1782

SPALC decile	Population at decile
1 st decile	19.9%
2 nd decile	12.6%
3 rd decile	10.5%
4 th decile	9.4%
5 th decile	8.9%
6 th decile	8.4%
7 th decile	8.02%
8 th decile	7.6%
9 th decile	7.3%
10 th decile	6.9%

Region 9

gini-E2SFCA

0.2276

SPALC decile	Population at decile
1 st decile	26.9%
2 nd decile	10.6%
3 rd decile	9.1%
4 th decile	8.3%
5 th decile	7.9%
6 th decile	7.7%
7 th decile	7.5%
8 th decile	7.3%
9 th decile	7.2%
10 th decile	7.0%

Figure 4-13: Along with previous Figure (4-12), SPALC and SPALC decile summary for region 3 and the 5 regions with significantly different SPAGI—regions 0, 5, 7, 8, and 9. SPALC and summaries are from 1 model run.

basic trend with a difference in the top decile. A disproportionate fraction of the population has very poor access (at or near zero in the case of region 7). The access curve is then nearly linear from the 3rd through 9th deciles indicating near equal access for that segment of the population, a small fraction of the population have the very best access, as indicated by the sharp uptick at the right-most side of the curve.

Region 8, on the other hand, has a smaller portion of the population with the worst access a gentle concavity to the Spatial Potential Access curve. Relative to region 3, access is more equally distributed across all populations.

Figure 4-14 shows a heat map for each region by individual E2SFCA Spatial Potential Access Scores. The color coding represents deviation from equal proportional share. The warm, red end of the spectrum represents having less than one's proportional share, and the cool, blue end of the spectrum represents having more than one's proportional share. If every person were allocated his or her proportional share of the total supply in the system, there would be no deviation from equal proportional share, and all individuals would be green. In an extremely unequal allocation, most people would be orange and red and a small number of people blue.

Examination of the heat maps gives some insight into the sharp uptick at the highest access decile in regions 5 and 7. There is a deep blue area in the Southwest quadrant of region 5 and a small deep blue area in the Southeast quadrant of region 7. In these areas there is less competition for the treatment spots and those spots are

Figure 4-14: Heat maps generated by individual deviation from equal proportional share of the total capacity in the system as measured by E2SFCA weighted Spatial Potential Access Scores

within ten miles of where those relatively privileged people live. However, like SPAGI and SPALC, the heat maps of Spatial Potential Access Scores do not give information about the adequacy of supply to meet demand.

In general, the heat maps show that when ability to travel or preference for travel is not considered, assumptions about provider and demander locations generally result in city center residents having access to more than their proportional share of the limited supply of treatment capacity, rural residents having less than their proportional share, and residents of the suburbs having about their proportional share. This is not always the case, as when a provider happens to practice in a small community with less

demand pressure for her limited capacity, as in regions 5 and 7. The assumptions that result in these trends are that high waiver, high capacity providers tend to practice in the most densely populated regions; that OTPs are also located in dense population centers; and that rural and remote areas have more people with OUD than might be expected by population density alone.

4.5.1 Willingness-weighted SPAGI Results

Box plots of willingness-weighted SPAGI in Figure 4-11(a, c-e) show similar trends for each measure. Clearly, region 7 is different from the other regions, with the lowest population density and the lowest SPAGI, and region 8 has the highest population density and SPAGI. These apparent differences in SPAGI are significant by Dunn pairwise comparison tests after a significant Kruskal-Wallis rank sum test of difference in medians for region 7, but not necessarily so for region 8. In region 8 no significant differences can be detected between region 8 and regions 2 and 4, which have the second and third highest populations and a large, dense urban region, nor between region 8 and 9 by 2SFCA and Exponential SPAGI.

Visual inspection of SPAGI box plots and the population density bar chart show apparent correlation between population density and SPAGI. Pearson correlation tests between total population and SPAGI are significant and high, at 0.68, 0.74, 0.75, and 0.76 for 2SFCA, Logistic, Gaussian and Exponential weighted SPAGI respectively. This begs the question, do SPAGI measures tell us anything about the allocation of the population inside the regional container that is not summarized by the population

density? The Allocation exploration in 4.1.2 suggests they do, but can they detect equity differences in plausible allocations?

Comparison of actual geographies suggests that SPAGI can, in fact, detect differences between regions with similar population levels, but different population allocations. To analyze differences detected by willingness-weighted SPAGI post hoc pairwise comparison tests, I compared SPALCs, and SPALC decile summaries. For illustration, I present two analyses of regions with similar population levels, but differences in SPAGI scores.

Regions 3 and 1 have similar population densities, but different 2SFCA SPAGI scores, as do regions 5 and 1. Both region 5 and 3 have more equitable spatial allocation of supply than region 1. Comparison of SPALCs and SPALC decile summaries suggest that SPAGI is different for different reasons, and are shown in Figure 4-15. Region 3 has a much smaller fraction of the population in the lowest access decile than region 1. The region 3 curve is nearly parallel to the line of perfect equality for the middle 50% of the population, and bowed out for region 1. This suggests that the proportion of access apportioned to the 50% of the population with neither the best nor the worst spatial potential access scores is shared approximately equally within that group. Whereas in region 1, there are substantial differences in access equity within this subpopulation. This may be because providers are spread fairly evenly across the population in small urban pockets, rather than in a concentrated zone as in region 1.

Figure 4-15: SPALCs (left) and SPALC decile summaries (right). Region 1 (a) is different from region 3 (b) and region 5 (c), but regions 3 and 5 are not different from each other.

Region 5 has fewer people in the lowest access decile, but the difference is not large (comparing Figure 4-15a and 4-15c). The SPALC curves are similar for the lowest 40% of the population, after which the curve for region 5 becomes nearly linear. Access is nearly equally distributed among this subpopulation.

The willingness-weighted measures can also detect a difference in spatial access equity between region 0 and region 2, which have similar population densities. SPALCs and SPALC decile summaries for both regions are shown in Figure 4-16. There are no linear regions in the curves, so Spatial Potential Access inequity is present across all populations.

Figure 4-16: Region 0 and region 2 Logistic SPALCs and SPALC summaries

Heat maps of deviation from proportional access are difficult to interpret for willingness-weighted Spatial Potential Access because people with high and low ability to travel are randomly mixed. However, mapping the people with the lowest access is instructive. About the same fraction of people in both regions have no reachable providers. Region 2 has many more people who have access to a tiny fraction ($\sim 0.01\%$) of total supply as shown in Figure 4-17. (Recall that individuals are indexed on the Spatial Potential Accessibility Lorenz curve by their Spatial Potential Accessibility Score

divided by the total supply in the system, detailed in Section 3.5.) Region 2 has two corridors of low access, in the South-west and the North-central regions. Those regions have a few low capacity providers, but a large number of fellow demanders, taxing that supply. The people with the lowest access in those regions are likely penalized for being near their willingness-to-travel limit, unlike other people needing services in the same region.

Figure 4-17: Maps of region 0 and region 2, with low access agents highlighted. Agents represented by white triangles have no access, while those represented by black triangles have access to $\sim 0.01\%$ of the total provider capacity.

4.5.2 Implications of Exploration of Detecting Regional Differences in Equity using

SPAGI

SPAGI measures can detect differences in Spatial Potential Access equity among regions. SPAGI measures are highly correlated with population density, especially the willingness weighted measures. This means that SPAGI will tend to find that regions

with high populations have more disparity is Spatial Potential Access than regions with low populations. However, SPAGI does not always detect differences where regions have dramatically different population densities (as with regions 8 and 9), and can sometimes detect differences in regions where overall population density is about the same, but the geography is different in character. So, I argue, even though SPAGI tends to track with population density, it does give additional spatial information, and can be a useful addition to a spatial analysis of a region.

E2SFCA and willingness weighted SPAGI measures do not necessarily give the same information about potential access equity. E2SFCA clearly gives information on equity based on location. By adding heterogeneity in ability to travel that is random but partially determined by location type (e.g. remote, rural, high density urban) into the calculation of Spatial Potential Access, access equity comparisons based on the willingness weighted SPAGI point to disparities in access that are not entirely based on location, but on the many factors considered when people state how far they can travel for treatment.

Because of this, heat maps of deviation from proportional access are useful visual aids when analyzing differences in E2SFCA SPAGI, but not necessarily useful when analyzing differences in willingness weighted SPAGI measures. When individuals' Spatial Potential Access scores are weighted by their stated willingness to travel, heat maps do not show a smooth rural to urban equity gradient. Heat maps by Logistic weighted Spatial Potential Access Scores are shown in Figure 4-18. People who are willing and able to

travel long distances live side by side with people who are unable or unwilling to reach many (or any) providers. This is due to a critical assumption, the validity of which I discuss at length in Section 6.4.2. At high population density, people overlap and the visual information conveyed by the heat map becomes muddled.

Figure 4-18: Heat maps generated by individual deviation from equal proportional share of the total capacity in the system as measured by Logistic weighted Spatial Potential Access Scores

4.6 Exploration of Doubling Capacity

Does expanding capacity without adding new supply locations result in changes in Spatial Potential Access Equity? Do SPAGI measures detect differences in Spatial Potential Access equity when the treatment capacity of each provider is doubled? The null hypothesis is that the simulation mean for 35 replications at baseline capacity and double capacity are equal, and was tested using the Welch Confidence Interval Approach.

Results of whether each of the SPAGI measures can detect differences in access equity when doubling the capacity of each provider are presented in Table 4-4. In most cases, no significant difference between baseline and doubled capacity was detected.

4.6.1 Typical Results

It is not surprising that most regions showed no difference in SPAGI measures when doubling capacity. Recall from Figure 3-7, that SPAGI of a system with one provider with capacity 4 and 8 equidistant demanders was equal to the same system when the capacity of the provider was increased four-fold.

Table 4-4: Results modified two-sample-t confidence interval Welch procedure on the difference in mean SPAGI when doubling capacity. Confidence intervals greater than 0 indicate that doubling capacity resulted in lower (more equal) SPAGI. Confidence intervals that span 0 indicate that a difference could not be detected between SPAGI at $\alpha = 0.05$. Significant differences noted in grey.

region	95% Confidence Interval of difference in SPAGI when doubling supply (p-value)				
	2SFCA	E2SFCA	Logistic	Gaussian	Exponential
0	[-0.001, 0.014] (p = 0.104)	[0.0009, 0.041] (p = 0.040)	[-0.001, 0.020] (p = 0.085)	[-0.001, 0.019] (p = 0.087)	[-0.0018, 0.017] (p = 0.109)
1	[-0.026, 0.005] (p = 0.179)	[-0.058, -0.003] (p = 0.026)	[-0.364, 0.005] (p = 0.148)	[-0.036, 0.0047] (p = 0.126)	[-0.039, 0.001] (p = 0.064)
2	[-0.004, 0.007] (p = 0.64)	[-0.01, 0.023] (p = 0.44)	[-0.0057, 0.009] (p = 0.589)	[-0.005, 0.009] (p = 0.60)	[-0.005, 0.009] (p = 0.54)
3	[0.0026, 0.034] (p = 0.023)	[-0.014, 0.045] (p = 0.318)	[0.0039, 0.041] (p = 0.019)	[0.0024, 0.039] (p = 0.027)	[0.0003, 0.035] (p = 0.046)
4	[-0.003, 0.007] (p = 0.48)	[-0.008, 0.02] (p = 0.41)	[-0.004, 0.009] (p = 0.51)	[-0.004, 0.009] (p = 0.509)	[-0.004, 0.009] (p = 0.49)
5	[-0.006, 0.015] (p = 0.42)	[-0.024, 0.024] (p = 0.995)	[-0.008, 0.024] (p = 0.423)	[-0.009, 0.019] (p = 0.47)	[-0.01, 0.017] (p = 0.637)
6	[-0.014, 0.02] (p = 0.605)	[-0.040, 0.010] (p = 0.232)	[-0.016, 0.025] (p = 0.676)	[-0.017, 0.022] (p = 0.810)	[-0.018, 0.021] (p = 0.88)
7	[-0.048, 0.026] (p = 0.558)	[-0.037, 0.022] (p = 0.61)	[-0.042, 0.030] (p = 0.72)	[-0.040, 0.026] (p = 0.68)	[-0.039, 0.019] (p = 0.511)
8	[-0.002, 0.0039] (p = 0.73)	[-0.012, 0.016] (p = 0.812)	[-0.004, 0.005] (p = 0.80)	[-0.004, 0.005] (p = 0.78)	[-0.004, 0.005] (p = 0.81)
9	[-0.004, 0.006] (p = 0.663)	[-0.010, 0.016] (p = 0.702)	[-0.006, 0.010] (p = 0.651)	[-0.006, 0.0092] (p = 0.677)	[-0.006, 0.008] (p = 0.723)

4.6.2 Atypical Results

The particular distribution of supply and demand in regions 0, 1 and 3 resulted in discernable, though small, differences in SPAGI when doubling the treatment supply of all providers. To unpack these differences, I inspected the SPALCs, considered the SPALC deciles, and the relative Spatial Potential Access heat maps for one run at baseline capacity and one run at double capacity, shown in Figure 4-19. In region 0, random allocation of more providers to the small city in the Southeast and doubling the capacity of all providers resulted in a smaller fraction of people in the lowest SPALC decile, more people with near proportional share of the treatment supply over all (broader swath of yellow and green in the urban corridor), and a new region of near proportional access in the Southeast.

On the other hand, in region 1, doubling provider capacity resulted in an *increase* in E2SFCA SPAGI, meaning *less* equitable distribution. Inspection of SPALCs, SPALC deciles, and heat maps for one run at baseline capacity and one run at double capacity show subtle differences. About the same proportion of the population is in the lowest SPALC decile. In the double capacity scenario, a higher proportion of the population is in the second and third access deciles. In both cases SPALCs are near linear thereafter. The heat map shows a much larger yellow region of less than proportional access and a contraction of the green proportional access band to the north of the city center.

In region 3, doubling provider capacity resulted in detectable decreases in all willingness-weighted SPAGI—indicating greater equity. Inspection of SPALCs and SPALC

deciles for a single run at baseline capacity and a single run at double capacity show that the bottom three deciles are essentially unchanged, but that access is more equally distributed among the higher deciles in the double capacity case as shown in Figure 4-20.

a. Region 0 baseline capacity

SPALC decile	Population at decile
1 st decile	30.2%
2 nd decile	12.2%
3 rd decile	10.2%
4 th decile	8.5%
5 th decile	7.3%
6 th decile	6.8%
7 th decile	6.5%
8 th decile	6.3%
9 th decile	6.1%
10 th decile	5.9%

b. Region 0 double capacity

SPALC decile	Population at decile
1 st decile	22.4%
2 nd decile	12.2%
3 rd decile	10.3%
4 th decile	9.5%
5 th decile	8.7%
6 th decile	8.2%
7 th decile	7.8%
8 th decile	7.4%
9 th decile	7.1%
10 th decile	6.7%

Figure 4-20: SPALCs and SPALC decile summaries for region 3 for one run at baseline capacity and double capacity.

4.7 Exploration of High Demand Hotspots

Can SPAGI detect hotspots, small concentrated regions of high demand? I conducted Kruskal-Wallis rank sum tests comparing the three high demand “hotspot” scenarios—rural hotspot, rural low-transportation hotspot, and urban hotspot—in region 0 for each SPAGI measure. The null hypothesis is that medians for 35 replications of baseline, and the “hotspot” scenarios are equal. Rejection of the null hypothesis

means that the SPAGI measure can detect small regions of high demand within a larger region. Scenario details were presented in Section 3.6.1.5. Significant differences in medians were detected by each of the 5 SPAGI measures. For simplicity, I present results of the Dunn pairwise post-hoc tests for comparisons to baseline in Table 4-5, rather than all pairwise comparisons. No difference between the rural hotspot scenario and baseline could be detected by any SPAGI measure. In cases where differences were detected from baseline, SPAGI measures were larger, indicating less equitable access.

Table 4-5: Dunn pairwise comparisons for hotspot scenarios versus baseline. Scenarios where significant differences were detected are highlighted in grey, and differences from baseline were positive—indicating greater inequity in hotspot scenarios.

	mean rank difference (p-value)				
	2SFCA	E2SFCA	Logistic	Gaussian	Exponential
baseline—rural	15.03 (p=0.565)	12.7 (p=0.937)	2.83 (p=2.83)	2.96 (p=1.0)	-1.6 (p=1.0)
baseline— rural-low-transport	41.3 (p=2.5e-5)	16.3 (p=0.410)	31.0 (p=0.003)	32.56 (0.0017)	33.9 (p=0.00096)
baseline—urban	64.3 (p=4.9e-12)	61.0 (p=6.5e-11)	55.36 (p=4.2e-9)	56.2 (p=2.3e-9)	56.1 (p=2.5e-9)

4.7.1 E2SFCA SPAGI Results

E2SFCA could not detect difference between the rural hotspot-low-transport scenario and baseline because E2SFCA does not account for individuals' transport ability. Figure 4-21 shows heat maps, SPALCs and SPALC decile summaries for the urban scenario and baseline as measured by E2SFCA weighted spatial potential access.

Figure 4-21: Baseline (a) and urban hotspot (b) heat maps, SPALCs and SPALC summaries for E2SFCA weighted Spatial Potential Access

Inspecting SPALCs and SPALC decile summaries comparing the urban hotspot scenario and baseline for E2SFCA weighted spatial potential access shows that a greater proportion of the population is in the lowest decile in the urban hotspot scenario. Both curves are approximately linear in the top five deciles. The heat maps show that capacity that was already strained in the baseline scenario, showing less than proportional access (50-90% of equal share) in the southeastern city, which becomes overwhelmed with a demand spike. Competition for strained capacity results in far less than proportional access for the whole southeastern region (25-50% of equal share).

4.7.2 Willingness-weighted SPAGI Results

Figure 4-22 shows heat maps, SPALC and SPALC decile summaries for the four scenarios as measured by Logistic weighted spatial potential access (as there is little difference among the willingness-weighted measures).

Inspection of SPALCs and SPALC decile summaries for the urban hotspot scenario (Figure 4-22d) compared to baseline (Figure 4-22a) in the Logistic weighted Spatial Potential Access analysis, shows that in the urban hotspot case 50% of the population is in the lowest access decile, as compared to 40% in the baseline scenario. This results in a SPAGI score that is twenty percent higher than baseline. The entire southeast quadrant of region 0 has extremely low access. In the baseline scenario, some of the best access occurs in the rural zone between the western urban corridor and the small eastern city. In this zone people who are willing to travel long distances have access to many providers. In the urban hotspot scenario, when supply in the eastern urban region

a. Baseline scenario

gini logisitc
0.4812

SPALC decile	Population at decile
1 st decile	39.8%
2 nd decile	14.9%
3 rd decile	10.3%
4 th decile	8.1%
5 th decile	6.9%
6 th decile	5.8%
7 th decile	4.7%
8 th decile	3.9%
9 th decile	3.1%
10 th decile	2.4%

b. Rural hotspot (marked red)

gini logisitc
0.513

SPALC decile	Population at decile
1 st decile	42.3%
2 nd decile	15.2%
3 rd decile	10.8%
4 th decile	7.9%
5 th decile	6.1%
6 th decile	4.9%
7 th decile	4.1%
8 th decile	3.5%
9 th decile	2.9%
10 th decile	2.4%

Figure 4-22: Baseline (a), rural hotspot (b), rural hotspot low transport (c) and urban hotspot (d) heat maps, SPALCs and SPALC summaries. Hotspot regions are marked by a red square. No significant difference was detected between baseline (a) and rural hotspot (b) scenarios. Differences in SPAGI between the rural hotspot scenario (b) and rural hotspot low-transport (c) and urban hotspot (d) were significant at $p < 0.05$, Dunn pairwise comparisons not shown.

is overwhelmed by high demand, rural residents who are willing to travel far have less choice. So a spike in urban demand has implications for people who live in the surrounding rural regions.

Inspection of SPALCs and SPALC decile summaries for the rural hotspot scenario when residents are unable to travel long distances, shows small increase in the proportions of the population in the lowest three deciles. The increase in the lowest decile is much smaller than in the urban hotspot case because the hotspot population is one quarter the size. The heat map shows that in the rural low-transportation hotspot case, people in the eastern two thirds of the hotspot region can't reach any providers because there are no providers in the community. Those in the eastern third of the hotspot region can reach providers located in the suburbs of the urban corridor, but because those providers are outside the community, they are likely highly discounted by the distance decay function. Furthermore, all of the people in the hotspot are competing for the same treatment spots, driving each provider's supply to demand ratio down.

Because no significant difference was detected between the rural hotspot scenario and baseline, I am not comparing SPALCs, but the heat map is still interesting (Figure 4-22b). Even though there is a greater density of demanders in the hotspot region, the mix of greater than proportional and lower than proportional access appears to be about the same as in other rural zones about the same distance from dense urban centers. There may be strain on small local providers, but it can't be detected as a difference in the aggregated SPAGI.

4.7.3 Implications of High Demand Hotspot analysis

In general E2SFCA SPAGI cannot detect changes in region-wide Spatial Potential Access equity of a rural hotspot. The willingness weighted measures can detect changes in Spatial Potential Access equity when the people in the rural hotspot are unable to travel above 30 miles for treatment. This means that SPAGI may not detect spatial potential access equity in real regions where heavy rural demand is a known issue.

All measures did detect differences in region-wide Spatial Potential Access equity with an urban demand spike. The willingness weighted SPAGI showed that local strain on supply caused by a hotspot can have implications for the broader community. This is because competition for supply is a factor in Spatial Potential Access calculations. Overstrained providers are technically reachable, but far less desirable than providers with less competition. So local strain is felt as a diminution in choice by people outside the hotspot region.

4.8 Exploration of Supply Shocks

Can SPAGI detect the removal of particular providers? Specifically, can differences in median values of the five SPAGI measures be detected with the removal of up to 5 of the highest capacity providers, and up to 5 of the most remote providers? Rejection of the null hypothesis means that removing some providers does have implications for Spatial Potential Access equity in a region. Rather than report on all fifty analyses (ten regions, 5 measures) for both sets of experiments, I will report only

those cases where differences in SPAGI medians were detected by Kruskal-Wallis rank sum tests.

4.8.1 High Capacity Provider Closures

Differences were detected by rank sum tests in Regions 1, 3, 5, and 6, as shown in Table 4-6. Some differences detected by Kruskal-Wallis rank sum tests could not appear as detectable differences in the conservative post hoc tests. Dunn pairwise tests failed to show pairwise differences at $p < 0.05$ in Region 3 by 2SFCA weight, or Region 5 by Exponential weight (lighter grey highlighting).

Table 4-6: Kruskal-Wallis rank sum test results for Regions 1, 3, 5, and 6. Results significant at $p < 0.05$ are highlighted in grey.

	Kruskal-Wallis chi-squared (p-value)				
	2SFCA	E2SFCA	Logistic	Gaussian	Exponential
Region 1	7.78 (p=0.162)	5.12 (p=0.400)	15.22 (p=0.009)	13.80 (p=0.016)	14.78 (p=0.011)
Region 3	11.41 (p=0.043)	16.72 (p=0.005)	16.77 (p=0.005)	15.76 (p=0.0075)	18.59 (p=0.002)
Region 5	3.19 (p=0.669)	12.62 (p=0.027)	8.296 (p=0.140)	8.49 (p=0.131)	14.29 (p=0.013)
Region 6	18.55 (p=0.002)	16.61 (p=0.0052)	17.25 (p=0.004)	18.26 (p=0.0026)	16.70 (p=0.005)

4.8.1.1 Typical Results

In six of ten regions, removing up to 5 high capacity providers did not result in detectable differences in Spatial Potential Access equity across the whole region by any SPAGI measure.

4.8.1.2 Atypical Willingness Weighted Results

Because the willingness-weighted measures showed similar pairwise differences, I am electing to analyze the Gaussian weighted results, commenting how results differ for the other measures. Figure 4-23 shows boxplots of Gaussian weighted SPAGI for regions 1, 3, and 6, and the caption notes pairwise difference results of Dunn's post hoc tests.

Figure 4-23: Boxplots for Gaussian SPAGI measures for regions 1, 3, and 6.

To dig deeper into these counter-intuitive results, I inspected Gaussian weighted SPALCs and SPALC deciles and heat maps for Region 6 and compared baseline and the 'closure of 4 providers' scenarios (showing one run of each in Figure 4-24). In the baseline scenario, there were 71 providers and the mean treatment capacity was 56.35 patients per provider. In the closure scenario, there were 67 providers and mean treatment capacity was 38 patients per provider. In the closure scenario, there were fewer treatment spots in the whole system, but the spatial allocation of this supply was more equitable as measured over 35 replications at each closure level.

Figure 4-24: Region 6 heat maps (left), SPALCs (center), and SPALC decile summaries (right). Maps and plots show one possible allocation of providers and demanders each.

In these particular allocations of supply and demand, a concentration of providers in the small city in the northeast in baseline afforded people in that region a disproportionate share of potential access. Region 6 has many small cities surrounded by rural areas; (refer to Figure 4-1 for a population density map). In regions with small high density towns, equality of access is sensitive to the particular allocation of high capacity providers. If a few high capacity providers locate in a small city, access for that fairly small population is much greater than proportional—as in the northeast in Figure 4-24a. It also means that access for some other small, dense community is going to be disproportionately low if it has few low capacity providers or none, since Gini-style indices are essentially zero sum. See, for example, the city in the north central region, in which people have much lower than proportional access. If one population gets disproportionately more than its fair share, some other population gets disproportionately less. Allocating fewer providers with lower capacity means that it is less likely any particular allocation of providers results in a super high capacity blip. Regions 1, 3, and 5 have similar geography to region 6, with tiny dense regions dotting the map, which may explain why differences were detected in these regions and not in others.

4.8.2 Remote Provider Closures

Kruskall-Wallis rank sum tests only showed differences from baseline in Region 7, the region with the lowest population by far, and then only with 2SFCA, E2SFCA and Exponential weighted SPAGI. Dunn post hoc tests showed significant differences from

baseline when the 5 most remote providers were removed from the region, at $p < 0.05$.

Figure 4-25 shows boxplots of Region 7 2SFCA, E2SFCA and Exponential weighted SPAGI when 0-5 remote providers are removed from the simulation. Differences are small because remote providers tend to have low numbers, and most people in this rural region are willing to travel to the urban center.

Figure 4-25: Region 7 boxplots showing SPAGI when 0 to 5 of the remotest providers are removed from the simulation. Differences are detectable when 5 providers are removed, but the differences are small.

4.8.3 Implications of Supply Shock Exploration

In general, SPAGI cannot detect region-wide equity implications of removals of individual providers. This is likely because there is considerable run-to-run variation in the actual locations of providers which makes it difficult to detect that a few providers are missing. In regions with a dense urban center or two, highest capacity providers are in high provider-density regions. So when total supply goes down, the overall spread remains about the same because people in dense urban zones can reach a large number of providers.

The fact that in regions dotted with small cities removing the highest capacity providers can result in more equitable access has an important implication to consider. There are ways to increase equity which may not be desirable or particularly fair. Removing a provider from a small city because people in that city have it too good when considering equity in broader defies a commonsense notion of fairness. The broader implication is this: equity shouldn't be the only criterion of goodness when allocating scarce supply to meet demand.

4.9 Reflections on Exploring SPAGI in Idealized Test Cases

To answer research question 1—What functional form should an aggregated individual-level access inequality metric have for it to be sensitive enough to detect differences in access equity in different regions and/or due to different policy choices?—I generated individual Spatial Potential Access Scores using gravity model of spatial potential access with 5 different weighting schemes (specifically, by using the weighted 2 Step Floating Catchment Area method). I aggregated these individual Spatial Potential Access Scores into a Spatial Potential Access Lorenz Curve (SPALC) for a given region. I then further condensed the information captured in the Lorenz curve into a single index, the Spatial Potential Access Gini Index (SPAGI). I then tested differences in SPAGI across a wide variety of idealized test scenarios using simple statistical tests of differences in medians. If statistical tests showed a difference in medians across several simulation replications, I disaggregated the measure to understand the possible reasons behind the difference.

Research question 1 is exploratory, and its answer requires quantitative analysis and argumentation. For this, I break the question into the following parts:

- Is SPAGI useful and what information does SPAGI provide?
- What does it mean when SPAGI is higher or lower in the context of an experiment?
- How are the five weighting schemes different, which should be used for an experiment?
- What is a good analytic strategy for integrating spatial potential access analysis into the current simulation study?

4.9.1 Is SPAGI useful?

The aggregation of individual level Spatial Potential Access Scores using the Lorenz Curve and Gini Coefficient calculations results in an index that can summarize the distribution of Spatial Potential Access within a region. The index is not particularly informative on its own, but can be used along with simple statistical tests to discern differences in the equitability of access distribution due to spatial allocation of supply and demand (as shown by the allocation experiments in Section 4.3), regional differences (as shown in Section 4.5), spikes in demand (as shown in Section 4.7) and shocks to supply (as shown in Section 4.8). It does not provide information on the adequacy of supply to meet demand (as shown in Section 4.8.1.2). It also tends not to be able to detect differences at the regional level (150x150 square mile) of the removal of a small number of individual providers (as shown in Section 4.8.2). This may also be

an artifact of simulation, in which simulation-to-simulation variability masks small regional effects that could be detected if SPAGI were used for empirical analysis.

These comparisons of Spatial Potential Access in simulations would be difficult without aggregating the diffuse, individual-level access scores. Simulations that include random inputs have random outputs, and comparisons across simulation scenarios requires multiple runs of each. This precludes side-by-side visual comparison of heat maps because of run-to-run variability. SPAGI is one way of aggregating and comparing spatial potential access and its response to policy.

4.9.2 What does it mean when SPAGI is higher or lower in the context of an experiment?

Sometimes interpreting differences in SPAGI is difficult. SPAGI can get worse when overall capacity in the system gets better, (as shown when total capacity doubled in Region 1 in Section 4.6), or better when overall capacity in the system gets worse (as shown with high capacity provider closures in Region 6 in Section 4.8.1.2). When SPAGI is better, Spatial Potential Access is more equitably distributed; each person has closer to his or her proportional share of the supply in the system, considering all the factors that go into calculating that person's spatial potential access score: how close he or she is to providers, the capacity of those providers, the other demand on those providers, and in some calculations, how far he or she is able to go to reach providers.

If the people were the same from one simulation to the next, improvement in SPAGI from one scenario to the next would mean that some people who had greater than their proportional share of access to supply in the system would have less in the new scenario. Colloquially, there is no way for everyone to be above average. Since the simulated people are not the same from one simulation to the next, improvement of SPAGI from one scenario to the next means that the proportion of the people who have less than their proportional share decreases, and the people with the best access have a smaller piece of the total. This is easier to see in the context of wealth disparity. “The poorest 50% have 10% of the total wealth” is clearly worse than “the poorest 50% have 40% of the total wealth.” “The richest 5% have 20%” of the total wealth is less equal than the richest “5% have 10% of the wealth.”

In the access to treatment context, if 50% of the population with the lowest Spatial Potential Access scores are in the lowest access decile, it means that the “access-poorest” 50% has access to just 10% of the total supply in the system. And when 1.5% of the population is in the highest access decile means that the “access-richest” 1.5% has access to 10% of the total supply in the system.

4.9.3 How are the five weighting schemes different and which should be used in the context of an experiment?

The five weighting schemes for calculating individual Spatial Potential Access scores are of two types: those that are based on how far an individual is willing to travel, and one that is strictly based on distance. The four willingness-based weights:

dichotomous (2SFCA), Logistic, Gaussian, and Exponential, appear to be equally sensitive and give similar results in most experiments. I would recommend the dichotomous weighted measure for experiments in mostly urban regions, and any single continuous measure for more rural, or rural/urban mixed regions. But I would not recommend using more than one willingness-based measure in one experiment, as an additional measure does not seem to give more information.

The dichotomous measure assumes that all providers within a persons' stated travel range are equally accessible. People in the densest population areas tended to pick the smallest search radii possible, five or ten miles. Continuous weighting results in heavy discounting of providers that are within two or three miles, which may not be reasonable. On the other hand, dichotomous weighting may be problematic in rural or mixed urban/rural areas, because the assumption that a provider that is 100 miles away affords the same treatment access as a provider that is 10 miles away may be untenable.

The E2SFCA measure is not based on travel preference, and doesn't provide the same information as the other measures. Median SPAGI values are incomparable to the other SPAGI values, as shown in Section 4.2. Differences in SPAGI may be detected by E2SFCA and not by the willingness-weighted measures, vice versa, or the differences detected by each type of measure may be of opposite sign, as shown in Section 4.5, Table 4-3.

Spatial Potential Access as measured by E2SFCA removes individual heterogeneity and provides more general information about residents of a region. Because it gives different, and sometimes clearer information than the preference-weighted measures, I recommend including one willingness-weighted measure along with E2SFCA in a Spatial Potential Access analysis.

4.9.4 What is a good analytic strategy for integrating Spatial Potential Access analysis into the current simulation study?

In order to answer research questions 3 and 4 in Chapter 5, I integrated Spatial Potential Access analysis into policy analysis that also measured treatment utilization, medication diversion, and opioid overdose deaths. Spatial Potential Access analysis complements but does not replace the direct analysis of utilization, a possible side effects and outcomes. This is because SPAGI and SPALCs only provide information on the distribution of access, not whether access is adequate to meet need, or if any of the treatment capacity is used.

To integrate SPAGI and SPALCs into the policy analysis, simulations were run 35 times at each policy level, and Logistic SPAGI and E2SFCA SPAGI calculated for each set of simulation runs. Differences in SPAGI at different policy levels were tested with Kruskal-Wallis rank sum tests and Dunn pairwise post hoc tests. When pairwise differences from baseline were detected, I inspected SPALCs, SPALC decile summaries, and heat maps for one baseline simulation run and one policy simulation run to get a better understanding of what lay behind the statistically significant differences. Because

there can be considerable run-to-run variation, for this stage of the analysis, I chose runs whose SPAGI values lay near the median SPAGI for 35 runs for both the baseline simulation run and the policy simulation run.

Aggregating individual-level spatial potential access information into a curve, and further into a single index allows for policy impact comparisons using simple statistical tests. Disaggregating from the index to the curve to the individual-level potential access information allows examination and understanding of the spatial supply and demand factors that generated the difference at the highest aggregation level. This analysis of the disaggregated information is important, but not statistically rigorous. Comparing single runs of simulations with random inputs always risks that the particular runs compared are not representative. Generation of statistical tests at lower levels of aggregation of spatial potential access information is a direction for future research.

In summary, the answer to Research Question 1—What functional form should an aggregated individual-level access inequality metric have for it to be sensitive enough to detect differences in access equity in different regions and/or due to different policy choices?—is as follows:

The Spatial Potential Access Gini Index is an aggregated individual-level access inequality metric that can detect differences in access equity in different regions and due to different policy choices that effect total supply, total demand, or the spatial allocation of supply or demand within a given region. The Spatial Potential Access Gini

Index is generated by the two-step floating catchment area method of calculating spatial potential access scores, as detailed in Section 3.5, using either a willingness-to-travel based weighting scheme, or a weighting scheme based on Euclidean distance, as detailed in Section 3.5.1. It is then aggregated by generating a Spatial Potential Access Lorenz Curve and Spatial Potential Access Gini Index, as detailed in Section 3.5. Both a willingness-weighted Index and a Euclidean distance weighted Index should be generated because they convey complementary information about access equity in a region.

5 Policy Analysis Results

In Chapter 5, I present the results of policy analysis addressing research questions two, three, and four with little commentary. Research Question 2 establishes the baseline scenario including SPAGI measures, and Research Question 3 and 4 analyze specific policies to increase buprenorphine access and access equity through supply expansion. Discussion of policy analysis results follows in Chapter 6.

5.1 Model Baseline including Logistic and E2SFCA SPAGI

Descriptive statistics for the baseline simulation region are presented in Table 4-1 (Region 0). I initialized the 35 baseline simulation runs using the Initialization data detailed in Section 3.3.1, and the model was run with input data detailed in Section 3.3.2, and the specific input and policy parameter settings detailed in Table 5-1. The

Table 5-1: Parameter settings for input and policy variables for baseline model simulation

parameter	value
High waiver patient limit weeks 1-26	100 people/provider
High waiver patient limit weeks 27-52	275 people/provider
Opioid Overdose Crude Mortality Rate	12/1000 person-years
Percentage NPs, PAs prescribing buprenorphine	0%
Percentage of providers accepting Medicaid	59%
Percentage of uninsured with Medicaid	0%

patient limit for providers with the high waiver was raised from 100 to 275 in week 26

because the regulation raising the patient limit went into effect in mid-2016.

All model outputs, including SPAGI measures, were calculated at year end. As reported in Section 3.3.3, unique BUP recipients was adjusted to the model population:

total unique BUP recipients/ model population * 1000,000. Milligrams diverted BUP and Opioid overdose deaths are year-end model totals for the studied region. Means and 95% confidence intervals are presented in Table 5-2.

Table 5-2: Model outcome variables for 35 baseline model simulations.

Outcome variable measured year end 2016	Mean [95% CI]	Scaled nationally Mean [95% CI]
Population Adjusted unique BUP recipients	469.72 [465.29, 474.15] people/100,000 population	1,516,000 [1,504,000; 1,529,000]
Milligrams diverted BUP	8580 [8373, 8787] mg	--
Opioid overdose deaths	283 [277, 290] people	34673 [33949, 35397]
E2SFCA SPAGI	0.31 [0.30, 0.32] dmnl	--
Logistic SPAGI	0.54 [0.53, 0.55] dmnl	--

Answering Research Question 2—How equitably distributed is access to OB

buprenorphine treatment in the current OB buprenorphine treatment system given: regulatory caps on patient numbers, physician preferences, and geographic distribution of treatment seekers and providers?—provides a baseline against which to compare supply expansion policies. As discussed in Section 4.9.1 (Is SPAGI useful?), SPAGI measures are not very informative on their own. However, in the context of the explorations conducted in Chapter 4, SPAGI results indicate that there is substantial inequity in spatial potential access in this region.

5.2 Patient Limit Change Policy Analyses

Results of the analysis to address Research Question 3—To what extent would changing the current DATA 2000 patient limit per provider change utilization of buprenorphine, spatial access equity, opioid overdose deaths and medication

diversion?—follow. Details of the experiment setup are presented in Section 3.7.2. For this analysis, I set the patient limit to 100 (for the entire year, in contrast to the baseline scenario presented in Section 4.3), 275, 500, and 4000. Because the purpose of the analysis is to test the impact of *changing* policy, the 275 person patient limit is taken to be the status quo, and the 100 patient limit the implementation of a policy roll-back to a more restrictive limit level. Boxplots of outcome variables and post hoc pairwise comparisons against the status quo when significant differences were detected are presented in Figure 5-1. The Cohen's d effect size was medium for the change in unique buprenorphine recipients ($d = -0.695$). To summarize results: the policy rollback to a 100 patient limit resulted in a small but significant decrease in utilization, but no detectable changes in opioid overdose deaths, medication diversion, or spatial potential access equity.

Figure 5-1: Boxplots (left) and statistical tests (right) for the patient limit policy

5.3 NP PA Buprenorphine Adoption Policy Analysis

Results of the analysis to address Research Question 4—To what extent would various levels of buprenorphine prescribing adoption by Nurse Practitioners and Physician Assistants change utilization of buprenorphine, equality of access, opioid overdose deaths, and medication diversion?—follow. For this analysis, I allowed the patient limit to rise to 275 for providers who qualified for a high waiver in week 26 of the simulation, because this reflected the actual policy in place at the time. So the NP PA 0% prescribing level is equivalent to the baseline scenario presented in Section 5.1. Significant differences were detected at all NP PA adoption levels for the number of unique buprenorphine recipients, above 10% adoption for E2SFCA SPAGI, and above 20%for logistic SPAGI. No differences were detected in diversion and opioid overdose deaths at any policy level. Boxplots, tests for differences in medians or means, and post hoc pairwise tests are presented in Figure 5-2. Unlike the patient limit policy, the SPAGI measures improved (decreased) at higher levels of NP PA adoption, as shown in 5-2d and 5-2e. Cohen's d calculations for the smallest detectable difference indicate

Figure 5-2: Boxplots (left) and statistical tests (right) for the NP PA prescribing adoption policy

that all effect sizes are large: unique recipients 5% vs 0, $d = -0.84$; E2SFCA SPAGI 10% vs 0, $d = 3.65$; Logistic SPAGI 20% vs 0, $d = 0.987$.

To summarize the results of the NP PA buprenorphine expansion policy:

Adoption of buprenorphine prescribing by NPs and PAs resulted in increases in utilization at all levels of adoption (5%, 10%, 20% and 30%) and in improvements in Spatial Potential Access equity at high levels of adoption (20%, 30%). Medication diversion and opioid overdose deaths were not affected by this treatment supply expansion policy.

6 Discussion

The implications of individual exploration experiments to address Research Question 1 were presented alongside each exploration in Sections 4.3 through 4.8. Section 4.9 closed with a discussion of how to interpret differences in SPAGI and how to use SPAGI in policy analysis. This Chapter begins with a discussion of the results of policy analysis experiments presented in Chapter 5 in Sections 6.1 through 6.3, presents limitations in Section 6.4, areas for future research in Section 6.5, implications for research in Section 6.6, implications for substance abuse treatment research practice in Section 6.7, and closes with a brief conclusion in Section 6.8.

6.1 How equitable is the spatial distribution of treatment supply (RQ2)

In the simulated area, a mixed rural-urban 225,000 square mile region of the country with providers and people with OUD sited in accordance with national trends, two measures of Spatial Potential Access equity—the E2SFCA weighted Spatial Potential Access Gini Index and the Logistic willingness-to-travel weighted Spatial Potential Access Gini Index—give different information about the how equitably distributed OB buprenorphine access is in the current treatment system.

6.1.1 E2SFCA weighted SPAGI discussion

E2SFCA takes into account 1.) provider locations, 2.) the number of people those providers are willing to treat given personal preference and patient limits, 3.) the locations of people with OUD, and 4.) competition for the scarce provider resource, but *not* the willingness or ability of people to travel. Providers within 10 miles are

considered 100% accessible, providers between 10 and 30 miles are 60% accessible, providers between 30 and 60 miles are 12.3% accessible.

The E2SFCA SPAGI for the region at the end of 2016 after the patient limit rose to 275 is 0.31 (95% CI is [0.30, 0.32]). This is higher than the median E2SFCA SPAGI (0.29, IQR 0.079) for all regions explored in this study, as shown in Table 4-2. Like the Gini Index for wealth or income, the Index on its own is only useful for comparison. To understand how access is apportioned, I examined the heat map of deviation from proportional access, Spatial Potential Access Lorenz Curve (SPALC), and SPALC decile summary, shown in Figure 6-1a.

The heat map shows that almost no people with OUD in the region have 0 access, but the SPALC decile summary shows that in this model run about 32% of the population is in the lowest access decile and 44% of the population is in the lowest 20% access decile. E2SFCA weighted Spatial Potential Access considers both distance effects and competition for scarce supply. The heat map shows that in this region with this particular allocation of providers, the source of inequity for the worst off appears to be due to distance decay and demand competition for limited rural provider spots in the northeast, the west coast, and the southwest corner of the region. Heavy demand on providers at the southern tip of the western urban corridor and outside of two pockets in the southeastern city mean that people there have less than proportional demand even though there are providers near by.

a. E2SFCA Heat map, SPALC and SPALC decile summary

b. Logistic Heat map, SPALC and SPALC decile summary

Figure 6-1: One simulation run of the baseline region after one modeled year.

Similarly, people with access to 25% to 50% of their proportional share of supply (brown) and 50-90% of their proportional share of supply (yellow) are distributed in all types of communities. The lowest decile of access includes people in the red (12%), orange (13%), brown (11%), and yellow (24%) groups.

Far fewer people have near their fair share or greater than their proportional share of access to supply. People on the periphery do not have near equal or greater than proportional access to the supply in the region. This is likely due to edge effects because providers outside the 150x150 mile region aren't represented. People with the most choice of providers and greatest access to treatment spots are either those who live in rural regions around the urban corridor but can travel far and can reach almost all providers in the urban corridor, or those who live closer to the densest urban center in the north and can reach all providers in that city.

People in the periphery of southeastern city (but not the suburbs) have about their proportional share of total supply. And in the densest population center in the North, people have better than their proportional share of the total supply in the region. Here people have about 50% more than their proportional share. If the total supply in the system were known to be adequate to meet demand, this would suggest oversupply of treatment providers in that region. However, this is a problematic interpretation. One cannot infer adequacy of treatment supply in a region (or a sub-region, such as the city in the southeast) based how close to an equal proportional share of the supply people in the region can access. The people in the western central region appear to

have more choice and less competition for treatment spots than people elsewhere, even though the population of demanders is dense.

This interpretation is just *one possible* allocation of treatment supply and demand in this region. Close examination of heat maps and SPALCs can give a feel for the supply and demand pressures in a simulated region, but policy analysis using simulation requires comparison of E2SFCA SPAGI over several simulations to discriminate between policy effects and run-to-run variation.

6.1.2 Logistic Willingness Weighted SPAGI Discussion

Logistic willingness-to-travel weighted SPAGI tells a more complex story because it incorporates how far people are willing to travel into the individual Potential Spatial Access scores. Using the Logistic willingness-to-travel weighting scheme means that providers closer than $1/6 * \text{stated willing-to-travel distance}$ are 100% accessible, about $1/3 * \text{willing-to-travel distance}$ are ~95% accessible, $2/3 * \text{willing-to-travel distance}$ are ~50% accessible, and exactly at willing-to-travel distance is about 10% accessible, refer to Section 3.5.1.2 for the mathematical formulation. This means for many people in densely populated regions, a provider must be within about 3 miles to be 100% accessible, since many people in the model cities are willing to travel 10 miles for treatment. It also means that many people in cities find providers greater than 10 miles away completely inaccessible.

Logistic SPAGI for the study region at the end of 2016 after the patient limit rose to 275 is 0.54 (95% CI is [0.53, 0.55]). This is higher than the median (0.512, IQR 0.124) for Logistic SPAGI for all regions explored in this study shown in Section 4.2. Again, like other Gini Indices, Logistic SPAGI is primarily used for comparison and gives little information on its own. Again, I examined a heat map of deviation from proportional access, the SPALC, and SPALC decile summary for one simulation replication, shown in Figure 6-1b. The same simulation run was used to generate the E2SFCA heat map discussed above. Providers and people with OUD are located in the same places; all that has changed is the weighting term in the Spatial Potential Access Score calculations.

The SPALC has a near zero slope near the origin, and 47% of the population is in the lowest access decile. 60% of the population has access to 20% of the supply in the system, taking into account weighting and preference. Because two people occupying the same square mile of the model can have completely different travel preferences, their Spatial Potential Access scores can be different. The heat map becomes too crowded in urban areas for easy interpretation. To aid interpretation, I generated Figure 6-2, in which each heat map color is shown separately.

People with zero access (red) tend to live in rural areas outside the large city centers. However, people with non-zero access scores under a quarter of what would be their proportional share (orange) are present in every community. The lion's share of these people with poor access are in the dense urban region in the north, where there is high demand and low willingness to travel, and a large population.

Figure 6-2: Heat map of deviation from proportional access in Spatial Potential Access Scores with colors separated out.

Similarly, people with access to 25% to 50% of their proportional share of supply (brown) and 50-90% of their proportional share of supply (yellow) are distributed in all types of communities. The lowest decile of access includes people in the red (12%), orange (13%), brown (11%), and yellow (24%) groups.

Far fewer people have near their fair share or greater than their proportional share of access to supply. People on the periphery do not have near equal or greater than proportional access to the supply in the region. This is likely due to edge effects because providers outside the 150x150 mile region aren't represented. People with the most choice of providers and greatest access to treatment spots are either those who live in rural regions around the urban corridor but can travel far and can reach almost all providers in the urban corridor, or those who live closer to the densest urban center in the north and can reach all providers in that city.

6.1.3 Summary Regarding Baseline Spatial Potential Access Equity (RQ2)

The Spatial Potential Access Gini Indices, Spatial Potential Access Lorenz Curves and heat maps indicate that treatment access is not equitably distributed in the current treatment system. If ability to travel is not considered, there seems to be relative oversupply in dense urban zones and undersupply in rural zones, some small cities and exurbs. When ability to travel is considered, the situation is more complicated. People with the best access live alongside people with the worst access, in all community types—rural, urban, center city, suburban, exurban zones. Some of this may reflect reality, as people with high incomes and means to travel may live very close to people of

very limited means. This makes it difficult to devise strategies to reduce inequality of access. Increasing the number of urban providers in the dense city center would certainly improve access for people with limited ability to travel located near the city center, but it would also improve access for the people who already have more than their proportional share. SPAGI scores could go up, down or remain the same by increasing supply in these zones.

However, it's important to remember that the random collocation of people with high and low ability to travel is due to simplifying model assumptions. The model does not specify affluent or impoverished neighborhoods. If it did, the apparent random mixing might be replaced by clear pockets of high demand with low ability to travel as in the hot-spot exploration experiments in Section 4.7, and strategies to target people living in specific small areas could emerge.

6.2 Discussion of Results for the Patient Limit Policy (RQ3)

As shown in Section 5.2, under model assumptions of individual provider preferences for patient loads, a roll back to 100 patient per provider resulted in a 5% decrease in the number of unique buprenorphine recipients in the model year. Further expansion of the patient limit did not result in statistically detectable differences in utilization. There were no differences detected in medication diversion, opioid overdose deaths among, or SPAGI measures at any of the patient limit levels.

6.2.1 Patient Limit and Buprenorphine Utilization

To generate an individual provider's personal patient preference level, a provider agent generates a random variable from a random distribution based on provider type. A provider's capacity may then be truncated at the patient limit, if the limit is lower than the preferred patient number. To understand the relative impact of patient limits and provider preference on total OB BUP utilization, I compared the population sizes of two types of providers: those whose patient census counts are within 10% of the patient limit, those whose patient census counts are within 10% of their preference level. Results of 35 replications at each patient limit level are shown in Table 6-1. Preferences are unchanged for each simulation run, so 95% confidence intervals for the number of providers near maximum preferred capacity are pooled from all 140 runs.

Table 6-1: Number and percentage of providers within 90% of either their personal maximum patient levels or the regulatory patient limit.

	Number providers $\geq$ 90% capacity [95% CI]	Percent providers $\geq$ 90% capacity [95% CI]
Preferred (unlimited) capacity	70.36 [68.73; 71.98]	27% [26%; 28%]
Capacity given limits		
100	17.43 [16.42; 18.44]	7% [6%; 7%]
275	0.4 [0.23; 0.57]	0%
500	0.03 [-0.03; 0.09]	0%
4000	0.00 [0.00; 0.00]	0%

At each patient limit level, about 27% of providers are treating about their maximum preferred level of patients. For some providers this number may be zero. When the patient limit is 275 only one provider is treating up to the 275 limit in about

40% of the replications. When the patient limit is 500, this drops to 1 provider in only 1 of the simulation runs. At 4000, no providers are near the patient limit.

This explains why the number of unique buprenorphine recipients dropped when the patient limit policy was dropped to 100, but remained unchanged when patient limits were further relaxed. At higher patient limit levels, the patient limit is not meaningfully constraining utilization. This is despite the fact that patient limits are lower than the number of patients some providers are willing to treat at all limit levels, as shown in Table 6-2.

Table 6-2: Total and mean unconstrained capacity, and capacity given patient limits.

	Total treatment spots Mean 100 replications [95% CI]	Mean treatment spots Mean 100 replications [95% CI]
Preferred (unlimited) capacity	26,900 [26,300; 27,600]	105 [103; 108]
Capacity given limits		
100	10,200 [10,100; 10,300]	40 [39; 40]
275	17,300 [17,000; 17,600]	67 [66, 69]
500	21,700 [21,200, 22,100]	84 [83, 86]
4000	23,700 [23,200; 24,300]	93 [91; 95]

This is likely due to simplifying assumptions about how patients select providers. Patients simply choose providers that are close, who accept the right insurance, starting with providers on who are on the SAMHSA online provider list. Advertising, word of mouth, or reputation effects are absent from the model. Word of mouth and positive reputation are known positive reinforcement effects that could drive potential patients to high capacity providers who already have a lot of patients. This provider selection effect was highlighted in the face validity interview with Dr. O'Connor. It is possible that

more providers would be closer to the regulatory limits if the model included these kinds of effects.

Though Cohen's d suggests that the effect size of rolling back to a 100 patient limit is medium, a 5% effect seems small, given the 40% reduction in capacity given patient limit shown in Table 6-2. The patient limit was raised in 2016, and many providers did elect to apply for the 275 waiver. Theoretical capacity (patient limit x number of providers) nearly doubled from 2015 to 2016 as shown in Figure 2-3. If there were a large reservoir of providers "capped out" at the 100 patient limit, the number of unique buprenorphine recipients should have jumped from 2015 to 2016. Estimates of unique buprenorphine recipients in 2016 were roughly the same as the number of unique providers in 2015. Analysis conducted by Indivior, the maker of Suboxone estimated 1,387,815 total buprenorphine recipients in 2015 and 1,380,616 recipients in 2016. The data seem to support the finding of a modest change in utilization despite a much larger change in capacity. The model may be showing a small effect where none was seen in the data because in the model the limit levels persisted for the whole year, without any adoption implementation phase, or practice change rollout among providers.

Even at the 100 patient limit, only 17% of simulation providers were at or near the patient limit, while 27% of providers were up against their personal practice limits. This is consistent with literature on barriers to buprenorphine adoption and utilization, in which many providers list other barriers as equally or more important in their decisions around buprenorphine use (see for example Hutchinson, Catlin, Andrilla, Baldwin, &

Rosenblatt, 2014). In the simulation these barriers are not modeled explicitly, but are assumed to be latent factors that drive preferences for patient loads.

6.2.2 Patient Limit and Opioid Overdose Deaths

It is not surprising, though distressing, that changes in buprenorphine utilization due to patient limit changes do not appear to result in changes in opioid overdose deaths. This is consistent with the sensitivity analysis (Section 3.4.4.1) which showed that only changes in the opioid overdose crude mortality rate resulted in changes in the number of opioid overdose deaths. Again, this is due to model assumptions. Opioid use disorder incidence is held to a constant rate, as is the rate of treatment seeking.

Changes in policy alter how many people who seek treatment actually get treatment, not the total number of people who seek treatment. Modeled changes in policy effect only about 10% of the population with OUD, the 10% seeking but not yet receiving treatment. Even if all of these people seeking treatment got treatment, the number of overdoses avoided would be small. Further, people who seek treatment may self-treat with buprenorphine, reducing their risk of overdose death. Transitioning these people from informal self-treatment to formal treatment might not result in much change in modeled overdoses.

For policies to affect the number of opioid overdose deaths, they would have to impact the 70% of the model population at highest overdose risk—those who are not interested in treatment. Sensitivity analysis showed that a 30% change in the incidence of treatment seeking (from 10% to 13%) was not enough to see significant changes in

overdose deaths. In fact, the only parameter that impacted overdose deaths was the opioid overdose crude mortality rate. Increasing the mortality rate directly, due to the influx of potent opioids such as fentanyl, or because of random fluctuations in heroin purity, results in more deaths. Decreasing the mortality rate directly, through such strategies as increased adoption naloxone for overdose reversal, results in fewer deaths.

6.2.3 Patient Limit and Diversion

In the analysis of changes in the level of diversion with changes in the patient limit I could not reject the null hypothesis that the mean diversion levels were all equal. This is not surprising, given model assumptions. The people who sell or give away their medication are a fraction of those who are in treatment who need money. Utilization was about the same at three of the four patient limit levels. At the lowest patient limit level, utilization was only 5% lower, which means the fraction of people who divert buprenorphine would have gone down by perhaps 2%. Diversion model logic involves a lot of random processes, a small reduction in the population of people diverting would likely be obscured by random variation in the model.

Sensitivity analysis in Section 3.4.4.1 suggests that policies which impact treatment cost and the number of people in treatment are likely to impact diversion, if model assumptions regarding the reasons for diversion are valid. The patient limit policy only affects the number of people in treatment, but not to a large enough degree to see changes in diversion supply.

6.2.4 Patient Limit and Spatial Potential Access

Changes in the patient limit did not result in detectable differences in either E2SFCA SPAGI or Logistic SPAGI despite the large differences in total capacity, shown in Table 6-2. New capacity (or in the case of the 100 patient limit rollback, removal of capacity) is located in the same places at each policy level. The supply is divided the same way, even though the size of the total supply expands or contracts. This echoes the findings in the Doubling Capacity Exploration in Section 4.6, and the toy example in Section 3.5, Figure 3-7. In general, changes to treatment capacity that do not change the allocation of treatment supply are unlikely to change Spatial Potential Access equity. Policy-makers interested in spatial equity should be aware that expanding capacity for everyone does not necessarily mean that previously disadvantaged areas are less disadvantaged when compared to all others. More does not necessarily mean more equal. However, exclusive focus on equity could miss the important fact that in this case, return to a more restrictive patient limit level means that everyone gets less. The allocation of that smaller supply is no more or less equal spatially than at other patient limit levels, but fewer people get treatment.

6.3 Discussion of Results of NP PA Buprenorphine Adoption Policy (RQ4)

As shown in Section 5.3, increasing adoption of buprenorphine prescribing by NPs and PAs resulted in increases in the number of unique buprenorphine recipients at all levels of adoption, and improved Spatial Potential Access equity at higher adoption levels. The policy did not result in detectable differences in opioid overdose deaths or medication diversion.

6.3.1 NP PA Adoption and Buprenorphine Utilization

When I added NP and PA buprenorphine prescribers to the model, I did so under the following assumptions: NPs and PAs buprenorphine prescribers are primary care providers; they may prescribe under their own authority; 30% practice in medically underserved areas (MUAs) and 25% of those practice in isolated rural areas; and they are willing to treat the same number of patients as primary care physicians. I also assumed that all NP or PA providers were new providers, which meant that they could treat a maximum of 30 patients. As in the discussion of the Patient Limit policy, I examine how much capacity was added to the region at each adoption level, which is shown in Table 6-3.

For every percentage point increase in NP PA prescribing, there is about a 2 percentage point increase in the number of treatment spots in the simulated region. Because NPs and PAs are new providers and are constrained to at most 30 patients, the mean number of treatment spots per provider steadily decreases as the number of NPs

Table 6-3: Total capacity, increase in capacity, and mean capacity per provider given a 30 patient limit for new providers, a 275 patient limit for high waiver holders, and provider preferences for patient case-loads at 4 adoption levels of NP and PA prescribing.

	Total treatment spots Mean 100 replications [95% CI]	% capacity increase	Mean treatment spots Mean 100 replications [95% CI]
Baseline	18,300 [18,100; 18,600]		70 [69; 71]
% NP and PA prescribing			
5%	20,400 [20,100; 20,700]	11%	60 [60; 61]
10%	22,100 [21,800; 22,500]	20%	53 [52; 54]
20%	26,000 [25,700; 26,300]	41%	46 [45; 46]
30%	30,100 [29,800; 30,500]	64%	42 [41; 42]

and PAs increases. Unlike in the patient limit expansion, all these increases in capacity also resulted in increases in utilization. The number of unique buprenorphine recipients increased by 2.8%, 5.9%, 7.9%, 10.7% at each of the five levels of prescribing adoption.

Since increasing treatment capacity doesn't feedback into treatment seeking, the increased utilization arises when people seeking treatment are able to get into treatment rather than wait or return to use. As shown in Table 6-4, at high levels of NP and PA adoption there seems to be some shifting of patients from overburdened physician providers to the large pool of NP and PA providers. The percentage of providers within 10% of their personal limit drops from 26% at baseline to 21% at 20% NP/PA adoption, and 15% at 30% NP/PA adoption. However, at lower NP/PA adoption levels, the percentage of providers near their personal limits increases because the decrease in physician providers near their limit is outpaced by NPs and PAs near their limits. This supports the Dr. O'Connor's assumption that NPs might relieve some of the

pressure on busy addiction medicine practices initially, until those freed up spots are backfilled by new patients. In the model, the backfilling process does not occur because the rate of treatment seeking is held fixed.

Table 6-4: Mean patient census levels for NPs and PAs, and physicians, and the percentage of providers who are within 10% of their personal limit on the number of patient they are willing to treat.

	Mean NP PA patient census	Mean physician census	% providers within 10% of personal limit
Baseline	0	26 [26; 27]	26% [26%; 27%]
% NP and PA prescribing			
5%	21 [20; 21]	21 [20; 21]	31% [30%; 31%]
10%	19 [18; 19]	16 [16; 16]	29% [29%; 30%]
20%	15 [15; 15]	11 [11; 11]	21% [21%; 22%]
30%	12 [12; 12]	8 [8; 8]	15% [15%; 15%]

Because NP and PA providers in the model are limited to 30 patients, capacity would rise in the second and third modeled years, as higher capacity NPs and PAs choose to apply for the higher level DEA waivers. This would likely have an impact at the lower adoption levels because the mean patient census level for NPs and PAs is high, indicating that some of these providers are at their 30 patient limit.

I was initially reluctant to model buprenorphine prescribing adoption by over 10% of primary care NPs and PAs because there has been such resistance to buprenorphine prescribing among primary care physicians, where adoption has stalled at 3-5%. I was encouraged to model high adoption by Dr. O'Connor, a primary care Nurse Practitioner with long experience working with patients with OUD in the context of primary care. If the enthusiasm she has seen among her colleagues translates into high adoption of buprenorphine prescribing among NPs and PAs, the OAT treatment system might come

closer to resembling a diffuse, primary care based system that may have been the original vision of DATA 2000. However, the same barriers that may be preventing higher adoption of buprenorphine prescribing among primary care physicians are present for primary care NPs and PAs, and may even be more severe. NPs and PAs tend to be reimbursed at lower rates than physicians for the same services. Low reimbursement may make offering OAT cost prohibitive for some practices. Adoption may also be hampered by laws limiting the prescribing authority of non-physician prescribers. All states allow NPs to prescribe Schedule III drugs, and all states but Kentucky allow PAs to prescribe Schedule III drugs, but most states limit prescriptive authority in some way. It is not yet clear how limitations on prescriptive authority and requirements for physician supervision may impact the ability of NPs and PAs to provide OAT.

Given the barriers and unanswered questions regarding high adoption of buprenorphine prescribing by NPs and PAs, it is encouraging that the model shows increased utilization at the lowest level of adoption—5%. If model assumptions on NP and PA practice locations are valid, 30% of these new providers may serve patients in medically underserved areas, including remote areas where community-based OAT may not currently exist.

6.3.2 NP PA Adoption and Opioid Overdose and Diversion

As was the case in with the patient limit policy, no changes in opioid overdose deaths or diversion were detected with changes in policy. The fact that opioid overdose deaths did not change despite increases in treatment utilization underscores the

reasons given in Section 6.2.2, above. Under model assumptions, expansions in treatment supply meant that people already seeking treatment were able to get a treatment spot. In the model, these people represented only 10% of the people with OUD and were already at lower risk due to self-treatment with illicit buprenorphine. The 70% of the population at high risk did not change, so overdose deaths did not change. If the model were coded so that increasing treatment capacity and availability induced more people to seek treatment, I would expect the number of opioid overdose deaths to decrease with increases in treatment capacity.

I had expected to see some change in diversion with the changes in utilization because of the logic governing diversion demand. Demand for diverted buprenorphine has two sources: explicit demand by people seeking and waiting to begin treatment, and implicit demand as people who need money can divert medication to “the street.” Increases in supply allow people who are seeking treatment to enter treatment, reducing the size of the population explicitly requesting diverted buprenorphine from friends in treatment. Reducing explicit demand should reduce total diversion.

However, it may be that decreasing demand is obscured by more people in treatment who may need money. Implicit demand is not modeled directly. I assume that “the street” will always demand buprenorphine from people in treatment, so that people who need money will always get money for diverted medicine. In early interviews with Dr. Clark, ASAM president and addiction medicine specialist treatment provider, she predicted that a curve relating diversion and the number of people in

treatment would be roughly hill shaped. As more people get treatment, there would be more diversion because there are more patient sources of diverted medicine, but after a certain threshold level of people in treatment, diversion would go down because there would be less demand as people who would be self-treating are folded into the formal treatment system.

It could be that in the model, both processes are occurring, canceling out the effects of each. Explicit demand from treatment seekers reduces demand, but increased utilization increases supply to the ever-present implicit “street” demand for people who are in treatment but need money.

6.3.3 NP PA Adoption and Spatial Potential Access Equity

In addition to increasing utilization of buprenorphine, the NP PA buprenorphine adoption policy also resulted in detectable improvements in the two SPAGI measures. Statistical tests for differences when the NP PA adoption levels were treated as factors only found significant differences at the 20% and 30% adoption levels. However, if NP and PA prescribing adoption were treated as a continuous variable, linear regression models predicting E2SFCA SPAGI and Logistic SPAGI from NP PA prescribing are significant. The model predicting E2SFCA SPAGI:

$$E2SFCA\ SPAGI = 0.305 - 0.0012\ (NP/PA\ pct\ adopting)$$

is significant ($p = 4.81e-11$), and 21% of the variance in E2SFA SPAGI can be explained by NP PA prescribing level. The model predicting Logistic SPAGI:

$$\text{Logistic SPAGI} = 0.5374 - 0.000364 (\text{NP/PA pct adopting})$$

is significant ($p = 1.37\text{e-}5$), and explains 9% of the variance in Logistic SPAGI.

The linear models show that at low adoption levels, changes to SPAGI measures would be very small, and analyses treating the adoption levels as factors show that these small changes to SPAGI are not detectable above the considerable run-to-run variation, even though we may observe a linear trend in the plots.

To understand the response of E2SFCA SPAGI to changes in NP and PA prescribing, I examined the heat maps, SPALCs and SPALC summaries for the 20% and 30% adoption levels and compared each to baseline, as shown in Figure 6-3. There is no statistically significant difference between 20% and 30% adoption, so I did not compare these two scenarios directly. In the model run shown in Figure 6-3a, 32.1% of the population is in the lowest spatial potential access decile, and 44.4% in the lowest 20%. People whose spatial potential access scores are below one quarter of their proportional share of supply are concentrated in the northeast and southwest corners. The large population living at the southern tip of the urban corridor have less than proportional access, while those in and around the dense urban core have much greater than their proportional share of access.

E2SFCA SPAGI is almost 5 percentage points better with 20% NP and PA adoption, but the differences in distribution of spatial access equity are diffusely spread over all SPALC deciles. A smaller fraction of the population is in the lowest decile meaning that

the new allocation of supply is felt by the population that previously had the least choice and the most competition for distant providers. In the 20% adoption heat map, there are no people with “orange level” disparity in the small city in the northeast, nor on the central western coastal cities.

In the SPALC decile summary, when we consider the 50% of the population that has the best access, larger populations in each decile means that allocation is more equitable. Using the income metaphor, if the top 5% of earners earn 10% of the income, they have more equal a share of total income than if 1% of earners earned 10%. At the 5th decile and up, each access decile contains a slightly larger proportion of the population, so the area between the line of perfect equality and the Spatial Potential Access Lorenz Curve is smaller. The best access is shared by more people, which means that access is less skewed to the “access-rich.”

In a heat map, a society with totally equal spatial potential access would be entirely green. Changes toward the center of the color legend indicate greater access equity. In the heat map of Figure 6-3b, high concentration orange areas were eliminated as discussed above, a brown region in the south central area changed to yellow. Striking changes can be seen in the urban corridor. Access equity improved for the suburbs and

a. 0 NP PA adoption

gini-E2SFCA
0.3277

SPALC decile	Population at decile
1 st decile	32.1%
2 nd decile	12.3%
3 rd decile	10.1%
4 th decile	8.3%
5 th decile	7.2%
6 th decile	6.5%
7 th decile	6.2%
8 th decile	6.0%
9 th decile	5.8%
10 th decile	5.6%

b. 20% NP PA adoption

gini-E2SFCA
0.2784

SPALC decile	Population at decile
1 st decile	29.9%
2 nd decile	11.7%
3 rd decile	9.4%
4 th decile	8.3%
5 th decile	7.5%
6 th decile	7.1%
7 th decile	6.8%
8 th decile	6.6%
9 th decile	6.4%
10 th decile	6.2%

Figure 6-3: E2SFCA Spatial Potential Access heat maps (left), SPALCs (center) and SPALC decile summaries (right) for baseline (a), 20% NP PA buprenorphine adoption (b) and 30% NP PA buprenorphine adoption (c)

exurbs as shown by the expansion outward of the yellow region, especially to the west. More people are closer to their proportional share of access at the southern tip of the urban zone, and the number of people enjoying disproportionately high choice and less competition for nearby providers in the dense urban center contracted.

The 30% penetration SPALC and SPALC summary tell a similar story by the numbers. There are small reductions in the size of populations with the worst access, and the best access is shared among a larger fractions of the populations resulting in a smaller areas between the SPALC and the line of perfect equality. The heat map tells a story that is different in the details, but similar in its implications. Random allocation of providers in the rural zone in the north east improved access for those residents. The orange zone in coastal cities is again eliminated. The urban corridor expanded, access improved at the southern end, and the access richest region in the dense urban core contracted.

If the simulations were run again, providers would be allocated differently and the particular story told by the heat maps would be different. However, the heat maps do tell the same general story. Allocation of providers in new places according to a different allocation rule results in changes in the geographic concentration of treatment availability, which means treatment spots are newly accessible to those who previously didn't have many options (orange → brown → yellow → green). Changes to geographic concentration by adding supply outside of treatment dense areas increases equity by

diluting the influence of high concentration zones. More access elsewhere means high access areas are less exceptional (blue → cyan → turquoise → green).

It is notable that increasing the patient limit did not result in allocation of new providers in new places, so the supply that was added to the system did not noticeably change the concentration gradient of treatment supply.

Despite a Cohen's d indicating a large effect on Logistic SPAGI at 20% NP PA adoption, at 20% adoption the mean of Logistic SPAGI decreases by less than 1 percentage point. At 30% adoption, the mean of Logistic SPAGI decreases by a little more than 1 percentage point. The difference is detectable even considering run-to-run variation. However, because the difference is so close to the normal range of variation in the Logistic SPAGI measure at baseline I concluded that SPALC, SPALC decile, and heat map analysis of individual replications are not useful.

As I opined in Section 6.1.3, I believe the model assumption regarding the random mixing of people with highest and lowest ability to travel based on population density muddies the spatial distribution of access picture. This limitation is further discussed in Section 6.4.2, below.

Even though SPALC and heat map analysis are not illuminating, and the effects are small, there is a measurable impact on SPAGI weighted by people's ability to travel. When NP and PA adoption is at high levels and new sources of supply are spread more evenly in the region, including to MUAs and remote areas, spatial potential access

equity improves. Limited ability to travel still puts treatment out of reach, or nearly out of reach, for many. This suggests that treatment accessibility policies that increase people's ability to travel or reduce the distance they have to go can have a positive impact on spatial potential access equity given ability to travel, as well as utilization and retention (see for example: Friedmann, Lemon, & Stein, 2001; Hall et al., 2014).

6.4 Limitations

The chief limitations of this study are its simplifying assumptions. Because the research questions were narrowly focused on buprenorphine treatment capacity, several important aspects of the treatment system were left out of the model. Though all modeling requires selection of model boundaries and each model assumption could be discussed in turn, I did not conduct exhaustive boundary assessment. However, several simplifying choices should be discussed because they have implications for the measurement of utilization, diversion, and equity, the primary foci of the research questions. I cover three main limitation areas: homogeneous population, homogeneous population allocation, and homogeneous providers and treatment experiences.

6.4.1 Population homogeneity

First, the population with OUD is generic. Agents are coded as male or female, but agent sex has no influence on other variables. Agents do not have variables for age, substance use history, treatment history, race or ethnicity, language, pregnancy status, employment status, criminal justice involvement, or comorbid physical or mental health problems. Several of these individual factors do impact retention in treatment, how long

treatment may last, which OAT type a person is likely to get. However, the research questions in this study are narrow and don't necessitate heterogeneous agents, that is: "Do supply side changes in capacity result in greater utilization in general, given spatial considerations?" The impact of characteristics of people with OUD on treatment outcomes is assumed to underlie the heterogeneity in the two primary patient outcomes: time to abstinence or reduced use, and treatment retention. Heterogeneity is also assumed to inform people's willingness or ability to travel. Some of the empirical data informing model parameters could have been stratified by any number of population characteristics, and a diverse, heterogeneous synthetic population generated through microsimulation techniques. I argue that this dramatic increase in agent complexity would not better answer the general questions on general utilization levels and spatial equity.

There are racial and ethnic disparities in access to treatment services, which must be included in studies of treatment access equity writ large. Racial and ethnic disparities are not included in this study of access equity, because questions of equity are narrowly limited to Spatial Potential Access. Equity is only assessed in this narrow Spatial Potential Access context. I do not consider equity in utilization, or outcomes, nor do I consider access equity across population groups. This is not because these studies would be unimportant, they are simply outside the narrow focus of this work. No non-spatial aspects of accessibility are included in the model. There is great potential to

expand the calculation of potential access to include non-spatial determinants of access, which is a promising thread for future work.

6.4.2 Population allocation homogeneity

While the regional population density maps represent real regions, people are placed on the maps in a plausible fashion and not directly from empirical data. There were two major reasons for this decision. First, there aren't good data on that would allow geo-coding of people with OUD, although there are ways to estimate populations by proxy measures such as those used by Dick and others (Dick et al., 2015). Second, the original impetus for the research was to model the national implications of policy. So rather than generate a single high resolution, high fidelity representation of a real region, which might not be suitable for a national analysis, I chose to generate a high-resolution (1 square mile), low-fidelity, plausible allocation of individuals.

People with OUD were initialized with randomly assigned poverty levels based on NSDUH, and insurance type based on poverty level. Then they were placed on the map so that population distribution in different types of regions (large MSA, small MSA, etc.) matched NSDUH survey data. Once people were placed on the map, willingness to travel were drawn from the empirical distribution for the population density of the person's residence (see Appendix A). This population allocation algorithm assumes independence of poverty level and willingness to travel.

This assumption of independence makes analysis of willingness to travel based SPAGI problematic. People with limited ability to travel are not spatially grouped.

In future research, this shortcoming could be addressed by better methods for generating synthetic populations. Rather than using population density to place agents and providers, providers could be placed by zip code, and agents generated by matching high-resolution census data and zip code data on willingness to travel and then merging this data with representative survey data from NSDUH using iterative proportional fitting. The resultant synthetic population would much better represent a plausible allocation of individuals with OUD, and would vastly improve willingness to travel based SPAGI analyses.

The resulting analyses would be regional, not national, however. National scaling of individual-level dynamic models is an active area of research in the Agent Based Simulation research community.

6.4.3 Provider and treatment homogeneity

The model does include some provider heterogeneity, but only on factors that impact capacity and utilization, such as accepted insurance and cost, and especially number of patients a provider is willing to treat. In the model, the number of patients a provider is willing to treat depends on whether the provider is a specialist, whether they have a high or low waiver, and whether they are on the SAMHSA searchable list. There are many other factors that determine how many patients a provider is willing to treat,

including practice barriers and facilitators (Barry et al., 2008; Gordon et al., 2011; Hutchinson et al., 2014; Roman, Abraham, & Knudsen, 2011; Schackman et al., 2006) and practice models (see SAMHSA 2014c for examples). A rich policy model could include barriers, facilitators, and practice models and their impact on how many patients a provider is willing to treat. However, there are no data on how many people a provider is willing to treat. Rather than model the impact of these variables on preference, the magnitudes of which are not known, I chose to simplify and generate preferences by drawing from probability distributions based on specialty and waiver level, and calibrating to patient census data.

Testing the impact of adopting different practice models could be a fruitful avenue for simulation research in OUD treatment.

6.5 Future Directions

There are several fruitful future directions for research using SPAGI measures and spatial agent based models of OUD treatment access. The current research could be strengthened substantially by using spatial synthetic population generation techniques to generate the population with OUD. The model could then be used to assess regional spatial potential access using geocoded provider locations. The model could be extended to allow exploring the spatial implications of any number of experiments for changing access and utilization, including different practice models and regional policy models such as hub and spoke, in which stable patients are transferred

to primary care providers closer to where they live; or telemedicine adoption for reaching people with limited ability to travel.

The Spatial Potential Access Gini Index itself could be developed in future research to incorporate methodological improvements in floating catchment area gravity models, including edge correction, different distance decay functions for urban and rural residents. Research could explore whether non-spatial aspects of accessibility could be incorporated into spatial potential access measures and SPAGI to give a richer picture of access disparities. Careful attention must be paid to whether changing how spatial potential access is measured preserves the property of 2SFCA measures which allows for aggregation using SPAGI by assuring that the weighted average of accessibility scores equals the total number of opportunities in the system.

More robust statistical analysis of differences in Spatial Potential Access Lorenz Curves could be explored in future research. I compared SPALCs and SPALC decile summaries of individual model runs to understand statistically significant differences in SPAGI measures. However, these analyses were informal comparisons of deciles rather than a statistically robust comparisons of all the information contained in the curves themselves. Development of formal curve analysis could allow better understanding of the nature of the inequity in systems described by Lorenz Curves.

Future research could explore whether SPAGI measures are useful in empirical analyses using standard floating catchment area estimates of demand at the census

tract level. Initial exploration could be used to compare regions for which spatial potential access analyses have already been conducted. Once initial exploration shows that SPAGI can detect differences between regions, SPAGI could be used to compare supply allocation experiments in real regions.

Finally, scaling of dynamic agent based models is an active area of research. How can researchers make national level inferences based on agent based simulation models when spatial heterogeneity is an important driver of dynamics? Must one agent represent one person, or can simulated individuals be “statistical individuals?” Can a population centroid of a census tract represent a person in an agent based simulation, allowing for a direct synthesis of empirical spatial potential access research and agent based simulation? Can an agent based simulation of a region represent similar regions in a statistically robust way, in the way that a statistical individual represents a large number of people in survey research? I am currently involved in research on how to scale individual models and spatial representativeness, which has grown from the current work.

6.6 Implications for Research

Development of a method to aggregate complex Spatial Potential Access information into a single metric grows the field of spatial potential access measurement in a new direction. It addresses a fundamental question in spatial potential access measurement: how can researchers compare mapped regions? To date, much attention has been paid to identification of supply shortages, or supply deserts, using census-

based spatial potential access mapping (see, for example: Lee & Lim, 2009; Sharkey, Horel, & Dean, 2010; Wan, Zhan, Zou, & Chow, 2012). Methodological improvements have focused on how to improve the catchment area methods (Delamater, 2013; McGrail & Humphreys, 2009; Wan, Zou, et al., 2012), how to optimize allocation of new supply (Ngui & Apparicio, 2011; Wang, 2012; Wang & Tang, 2013), and how to choose distance measures and aggregation levels (Apparicio et al., 2017) or representations of populations (Langford & Higgs, 2006). Equity is assessed within the mapped region, and quantitative information is displayed in rich maps. However, researchers appear not to have compared equitability of access across regions, or within regions after a policy experiment.

The Spatial Potential Access Gini Index and Spatial Potential Access Lorenz Curve compresses the rich information of access equity present in individual maps to allow for direct comparison of Spatial Potential Access across maps. Spatial potential access must be assessed the same way in all regions to be compared, and the weighted average of spatial potential access scores must equal the total supply in the system for Lorenz Curve aggregation to be mathematically sound. Care should also be taken to interpret differences in SPAGI across regions because of issues in interpretation noted in Section 4.9.2. The ability to compare equitability of Spatial Potential Access across regions could allow for hybrid empirical simulation studies, in which supply allocation policies are tested directly on data rich, empirical maps.

6.7 Implications for Substance Abuse Treatment Research Practice

This study shows the promise of simulation research in substance abuse treatment policy analysis. An earlier iteration of the simulation model had a larger scope, allowing for the exploration of more policies and policy impacts on more outcomes. The vision of the earlier model was as a flight simulator, in which treatment models could be swiftly operationalized, and the potential impacts explored in a participatory process with researchers and stakeholders working together. Simulations can be useful for testing simple what-if ideas for improving access to treatment, such as how could people with OUD in Oregon benefit primary care providers contracted with the Coordinated Care Organizations got and used DATA waivers to prescribe for people receiving Medicaid. It is a simple idea, but one that has met with resistance from providers as reported by Lucy Zammarelli, Health Equity Officer for Trillium, a Coordinated Care Organization and health insurer operating in several counties in Oregon. A simulation showing improved utilization and access equity when adding primary care providers and no improvement in equity from addiction specialist supply expansion could build evidence to support advocacy in treatment expansion in primary care.

6.8 Conclusions

If we as a society believe that equity is important, then we should measure it. This simulation exercise showed that if we allocate supply of OAT treatment services as it is allocated in the United States, and we allocate people with OUD in a way that it

consistent with representative surveys of OUD, there is substantial inequity in the spatial allocation of OAT. If we as a society believe that equitable access to OAT is important, then we should work to improve it. We can use simulation that includes measurement of Spatial Potential Access to take the first steps in improving equity. We can see what might work in simulation studies like this one, before post-hoc empirical policy analyses have been conducted. And then we could also use empirical policy evaluation tools, including mapping, measuring and comparing equity measures in post-hoc analyses to evaluate policies after the fact.

As we do these analyses, we should ask ourselves the difficult ethical questions that come with work to improve equity. Is it OK for things to get better for some people before it gets better for other people? Is it OK to define equity narrowly—can we pat ourselves on the back for improvements in Spatial Access Equity, if racial and ethnic disparities persist? Is it OK for people who are “access rich” to get less than they’ve grown accustomed to so that others get more? How do we make the ethical and practical argument for redistribution given political discomfort with that concept?

Measuring, mapping, and comparing equity is an important step toward improving equity. I hope that this work has advanced that work in some small way.

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Appendix A Patient Willingness to Travel Based on Zip Code 2006-May 2013

The histograms below chart frequency of stated willingness to travel in 5 mile increments for residents who live in regions with population densities within the stated range. People who used the NAABT.org physician locator website entered information about themselves including zip code, age and email address to the website, and might be contacted directly by buprenorphine providers. I received de-identified data, and grouped individuals according to the population density of their zip code. I then generated histograms of miles willing to travel for different population density ranges. Rather than fitting histograms with probability distributions, I used them directly in simulation because several distributions were multimodal.

Figure A-1: Miles willing to travel for people residing in areas with population density > 5000 people/square mile

Figure A-2: Miles willing to travel for people residing in areas with population density 2500-5000 people/square mile

Figure A-3: Miles willing to travel for people residing in areas with population density 1000-2500 people/square mile

Figure A-4: Miles willing to travel for people residing in areas with population density 500-1000 people/square mile

Figure A-5: Miles willing to travel for people residing in areas with population density 250-500 people/square mile

Figure A-6: Miles willing to travel for people residing in areas with population density 100-250 people/square mile

Figure A-7: Miles willing to travel for people residing in areas with population density 50-100 people/square mile

Figure A-8: Miles willing to travel for people residing in areas with population density 25-50 people/square mile

Figure A-9: Miles willing to travel for people residing in areas with population density 10-25 people/square mile

Figure A-10: Miles willing to travel for people residing in areas with population density 0-10 people/square mile

Appendix B Model Code

B.1 Graphical User Interface

Figure B-1: Model Graphical User Interface

B.2 Model code

B.2.1 Code tab

```

__includes ["GeoSetup1.nls" "ProviderSetup1.nls" "PtSetup1.nls"
"Declarations1.nls" "ProviderGol.nls" "PtGol.nls" "Reporters1.nls"
"SetupCommands1.nls" "GoCommands1.nls" "otp1.nls" ]

//////////
;;; SETUP PROCEDURES ;;;
//////////

to setup
  clear-all
  setup-globals
  set-initials
  setup-geography
  setup-OTPs
  setup-providers
  ask OTPs [init-OTPs]
  set-capacity
  if equity-experiments = "high-capacity-provider-closure"[
    repeat large-capacity-n[
      ask one-of real-providers with-max [total-capacity]
      [
        set total-capacity 0
      ]
    ]
  ]
  if equity-experiments = "rural-provider-closure"[
    let rxing-providers real-providers with [total-capacity > 0]
    repeat rural-provider-n [
      ask one-of rxing-providers with-min [[pop-den] of patch-here]
      [
        set total-capacity 0
        die
      ]
    ]
  ]
  if double-capacity?[
    ask real-providers [set total-capacity 2 * total-capacity]
  ]
  setup-people
  set lorenz-with-weights-2SFCA []
  set lorenz-with-weights-E2SFCA []
  set lorenz-with-weights-logistic []
  set lorenz-with-weights-gaussian []
  set lorenz-with-weights-exponential []
  set gini-index-weights-2SFCA 0
  set gini-index-weights-E2SFCA 0
  set gini-index-weights-logistic 0
  set gini-index-weights-gaussian 0
  set gini-index-weights-exponential 0

```



```

    if gini-at-setup? [
      do-gini
    ]
    reset-ticks
  end

  ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
  ;; GO PROCEDURES                                ;;
  ;; walk through time week by week. ;;
  ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
  to go
    tick
    ;set testlist[]
    do-street-market
    grow-deps
    chance-OD
    if model-year = 2016 and ticks = 34 [set high-cap 275 ask real-providers
    [if patients-per-provider > 100[set capped-patients-per-provider min list
    patients-per-provider high-cap set total-capacity capped-patients-per-
    provider + MTH-spots ]]]
    if model-year = 2015 and ticks = 85 [set high-cap 275 ask real-providers
    [if patients-per-provider > 100[set capped-patients-per-provider min list
    patients-per-provider high-cap set total-capacity capped-patients-per-
    provider + MTH-spots]]]
    age-patients
    age-providers
    compute-IQR
    if ticks = 59 or ticks = 111 [
      do-gini
    ]
    reset-flagged-vars
  end

  to do-gini
    do-two-step

    do-lorenz-2SFCA
    do-lorenz-E2SFCA
    do-lorenz-logistic
    do-lorenz-gaussian
    do-lorenz-exponential

    update-plots
  end

  to do-two-step
    do-step-one
    do-step-two

    do-step-one-E2SFCA
    do-step-two-E2SFCA

```

```

end

to do-step-one
; print "2SFCA"
ask real-providers [
  let sum-of-weights-2SFCA 0
  let sum-of-weights-logistic 0
  let sum-of-weights-gaussian 0
  let sum-of-weights-exponential 0
  let catchment-deps nobody
  let current-dep nobody
  set catchment-deps deps with [my-travel-distance > distance myself]

  ask catchment-deps[
    let my-weight-2SFCA 1
    let my-weight-logistic 1 - (1 / (1 + e ^ ((-10 / my-travel-distance)
* ((distance myself) - (my-travel-distance / 2))))))
    let my-weight-gaussian e ^ ( - ((distance myself) * (distance
myself)/(0.3 * my-travel-distance * my-travel-distance)))
    let my-weight-exponential e ^ ( - (distance myself) / (.3 * my-
travel-distance))
    set sum-of-weights-2SFCA sum-of-weights-2SFCA + my-weight-2SFCA
    set sum-of-weights-logistic sum-of-weights-logistic + my-weight-
logistic
    set sum-of-weights-gaussian sum-of-weights-gaussian + my-weight-
gaussian
    set sum-of-weights-exponential sum-of-weights-exponential + my-
weight-exponential
  ]
  ifelse sum-of-weights-2SFCA != 0 [
    set weighted-ratio-2SFCA total-capacity / sum-of-weights-2SFCA
  ]
  [
    set weighted-ratio-2SFCA 0
  ]
  ifelse sum-of-weights-logistic != 0 [
    set weighted-ratio-logistic total-capacity / sum-of-weights-
logistic
  ]
  [
    set weighted-ratio-logistic 0
  ]
  ifelse sum-of-weights-gaussian != 0 [
    set weighted-ratio-gaussian total-capacity / sum-of-weights-
gaussian
  ]
  [
    set weighted-ratio-gaussian 0 ;show "no-demand"
  ]
  ifelse sum-of-weights-exponential != 0 [
    set weighted-ratio-exponential total-capacity / sum-of-weights-
exponential
  ]
]

```

```

    [
      set weighted-ratio-exponential 0 ;show "no-demand"
    ]
  ]
end

to do-step-one-E2SFCA
  ask real-providers [
    let sum-of-weights-E2SFCA 0
    let catchment-deps nobody
    let current-dep nobody
    set catchment-deps deps with [distance myself < 60]

    ask catchment-deps[
      let my-weight-E2SFCA 1
      if distance myself < 60[
        set my-weight-E2SFCA .123
      ]
      if distance myself < 30[
        set my-weight-E2SFCA .6
      ]
      if distance myself < 10[
        set my-weight-E2SFCA 1
      ]
      set sum-of-weights-E2SFCA sum-of-weights-E2SFCA + my-weight-E2SFCA
    ]
    ifelse sum-of-weights-E2SFCA != 0 [
      set weighted-ratio-E2SFCA total-capacity / sum-of-weights-E2SFCA
    ]
    [
      set weighted-ratio-E2SFCA 0 ;show "no-demand"
    ]
  ]
end

to do-step-two-E2SFCA
  ask deps[
    set reachable-providers real-providers with [distance myself < 60]
    let my-weight-E2SFCA 1
    set weighted-sum-of-ratios-E2SFCA 0
    let current-provider nobody
    ask reachable-providers[
      let my-dist distance myself
      ask myself [
        if my-dist < 60[
          set my-weight-E2SFCA .123
        ]
        if my-dist < 30[
          set my-weight-E2SFCA .6
        ]
        if my-dist < 10[
          set my-weight-E2SFCA 1
        ]
      ]
    ]
  ]
end

```

```

        set weighted-sum-of-ratios-E2SFCA weighted-sum-of-ratios-E2SFCA
+ ([weighted-ratio-E2SFCA] of myself * my-weight-E2SFCA)

    ]
  ]
]
end

```

```
to do-step-two
```

```

  ask deps[
    set reachable-providers real-providers with [distance myself < [my-
travel-distance] of myself]

    let my-weight-2SFCA 1
    let my-weight-logistic 1
    let my-weight-gaussian 1
    let my-weight-exponential 1
    set weighted-sum-of-ratios-2SFCA 0
    set weighted-sum-of-ratios-logistic 0
    set weighted-sum-of-ratios-gaussian 0
    set weighted-sum-of-ratios-exponential 0
    let current-provider nobody
    ask reachable-providers[
      let my-dist distance myself
      ask myself [
        set my-weight-logistic 1 - (1 / (1 + e ^ ((-10 / my-travel-
distance) * ((my-dist) - (my-travel-distance / 2)))))
        set my-weight-gaussian e ^ ( - ((distance myself) * (distance
myself)/(0.3 * my-travel-distance * my-travel-distance)))
        set my-weight-exponential e ^ ( - (distance myself) / (.3 * my-
travel-distance))
        set weighted-sum-of-ratios-2SFCA weighted-sum-of-ratios-2SFCA +
([weighted-ratio-2SFCA] of myself * my-weight-2SFCA)
        set weighted-sum-of-ratios-logistic weighted-sum-of-ratios-
logistic + ([weighted-ratio-logistic] of myself * my-weight-logistic)
        set weighted-sum-of-ratios-gaussian weighted-sum-of-ratios-
gaussian + ([weighted-ratio-gaussian] of myself * my-weight-gaussian)
        set weighted-sum-of-ratios-exponential weighted-sum-of-ratios-
exponential + ([weighted-ratio-exponential] of myself * my-weight-
exponential)

      ]
    ]
  ]
end

```

```
to do-lorenz-2SFCA
```

```

  let num-patients (count deps)
  let sorted-ratios sort [weighted-sum-of-ratios-2SFCA] of deps
  let total-ratios sum sorted-ratios
  let ratio-sum-so-far 0
  let index 0
  set gini-index-weights-2SFCA 0

```

```

set lorenz-with-weights-2SFCA []
repeat num-patients[
  set ratio-sum-so-far (ratio-sum-so-far + item index sorted-ratios)
  set lorenz-with-weights-2SFCA lput ((ratio-sum-so-far / total-ratios)
* 100) lorenz-with-weights-2SFCA
  set index (index + 1)
  set gini-index-weights-2SFCA gini-index-weights-2SFCA + (index / num-
patients) - (ratio-sum-so-far / total-ratios )
]
set gini-index-weights-2SFCA (gini-index-weights-2SFCA / num-patients)
* 2
end

to do-lorenz-logistic
let num-patients (count deps)
let sorted-ratios sort [weighted-sum-of-ratios-logistic] of deps
let sorted-deps []
if show-log-map? [
  set sorted-deps sort-on [weighted-sum-of-ratios-logistic] deps
  ask patches [set pcolor black]
  ask otps [set shape "circle" set size 2 set color white]
  ask providers [set shape "circle" set size 2 set color white]
]
let total-ratios sum sorted-ratios
;show total-ratios
let ratio-sum-so-far 0
let prev-ratio-sum-so-far 0
let index 0
set gini-index-weights-logistic 0
set lorenz-with-weights-logistic []
repeat num-patients[
  set ratio-sum-so-far (ratio-sum-so-far + item index sorted-ratios)
  set lorenz-with-weights-logistic lput ((ratio-sum-so-far / total-
ratios) * 100) lorenz-with-weights-logistic
  if show-log-map?[
    ask item index sorted-deps
    [
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients = 0 ) [set size 3 set color red]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 0) [set size 3 set color ORANGE]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .25) [set size 3 set color brown]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .9 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .5) [set size 3 set color yellow]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.1 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .9) [set size 3 set color green]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.1) [set size 3 set color turquoise]
    ]
  ]
]

```

```

        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.25) [set size 3 set color cyan]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 2 and (ratio-sum-so-far - prev-ratio-sum-so-far) / total-
ratios * num-patients > 1.5) [set size 3 set color sky ]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients > 2) [set size 3 set color blue]

        if (ratio-sum-so-far / total-ratios < 1) [set decile 10]
        if (ratio-sum-so-far / total-ratios < .9) [set decile 9]
        if (ratio-sum-so-far / total-ratios < .8) [set decile 8]
        if (ratio-sum-so-far / total-ratios < .7) [set decile 7]
        if (ratio-sum-so-far / total-ratios < .6) [set decile 6]
        if (ratio-sum-so-far / total-ratios < .5) [set decile 5]
        if (ratio-sum-so-far / total-ratios < .4) [set decile 4]
        if (ratio-sum-so-far / total-ratios < .3) [set decile 3]
        if (ratio-sum-so-far / total-ratios < .2) [set decile 2]
        if (ratio-sum-so-far / total-ratios < .1) [set decile 1]

    ]
    set prev-ratio-sum-so-far ratio-sum-so-far
    set index (index + 1)
    set gini-index-weights-logistic gini-index-weights-logistic + (index
/ num-patients) - (ratio-sum-so-far / total-ratios )
  ]
  set gini-index-weights-logistic (gini-index-weights-logistic / num-
patients) * 2
  if show-log-map?[
    show word "1st " (precision (count deps with [decile = 1] / count
deps) 3)
    show word "2nd " (precision (count deps with [decile = 2] / count
deps) 3)
    show word "3rd " (precision (count deps with [decile = 3] / count
deps) 3)
    show word "4th " (precision (count deps with [decile = 4] / count
deps) 3)
    show word "5th " (precision (count deps with [decile = 5] / count
deps) 3)
    show word "6th " (precision (count deps with [decile = 6] / count
deps) 3)
    show word "7th " (precision (count deps with [decile = 7] / count
deps) 3)
    show word "8th " (precision (count deps with [decile = 8] / count
deps) 3)
    show word "9th " (precision (count deps with [decile = 9] / count
deps) 3)
    show word "10th " (precision (count deps with [decile = 10] / count
deps) 3)
  ]
end

to do-lorenz-gaussian

```

```

let num-patients (count deps)
let sorted-ratios sort [weighted-sum-of-ratios-gaussian] of deps
let sorted-deps []
if show-gaussian-map? [
  set sorted-deps sort-on [weighted-sum-of-ratios-gaussian] deps
  ask patches [set pcolor black]
  ask otps [set shape "circle" set size 2 set color white]
  ask providers [set shape "circle" set size 2 set color white]
]
let total-ratios sum sorted-ratios
;show total-ratios
let ratio-sum-so-far 0
let prev-ratio-sum-so-far 0
let index 0
set gini-index-weights-gaussian 0
set lorenz-with-weights-gaussian []
repeat num-patients[
  set ratio-sum-so-far (ratio-sum-so-far + item index sorted-ratios)
  set lorenz-with-weights-gaussian lput ((ratio-sum-so-far / total-
ratios) * 100) lorenz-with-weights-gaussian
  if show-gaussian-map?[
    ask item index sorted-deps
    [
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients = 0 ) [set size 3 set color red]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 0) [set size 3 set color ORANGE]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .25) [set size 3 set color brown]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .9 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .5) [set size 3 set color yellow]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.1 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .9) [set size 3 set color green]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.1) [set size 3 set color turquoise]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.25) [set size 3 set color cyan]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 2 and (ratio-sum-so-far - prev-ratio-sum-so-far) / total-
ratios * num-patients > 1.5) [set size 3 set color sky ]
      if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients > 2) [set size 3 set color blue]

      if (ratio-sum-so-far / total-ratios < 1) [set decile 10]
      if (ratio-sum-so-far / total-ratios < .9) [set decile 9]
      if (ratio-sum-so-far / total-ratios < .8) [set decile 8]
      if (ratio-sum-so-far / total-ratios < .7) [set decile 7]
      if (ratio-sum-so-far / total-ratios < .6) [set decile 6]
    ]
  ]
]

```

```

        if (ratio-sum-so-far / total-ratios < .5) [set decile 5]
        if (ratio-sum-so-far / total-ratios < .4) [set decile 4]
        if (ratio-sum-so-far / total-ratios < .3) [set decile 3]
        if (ratio-sum-so-far / total-ratios < .2) [set decile 2]
        if (ratio-sum-so-far / total-ratios < .1) [set decile 1]
    ]
]
set prev-ratio-sum-so-far ratio-sum-so-far
set index (index + 1)
set gini-index-weights-gaussian gini-index-weights-gaussian + (index
/ num-patients) - (ratio-sum-so-far / total-ratios )
]
set gini-index-weights-gaussian (gini-index-weights-gaussian / num-
patients) * 2
if show-gaussian-map?[
    show word "1st " (precision (count deps with [decile = 1] / count
deps) 3)
    show word "2nd " (precision (count deps with [decile = 2] / count
deps) 3)
    show word "3rd " (precision (count deps with [decile = 3] / count
deps) 3)
    show word "4th " (precision (count deps with [decile = 4] / count
deps) 3)
    show word "5th " (precision (count deps with [decile = 5] / count
deps) 3)
    show word "6th " (precision (count deps with [decile = 6] / count
deps) 3)
    show word "7th " (precision (count deps with [decile = 7] / count
deps) 3)
    show word "8th " (precision (count deps with [decile = 8] / count
deps) 3)
    show word "9th " (precision (count deps with [decile = 9] / count
deps) 3)
    show word "10th " (precision (count deps with [decile = 10] / count
deps) 3)
]
end

to do-lorenz-exponential
    let num-patients (count deps)
    let sorted-ratios sort [weighted-sum-of-ratios-exponential] of deps
    let total-ratios sum sorted-ratios
    ;show total-ratios
    let ratio-sum-so-far 0
    let index 0
    set gini-index-weights-exponential 0
    set lorenz-with-weights-exponential []
    repeat num-patients[
        set ratio-sum-so-far (ratio-sum-so-far + item index sorted-ratios)
        set lorenz-with-weights-exponential lput ((ratio-sum-so-far / total-
ratios) * 100) lorenz-with-weights-exponential
        set index (index + 1)
        set gini-index-weights-exponential gini-index-weights-exponential +
(index / num-patients) - (ratio-sum-so-far / total-ratios )
    ]
end

```



```

]
  set gini-index-weights-exponential (gini-index-weights-exponential /
num-patients) * 2
end

to do-lorenz-E2SFCA
  let num-patients (count deps)
  let sorted-ratios sort [weighted-sum-of-ratios-E2SFCA] of deps
  let sorted-deps []
  if show-e2-map? [
    set sorted-deps sort-on [weighted-sum-of-ratios-E2SFCA] deps
    ask patches [set pcolor black]
    ask otps [set shape "circle" set size 2 set color white]
    ask providers [set shape "circle" set size 2 set color white]
  ]
  let total-ratios sum sorted-ratios
  let ratio-sum-so-far 0
  let prev-ratio-sum-so-far 0
  let index 0
  set gini-index-weights-E2SFCA 0
  set lorenz-with-weights-E2SFCA []
  repeat num-patients[
    set ratio-sum-so-far (ratio-sum-so-far + item index sorted-ratios)
    set lorenz-with-weights-E2SFCA lput ((ratio-sum-so-far / total-ratios)
* 100) lorenz-with-weights-E2SFCA
    if show-e2-map?[
      ask item index sorted-deps
      [
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients = 0 ) [set size 3 set color red]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 0) [set size 3 set color ORANGE]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .25) [set size 3 set color brown]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= .9 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .5) [set size 3 set color yellow]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.1 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > .9) [set size 3 set color green]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.25 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.1) [set size 3 set color turquoise]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 1.5 and (ratio-sum-so-far - prev-ratio-sum-so-far) /
total-ratios * num-patients > 1.25) [set size 3 set color cyan]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients <= 2 and (ratio-sum-so-far - prev-ratio-sum-so-far) / total-
ratios * num-patients > 1.5) [set size 3 set color sky ]
        if ((ratio-sum-so-far - prev-ratio-sum-so-far) / total-ratios *
num-patients > 2) [set size 3 set color blue]

```

```

        if (ratio-sum-so-far / total-ratios < 1) [set decile 10]
        if (ratio-sum-so-far / total-ratios < .9) [set decile 9]
        if (ratio-sum-so-far / total-ratios < .8) [set decile 8]
        if (ratio-sum-so-far / total-ratios < .7) [set decile 7]
        if (ratio-sum-so-far / total-ratios < .6) [set decile 6]
        if (ratio-sum-so-far / total-ratios < .5) [set decile 5]
        if (ratio-sum-so-far / total-ratios < .4) [set decile 4]
        if (ratio-sum-so-far / total-ratios < .3) [set decile 3]
        if (ratio-sum-so-far / total-ratios < .2) [set decile 2]
        if (ratio-sum-so-far / total-ratios < .1) [set decile 1]
    ]
]
set index (index + 1)
set prev-ratio-sum-so-far ratio-sum-so-far
set gini-index-weights-E2SFCA gini-index-weights-E2SFCA + (index /
num-patients) - (ratio-sum-so-far / total-ratios )
]
if show-e2-map?[
show word "1st " (precision (count deps with [decile = 1] / count deps)
3)
show word "2nd " (precision (count deps with [decile = 2] / count deps)
3)
show word "3rd " (precision (count deps with [decile = 3] / count deps)
3)
show word "4th " (precision (count deps with [decile = 4] / count deps)
3)
show word "5th " (precision (count deps with [decile = 5] / count deps)
3)
show word "6th " (precision (count deps with [decile = 6] / count deps)
3)
show word "7th " (precision (count deps with [decile = 7] / count deps)
3)
show word "8th " (precision (count deps with [decile = 8] / count deps)
3)
show word "9th " (precision (count deps with [decile = 9] / count deps)
3)
show word "10th " (precision (count deps with [decile = 10] / count
deps) 3)
]
set gini-index-weights-E2SFCA (gini-index-weights-E2SFCA / num-
patients) * 2
end

to compute-IQR
let nonOTPproviders providers with [otp-doc? = false]
let RxingnonOTPproviders nonOTPproviders with [(count BUP-patients +
count tele-patients) > 0]
let sortedDocList sort-on [count tele-patients + count BUP-patients]
RxingnonOTPproviders
let firstQIndex round (length sortedDocList / 4) - 1
let thirdQIndex round (length sortedDocList * .75) - 1
let medianIndex round (length sortedDocList / 2) - 1
let firstDoc item firstQIndex sortedDocList
let thirdDoc item thirdQIndex sortedDocList

```

```

let medianDoc item medianIndex sortedDocList

set firstQuartile [count tele-patients + count BUP-patients] of
firstDoc
set thirdQuartile [count tele-patients + count BUP-patients] of
thirdDoc
set medianPts [(count BUP-patients + count tele-patients)] of medianDoc
set OneToThree round (100 * count RxingnonOTPproviders with [(count
BUP-patients + count tele-patients) > 0 and (count BUP-patients + count
tele-patients) < 4] / (count RxingnonOTPproviders))
set FourTo30 round (100 * count RxingnonOTPproviders with [(count BUP-
patients + count tele-patients) >= 4 and (count BUP-patients + count tele-
patients) <= 30] / (count RxingnonOTPproviders))
set ThirtyoneTo75 round (100 * count RxingnonOTPproviders with [(count
BUP-patients + count tele-patients) >= 31 and (count BUP-patients + count
tele-patients) <= 75] / (count RxingnonOTPproviders))
set MoreThan75 round (100 * count RxingnonOTPproviders with [(count
BUP-patients + count tele-patients) >= 76] / (count
RxingnonOTPproviders))

end

```

B.2.2 Declarations.nls

```

breed [providers provider]
breed[deps dep]
breed[OTPs OTP]

globals[
  filename
  lorenz-points
  untreated-dependent
  open-capacity
  number-docs
  number-patients
  max-patch-density
  total-number-dependent
  weekly-add-docs
  weekly-add-APN
  dead-number
  diverted-medicine
  all-insurance
  gini-index-reserve
  ods-deps
  ods-pats
  in-tx
  n
  men
  women
  gini-index-weights-2SFCA
  gini-index-weights-E2SFCA
  gini-index-weights-logistic
  gini-index-weights-gaussian

```

gini-index-weights-exponential
lorenz-with-weights-2SFCA
lorenz-with-weights-E2SFCA
lorenz-with-weights-logistic
lorenz-with-weights-gaussian
lorenz-with-weights-exponential
firstQuartile
thirdQuartile
medianPts
OneToThree
FourTo30
ThirtyOneto75
MoreThan75
dummy-doc
rural-areas
small-cities
large-cities
patches-with-pills
initial-pct-patients-in-tx
low-spec
high-spec
non-high-list
non-low-list
non-low-nolist
low-spec-random
high-spec-random
non-high-list-random
non-low-list-random
non-low-nolist-random
pa-pop
pa-pcp-pct
dep-incidence
seeking-incidence
initial-pct-deps-seeking-or-in-tx
remote-dep-pct
np-pop
np-pcp-pct
MUA-pct
remote-pct
APN-discount
lowest-cost
APN-random
small-city-pct
rural-threshold
small-city-threshold
divertAfford
wanted\$
percentSayYes
colleague-radius
rural-dep-pct
pct-of-income
pct-poverty
pct-twox-poverty
coinsurance-base

```

coinsurance-random
never-abstain-pct
abstinence-floor
abstinence-mean
dose-sixteen
dose-eight
dose-tfour
mth-cost
pct-try-bup-first
mth-weekly-quit-rate
first-week-bup-quit
second-week-bup-quit
show-street-market?
my-wait-time
total-population
docs-per-pop
pts-dependent
poverty-level
female-pct
num-otps
va-pct
gvt-pct
pnp-pct
ods-pts-in-tx
post-tx-die
]

providers-own [
  patients-per-provider
  capped-patients-per-provider
  BUP-years
  wait-list
  colleagues
  specialist?
  onList?
  Rxing?
  CapHigh?
  willAdd?
  provider-type
  accepted-insurance-list
  visit-cost
  OTP-doc?
  MTH-spots
  total-capacity
  no-pay?
  do-telemedicine?
  weighted-ratio-2SFCA
  weighted-ratio-E2SFCA
  weighted-ratio-logistic
  weighted-ratio-gaussian
  weighted-ratio-exponential
  tele-patients
  BUP-patients
  MTH-patients

```

```

    rxerType
]

deps-own[
  pt?
  seeking-BUP?
  getting-BUP-weeks
  stable-abstinence?
  abstinence-threshold
  provider-group
  provider-list
  my-provider
  my-travel-distance
  waitlisted?
  my-wait-threshold
  indexprovider
  too-far?
  weeks-waiting
  no-access-flag?
  sought?
  have-purchased-pills?
  pill-source
  dose
  weeks-of-pills
  total-tx-cost
  have-diverted?
  divert-reason
  insurance
  coinsurance
  cantAfford?
  monthly-out-of-pocket-payment
  monthly-medication-cost
  poverty
  income
  sex
  relapse?
  recipient-flag?
  got-any-tx-flag?
  weighted-sum-of-ratios-2SFCA
  weighted-sum-of-ratios-E2SFCA
  weighted-sum-of-ratios-logistic
  weighted-sum-of-ratios-gaussian
  weighted-sum-of-ratios-exponential
  reachable-providers
  decile
]

patches-own[
  pop-den
  lambda
  nn-distance
  xP
  yP
  MUA?

```

```

    pills-here
  ]

  OTPs-own
  [
    OTP-type
    accepted-insurance-list
    no-pay?
    OTP-docs
    give-BUP?
    MTH-spots
    MTH-pts
  ]

```

B.2.3 GeoSetup.nls

```

to setup-geography
  set small-city-pct 35.5
  set rural-threshold 35.0
  set small-city-threshold 1000
  make-MUA
  make-real-map
  set show-street-market? false
end

to make-MUA
  let mapfilename (word "map" map-number "MUA.png")
  import-pcolors mapfilename
  ask patches [set pcolor round pcolor ifelse pcolor = 109 or (pcolor >
14 and pcolor < 20) [set MUA? true][ set MUA? false]]
  ask patches [set pcolor black]
end

to make-real-map
  let mapfilename (word "map" map-number ".png")
  import-pcolors mapfilename
  ask patches [set pcolor round pcolor]
  ask patches [remove-lines]
  ask patches [set-density]
  diffuse pop-den .2
  ask patches [set pop-den round pop-den]
  set max-patch-density max [pop-den] of patches
  set rural-areas patches with [pop-den < rural-threshold]
  set small-cities patches with [pop-den < small-city-threshold and
pop-den > rural-threshold]
  set large-cities patches with [pop-den > small-city-threshold]
  set patches-with-pills patch-set nobody
end

to remove-lines
  if pcolor = 4 or pcolor = 5 or pcolor = 133 [set pcolor [pcolor] of
one-of patches in-radius 3 with [pcolor > 5] remove-lines]
end

```

```

to set-density
  if pcolor = 74 [set pop-den 1]
  if pcolor = 55 [set pop-den (1 + random 10)]
  if pcolor = 56 [set pop-den (10 + random 15)]
  if pcolor = 57 [set pop-den (25 + random 25)]
  if pcolor = 58 [set pop-den (50 + random 50)]
  if pcolor = 47 [set pop-den (100 + random 150)]
  if pcolor = 28 [set pop-den (250 + random 250)]
  if pcolor = 27 [set pop-den (500 + random 500)]
  if pcolor = 26 [set pop-den (1000 + random 1500)]
  if pcolor = 16 [set pop-den (2500 + random 2500)]
  if pcolor = 15 [set pop-den (5000 + random 2000)]
end

```

B.2.4 SetupCommands.nls

```

to set-initials
  set all-insurance ["public" "private" "none"]
  set diverted-medicine 0
  if model-year = 2013
  [
    set total-population 316500000
    set docs-per-pop (22631 / total-population)
    set pts-dependent 3556000
    set initial-pct-patients-in-tx .6
    set od-deps-CMR 8
  ]
  if model-year = 2014
  [
    set total-population 318600000
    set docs-per-pop (22218 / total-population)
    set pts-dependent 3400000
    set initial-pct-patients-in-tx .7
    set od-deps-CMR 10.5
  ]
  if model-year = 2015
  [
    set total-population 320900000
    set docs-per-pop (25504 / total-population)
    set pts-dependent 3418000
    set initial-pct-patients-in-tx .8
    set od-deps-CMR 12
  ]
  if model-year = 2016
  [
    set total-population 323100000
    set docs-per-pop (29961 / total-population)
    set pts-dependent 3538000
    set initial-pct-patients-in-tx .8
    set od-deps-CMR 12
  ]
end

```



```

to setup-people

  set total-number-dependent floor (pts-dependent * total-pop / total-
  population)
  calculate-number-patients (total-number-dependent / 1)
  ifelse dep-locations = "baseline-model" or dep-locations = "random-
  location"[
    create-deps (total-number-dependent / 1)
  ]
  [
    ask patches [sprout-deps (round (pop-den * total-number-dependent /
    total-pop))]
  ]
  ask deps[
    set-initial-dep-stats
    set-initial-pt-location
    set-distance
    if dep-locations = "random-location" [move-to one-of patches]
    if [pop-den] of patch-here = 0 [move-to one-of patches with [pop-
    den = 1]]
  ]
  if equity-experiments = "rural-hotspot" or equity-experiments =
  "rural-hotspot-low-transport"
  [
    let hotspot-pop sum [pop-den] of patches with [pxcor >= 75 and
    pxcor <= 100 and pycor >= 75 and pycor <= 100]
    create-deps hotspot-pop / 5 [
      move-to one-of patches with [pxcor >= 75 and pxcor <= 100 and
      pycor >= 75 and pycor <= 100]
      set-initial-dep-stats
      set color orange
      ifelse equity-experiments = "rural-hotspot"[
        set-distance
      ]
    ]
    [
      set my-travel-distance 10 + random 20
    ]
  ]
]
if equity-experiments = "urban-hotspot"
[
  let hotspot-pop sum [pop-den] of patches with [pxcor >= 130 and
  pxcor <= 145 and pycor >= 35 and pycor <= 50]
  create-deps hotspot-pop / 10 [
    move-to one-of patches with [pxcor >= 130 and pxcor <= 145 and
    pycor >= 35 and pycor <= 50]
    set-initial-dep-stats
    set color orange
    set-distance
  ]
]
  setup-patients
end

```

```

to set-initial-dep-stats
  ht
  set pt? false
  set abstinence-threshold 0
  set abstinence-mean 200
  set seeking-BUP? FALSE
  set getting-BUP-weeks -1
  set stable-abstinence? FALSE
  set my-provider NOBODY
  set provider-list []
  set provider-group nobody
  set indexprovider 0
  set waitlisted? false
  set relapse? false
  set too-far? false
  set my-wait-threshold random-exponential my-wait-time
  set weeks-waiting 0
  set cantAfford? false
  set weeks-of-pills 0
  set dose 0
  set monthly-out-of-pocket-payment 0
  set monthly-medication-cost 0
  set my-travel-distance my-travel-distance / 1.3 ;;converting crows
fly distance to taxicab distance

  set have-purchased-pills? false
  set pill-source []
  set have-diverted? false
  set divert-reason []

  set recipient-flag? false
  set got-any-tx-flag? false
  set no-access-flag? false
  set sought? false

  set-sex
  init-poverty-insurance
  set-abstinence-thresholds

end

to calculate-number-patients [total-deps]
  set number-patients floor (total-deps * initial-pct-deps-seeking-or-
in-tx)
end

to set-initial-pt-location
  ifelse random 100 < rural-dep-pct
  [
    move-to one-of rural-areas
    let big-neighborhood patches in-radius 5
    if random 100 < remote-dep-pct [move-to max-one-of big-neighborhood
[pop-den]]
  ]

```

```

]
[
  ifelse random 100 < small-city-pct
    [move-to one-of small-cities]
    [if large-cities != nobody [move-to one-of large-cities]]
]
end

to set-sex
  ifelse random 100 < female-pct [set sex "female"] [set sex "male"]
end

to init-poverty-insurance
  let m random 100
  if m < pct-poverty [set poverty 1]
  if m >= pct-poverty AND m < pct-poverty + pct-twox-poverty [set poverty 2]
  if m >= pct-poverty + pct-twox-poverty [set poverty 3]
  if poverty = 1 [
    let q random 100
    if q < 47 [set insurance "public" set coinsurance 100]
    if q >= 47 and q < 67 [set insurance "private" set coinsurance
      coinsurance-base + random coinsurance-random]
    if q >= 67 [set insurance "none" set coinsurance 0]
  ]
  if poverty = 2 [
    let q random 100
    if q < 30 [set insurance "public" set coinsurance 100]
    if q >= 30 and q < 64 [set insurance "private" set coinsurance
      coinsurance-base + random coinsurance-random]
    if q >= 64 [set insurance "none" set coinsurance 0]
  ]
  if poverty = 3 [
    let q random 100
    if q < 11 [set insurance "public" set coinsurance 100]
    if q >= 11 and q < 83 [set insurance "private" set coinsurance
      coinsurance-base + random coinsurance-random]
    if q >= 83 [set insurance "none" set coinsurance 0]
  ]
  set income (poverty - 1) * poverty-level + random poverty-level
  if medicaid-expansion? [if random 100 < pct-uninsured-now-have-medicaid
    [if insurance = "none" and poverty = 1
      [set insurance "public" set coinsurance 100]]]
  end

to set-abstinence-thresholds
  ifelse random 100 < never-abstain-pct ;;data?
    [set abstinence-threshold 10000]
    [while [abstinence-threshold <= abstinence-floor] ;
      [set abstinence-threshold round random-normal abstinence-mean
        abstinence-mean]
    ]
  end

```

```

to setup-globals
  set ods-deps 0
  set ods-pats 0

  set initial-pct-deps-seeking-or-in-tx .36
  set remote-dep-pct 52.0
  set low-spec .046
  set high-spec .12
  set non-high-list .2040
  set non-low-list .0780
  set non-low-nolist .48
  set low-spec-random 2
  set high-spec-random 2
  set non-high-list-random 2
  set non-low-list-random 2
  set non-low-nolist-random 2
  set pa-pop 101318
  set pa-pcp-pct .265
  set dep-incidence .1
  set seeking-incidence .4
  set np-pop 220000
  set np-pcp-pct .710
  set MUA-pct .3
  set remote-pct .25
  set APN-discount .7
  set lowest-cost 60
  set APN-random 2
  set divertAfford 54
  set wanted$ 14
  set percentSayYes 35
  set colleague-radius 5
  set rural-dep-pct 14.5
  set pct-of-income .30
  set pct-poverty 30
  set pct-twox-poverty 26
  set coinsurance-base 50
  set coinsurance-random 19
  set never-abstain-pct 50
  set abstinence-floor 10

  set dose-sixteen 63
  set dose-eight 18
  set dose-tfour 15
  set mth-cost 20
  set pct-try-bup-first 80
  set mth-weekly-quit-rate .0070
  set first-week-bup-quit 24
  set second-week-bup-quit 12
  set my-wait-time 4
  set poverty-level 1000
  set female-pct 30

  set ods-pts-in-tx 3
  set post-tx-die 8

```

```
end
```

B.2.5 ProviderSetup.nls

```
to setup-providers
  setup-docs
  if NP-PAs? [setup-APN]
  ask providers[
    set colleagues other providers in-radius colleague-radius
    if not any? colleagues [let other-guys min-n-of 2 providers
[distance myself] set other-guys other other-guys set colleagues other-
guys ]
  ]
  create-dummy-doc
end
```

```
to setup-docs
  set-doc-pop
  ifelse doc-locations = "baseline-model" or doc-locations = "random-
location"[
    create-providers number-docs
  ]
  [
    while [count providers < number-docs][
      ask one-of patches [if random-float 1 > (pop-den * number-docs /
total-pop) [sprout-providers (ceiling (pop-den * number-docs / total-
pop))]]
    ]
  ]
  ask providers[
    set size 4
    set color red
    set provider-type "doc"
    set OTP-doc? FALSE
    set do-telemedicine? FALSE
    set BUP-patients turtle-set nobody
    set tele-patients turtle-set nobody
    set MTH-patients turtle-set nobody
    set-practice-characteristics
    set-doc-characteristics
    set-initial-doc-location
  ]
end
```

```
to set-doc-pop
  set number-docs floor (docs-per-pop * total-pop)
  set weekly-add-docs growth-rate-docs / 52 * (total-pop / total-
population)
end
```

```
to set-practice-characteristics
```

```

while [visit-cost < lowest-cost] [set visit-cost visit-cost-mean +
random-normal visit-cost-mean visit-cost-mean]
  set-insurance
  if accepted-insurance-list = 0 [set accepted-insurance-list ["none"]]
end

to set-insurance
set accepted-insurance-list []
if random 100 < accept-cash [set accepted-insurance-list ["none"]]
if random 100 < accept-private [set accepted-insurance-list lput
"private" accepted-insurance-list]
if random 100 < accept-public [set accepted-insurance-list lput
"public" accepted-insurance-list]
if accepted-insurance-list = [] [set accepted-insurance-list ["none"]]
end

to set-doc-characteristics
  set willAdd? FALSE
  let r random-float 1
  ;set rxerType 0

  if r <= low-spec
  [
    set BUP-years random-float 1
    set specialist? TRUE set onList? TRUE set Rxing? TRUE set capHigh?
FALSE set willAdd? TRUE
    ifelse low-spec-random = 4 [set patients-per-provider high-cap]
    [
      ifelse low-spec-random = 2[set patients-per-provider 30 + round
random-exponential 250]
      [ifelse low-spec-random = 1 [set patients-per-provider random
150][set patients-per-provider random 1000]]
    ]
    set-telemedicine
    set rxerType 1
  ]
  if r > low-spec and r <= (low-spec + high-spec)
  [
    set BUP-years 1 + random-float 12
    set specialist? TRUE set onList? TRUE set Rxing? TRUE set capHigh?
TRUE set willAdd? TRUE
    ifelse high-spec-random = 4 [set patients-per-provider high-cap]
    [
      ifelse high-spec-random = 2[set patients-per-provider 30 + round
random-exponential 250]
      [ifelse high-spec-random = 1 [set patients-per-provider random
150][set patients-per-provider random 1000]]
    ]
    set-telemedicine
    set rxerType 2
  ]
  if r > (low-spec + high-spec) and r <= (low-spec + high-spec + non-
high-list)
  [

```

```

        set BUP-years 1 + random-float 12
        set specialist? FALSE set onList? TRUE set Rxing? TRUE set capHigh?
TRUE set willAdd? TRUE
        ifelse non-high-list-random = 4 [set patients-per-provider high-
cap]
        [
            ifelse non-high-list-random = 2[ set patients-per-provider 30 +
round random-exponential 220 ] ;; goosing high end
            [ifelse non-high-list-random = 1 [set patients-per-provider random
100][set patients-per-provider random 1000]]
            while [patients-per-provider < 30 and non-high-list-random = 2]
[set patients-per-provider 20 + round random-exponential 40]
        ]
        set rxerType 3
    ]
    if r > (low-spec + high-spec + non-high-list) and r <= (low-spec +
high-spec + non-high-list + non-low-list)
    [
        set specialist? FALSE set onList? TRUE set Rxing? TRUE set capHigh?
FALSE
        ifelse random 100 < pct-get-high-cap
        [
            ifelse non-low-list-random = 4 [set patients-per-provider high-
cap]
            [
                ifelse non-low-list-random = 2[set patients-per-provider 20 +
round random-exponential 40]
                [ifelse non-low-list-random = 1 [set patients-per-provider random
100][set patients-per-provider random 200]]
                while [patients-per-provider < 30 and non-low-list-random = 2]
[set patients-per-provider 20 + round random-exponential 40]
            ] ;; 7% will go on to get 100
            set BUP-years random-float 1
            set willAdd? TRUE
        ]
        [
            ifelse non-low-list-random = 4 [set patients-per-provider low-
cap]
            [
                ifelse non-low-list-random = 2[set patients-per-provider round
random-normal 20 7 ] ;; calibrate to lower
                [ifelse non-low-list-random = 1 [set patients-per-provider random
10][set patients-per-provider random 30]]
                while [(patients-per-provider < 0 or patients-per-provider > 30)
and non-low-list-random = 2] [set patients-per-provider round random-
normal 20 7]
            ]
            set BUP-years random-float 13
        ]
        set rxerType 4
    ]
    ifelse (low-spec + high-spec + non-high-list + non-low-list + non-
low-nolist) > (1 - pct-not-rxing) [

```

```

        if r > (low-spec + high-spec + non-high-list + non-low-list) and r
        <= (low-spec + high-spec + non-high-list + non-low-list + non-low-
        nolist )
        [
            set specialist? FALSE set onList? FALSE set Rxing? TRUE set
            capHigh? FALSE
            ifelse random 100 < pct-get-high-cap
            [
                ifelse non-low-nolist-random = 4 [set patients-per-provider
                high-cap]
                [
                    ifelse non-low-nolist-random = 2[set patients-per-provider 20 +
                    round random-exponential 40]
                    [ifelse non-low-nolist-random = 1 [set patients-per-provider
                    random 100][set patients-per-provider random 200]]
                    while [patients-per-provider < 30 and non-low-nolist-random =
                    2] [set patients-per-provider 20 + round random-exponential 40]
                    ] ;; 7% will go on to get 100
                    set BUP-years random-float 1
                    set willAdd? TRUE
                ]
            ]
            [
                ifelse non-low-nolist-random = 4 [set patients-per-provider
                low-cap]
                [
                    ifelse non-low-nolist-random = 2[set patients-per-provider
                    round random-normal 20 7]
                    [ifelse non-low-nolist-random = 1 [set patients-per-provider
                    random 10][set patients-per-provider random 30]]
                    while [patients-per-provider < 0 or patients-per-provider >
                    30] [set patients-per-provider round random-normal 20 7]
                    ]
                    set BUP-years random-float 13
                ]
                set rxerType 5
            ]
            if r > (low-spec + high-spec + non-high-list + non-low-list + non-
            low-nolist )
            [
                set BUP-years random-float 13
                set specialist? FALSE set onList? FALSE set Rxing? FALSE set
                capHigh? FALSE
                set patients-per-provider 0
                set rxerType 6
            ]
        ]
        [
            if r > (low-spec + high-spec + non-high-list + non-low-list) and r
            <= (1 - pct-not-rxing )
            [
                set specialist? FALSE set onList? FALSE set Rxing? TRUE set
                capHigh? FALSE
                ifelse random 100 < pct-get-high-cap
                [

```



```

        ifelse non-low-nolist-random = 4 [set patients-per-provider
high-cap]
    [
        ifelse non-low-nolist-random = 2[set patients-per-provider 20 +
round random-exponential 40]
        [ifelse non-low-nolist-random = 1 [set patients-per-provider
random 100][set patients-per-provider random 200]]
        while [patients-per-provider < 30 and non-low-nolist-random =
2] [set patients-per-provider 20 + round random-exponential 40]
        ]
        set BUP-years random-float 1
        set willAdd? TRUE
    ]
    [
        ifelse non-low-nolist-random = 4 [set patients-per-provider
low-cap]
    [
        ifelse non-low-nolist-random = 2[set patients-per-provider
round random-normal 20 7]
        [ifelse non-low-nolist-random = 1 [set patients-per-provider
random 10][set patients-per-provider random 30]]
        while [patients-per-provider < 0 or patients-per-provider >
30] [set patients-per-provider round random-normal 20 7]
        ]
        set BUP-years random-float 13
    ]
    set rxerType 5
]
if r > (1 - pct-not-rxing)
[
    set BUP-years random-float 13
    set specialist? FALSE set onList? FALSE set Rxing? FALSE set
capHigh? FALSE
    set patients-per-provider 0
    set rxerType 6
]
]

if specialist? = 0 ;; anyone left over goes in this pile
[
    set specialist? FALSE set onList? FALSE set Rxing? TRUE set
capHigh? FALSE
    ifelse random 100 < pct-get-high-cap
    [
        set patients-per-provider 20 + round random-exponential 40
        while [patients-per-provider < 30] [set patients-per-provider 20
+ round random-exponential 40]
        set BUP-years random-float 1
        set willAdd? TRUE
    ]
    [
        set patients-per-provider round random-normal 20 7
        while [patients-per-provider < 0 or patients-per-provider > 30]
[set patients-per-provider round random-normal 20 7]

```

```

        set BUP-years random-float 13
      ]
      set rxerType 7
    ]

  end

  to set-telemedicine
    if telemedicine?[
      if random 100 < pct-specialists-telemedicine[set do-telemedicine?
true]
    ]
  end

  to set-initial-doc-location
    if doc-locations = "random-location"[
      move-to one-of patches
    ]
    if doc-locations = "baseline-model"
    [
      ifelse capHigh? = false[
        let temp-my-patch-den random-lognormal 46300 9460
        while [temp-my-patch-den > max-patch-density] [set temp-my-patch-
den random-lognormal 46300 9460]
        let density-low-bound temp-my-patch-den - .4 * temp-my-patch-den
        let density-upper-bound temp-my-patch-den + 4 * temp-my-patch-den
        let move-to-patch one-of patches with [pop-den > density-low-
bound AND pop-den < density-upper-bound]
        if move-to-patch != nobody[ move-to move-to-patch]
      ]
      [
        let temp-my-patch-den random-lognormal 19600 5570
        while [temp-my-patch-den > max-patch-density] [set temp-my-patch-
den random-lognormal 19600 5570]
        let density-low-bound temp-my-patch-den - .4 * temp-my-patch-den
        let density-upper-bound temp-my-patch-den + 4 * temp-my-patch-den
        let move-to-patch one-of patches with [pop-den > density-low-
bound AND pop-den < density-upper-bound]
        if move-to-patch != nobody[ move-to move-to-patch]
      ]
    ]
  end

  to set-capacity
    ask providers with [BUP-years < 1 and provider-type != "MTH-doc"][
      ifelse (patients-per-provider > low-cap)
        [set capped-patients-per-provider low-cap]
        [set capped-patients-per-provider patients-per-provider]
      if OTP-doc? = false [set total-capacity capped-patients-per-
provider]
    ]
    ask providers with [BUP-years >= 1 and provider-type != "MTH-doc"][
      ifelse (patients-per-provider > high-cap)

```

```

        [set capped-patients-per-provider high-cap]
        [set capped-patients-per-provider patients-per-provider]
        if OTP-doc? = false [set total-capacity capped-patients-per-
provider]
    ]
    set open-capacity (sum [capped-patients-per-provider] of providers) -
(sum [count my-links] of providers)
end

to setup-APN
    setup-PAs
    setup-NPs
end

to setup-PAs
    let number-PAs pa-pop * (total-pop / total-population) * pa-pcp-pct *
pct-NPs-PAs-rxing / 100
    create-providers number-PAs[
        set size 3
        set color black
        set provider-type "PA"
        set OTP-doc? FALSE
        set do-telemedicine? FALSE
        set BUP-patients turtle-set nobody
        set tele-patients turtle-set nobody
        set MTH-patients turtle-set nobody
        set-APN-characteristics
        set-initial-APN-location
        set-APN-practice-characteristics
    ]
end

to setup-NPs
    let number-NPs np-pop * (total-pop / total-population) * np-pcp-pct *
pct-NPs-PAs-rxing / 100
    create-providers number-NPs[
        set size 3
        set color black
        set OTP-doc? FALSE
        set do-telemedicine? FALSE
        set BUP-patients turtle-set nobody
        set tele-patients turtle-set nobody
        set MTH-patients turtle-set nobody
        set provider-type "NP"
        set-APN-characteristics
        set-initial-APN-location
        set-APN-practice-characteristics
    ]
end

to set-APN-characteristics
    set BUP-years 0.02
    set specialist? FALSE set onList? TRUE set Rxing? TRUE set capHigh?
FALSE

```

```

    ifelse random 100 < pct-get-high-cap
    [
      if APN-random = 2[set patients-per-provider 30 + round random-
exponential 220]

      while [patients-per-provider < 0] [set patients-per-provider 30 +
round random-exponential 220]
      set willAdd? TRUE
    ]
    [
      if APN-random = 2[set patients-per-provider 20 + round random-
exponential 40 ]

      while [patients-per-provider < 0 or patients-per-provider > 30]
[set patients-per-provider 20 + round random-exponential 40 ]
      set willAdd? FALSE
    ]
  end

to set-APN-practice-characteristics
  while [visit-cost < lowest-cost] [set visit-cost visit-cost-mean +
random-normal visit-cost-mean visit-cost-mean]
  set visit-cost APN-discount * visit-cost
  set-insurance
  if accepted-insurance-list = 0 [set accepted-insurance-list ["none"]]
end

to set-initial-APN-location
  let t random-float 1

  ifelse t < MUA-pct [
    ifelse random-float 1 < remote-pct
    [move-to one-of patches with [MUA? and pop-den < rural-threshold
and pop-den > 0]]
    [move-to one-of patches with [MUA? and pop-den >= rural-threshold]]
  ]
  [
    move-to one-of patches with [MUA? = FALSE and count providers-here
> 0]
  ]
end

to create-dummy-doc
  create-providers 1 [
    ht
    set provider-type "dummy"
    set OTP-doc? FALSE
    set do-telemedicine? FALSE
    set accepted-insurance-list (list "none" "public" "private")
    set total-capacity 100000
    set capped-patients-per-provider 100000
    set patients-per-provider 10000
  ]
end

```

```

set rxing? false
set willAdd? false
set specialist? false
set capHigh? false
set onList? false
set BUP-patients turtle-set nobody
set tele-patients turtle-set nobody
set MTH-patients turtle-set nobody
set BUP-years 10
set dummy-doc self
]
end

```

B.2.6 Otp.nls

```

to setup-OTPs
  set num-otps 1368
  set va-pct 3
  set gvt-pct 6
  set pnp-pct 36
  let number-OTPs floor (num-otps * (total-pop / total-population))
  create-OTPs number-OTPs
  [
    set accepted-insurance-list (list)
    set-OTP-location
    set size 4
    set shape "square"
    set color 125
    set-OTP-type-insurance
  ]
end

to set-OTP-type-insurance
  let pct random 100
  let cash-pct random 100
  let private-pct random 100
  let public-pct random 100
  let nopay-pct random 100
  let give-bup random 100
  if pct < va-pct
  [
    set OTP-type "VA"
    if cash-pct < 64 [set accepted-insurance-list lput "none" accepted-
insurance-list]
    if private-pct < 91 [set accepted-insurance-list lput "private"
accepted-insurance-list]
    if public-pct < 35 [set accepted-insurance-list lput "public"
accepted-insurance-list]
    ifelse nopay-pct < 94 [set no-pay? true][set no-pay? false]
    ifelse give-bup < 94 [set give-BUP? true][set give-BUP? false]
    if empty? accepted-insurance-list [set accepted-insurance-list lput
"none" accepted-insurance-list]
    while [MTH-spots <= 0] [set MTH-spots round (random-normal 103 89)]
  ]
end

```

```

]
if pct >= va-pct and pct < va-pct + gvt-pct
[set OTP-type "gvt"
  if cash-pct < 92 [set accepted-insurance-list lput "none" accepted-
insurance-list]
  if private-pct < 49 [set accepted-insurance-list lput "private"
accepted-insurance-list]
  if public-pct < 71 [set accepted-insurance-list lput "public"
accepted-insurance-list]
  ifelse nopay-pct < 70 [set no-pay? true][set no-pay? false]
  ifelse give-bup < 35[set give-BUP? true][set give-BUP? false]
  if empty? accepted-insurance-list [set accepted-insurance-list lput
"none" accepted-insurance-list]
  while [MTH-spots <= 0][set MTH-spots round (random-normal 362 469
)]
]
if pct >= va-pct + gvt-pct and pct < va-pct + gvt-pct + pnp-pct
[set OTP-type "PNP"
  if cash-pct < 96 [set accepted-insurance-list lput "none" accepted-
insurance-list]
  if private-pct < 58 [set accepted-insurance-list lput "private"
accepted-insurance-list]
  if public-pct < 92 [set accepted-insurance-list lput "public"
accepted-insurance-list]
  ifelse nopay-pct < 44 [set no-pay? true][set no-pay? false]
  ifelse give-bup < 44[set give-BUP? true][set give-BUP? false]
  if empty? accepted-insurance-list [set accepted-insurance-list lput
"none" accepted-insurance-list]
  while [MTH-spots <= 0][set MTH-spots round (random-normal 235 213)]
]
if pct >= va-pct + gvt-pct + pnp-pct
[set OTP-type "PFP"
  if cash-pct < 100[set accepted-insurance-list lput "none" accepted-
insurance-list]
  if private-pct < 33[set accepted-insurance-list lput "private"
accepted-insurance-list]
  if public-pct < 46 [set accepted-insurance-list lput "public"
accepted-insurance-list]
  ifelse nopay-pct < 8 [set no-pay? true][set no-pay? false]
  ifelse give-bup < 48[set give-BUP? true][set give-BUP? false]
  if empty? accepted-insurance-list [set accepted-insurance-list lput
"none" accepted-insurance-list]
  while [MTH-spots <= 0][set MTH-spots round (random-normal 255 204)]
]
end

to set-OTP-location
  ifelse doc-locations = "random-location" [
    move-to one-of patches
  ]
  [
    let OTP-location-den 3 + random-lognormal 32900 9050
    let max-den max [pop-den] of patches
  ]

```

```

    while [OTP-location-den > max-den] [set OTP-location-den random-
lognormal 32900 9050]
    let density-low-bound OTP-location-den - .4 * OTP-location-den
    let density-upper-bound OTP-location-den + 4 * OTP-location-den
    if one-of patches with [pop-den > density-low-bound AND pop-den <
density-upper-bound] != nobody[ move-to one-of patches with [pop-den >
density-low-bound AND pop-den < density-upper-bound]]
  ]
end

to init-OTPs
  let temp-list accepted-insurance-list
  let my-patch patch-here
  let temp-MTH-spots MTH-spots
  let temp-no-pay? no-pay?
  ifelse give-BUP?
  [
    ask n-of 2 providers with [specialist? and capHigh?]
    [
      move-to my-patch
      set onList? TRUE set Rxing? TRUE
      set OTP-doc? TRUE
      set MTH-spots round (temp-MTH-spots / 2)
      set capped-patients-per-provider high-cap
      set total-capacity (capped-patients-per-provider + MTH-spots)
      set do-telemedicine? FALSE
      set BUP-patients turtle-set nobody
      set tele-patients turtle-set nobody
      set MTH-patients turtle-set nobody
      set accepted-insurance-list (list)
      set colleagues other providers in-radius colleague-radius
      foreach temp-list[x -> set accepted-insurance-list fput x
accepted-insurance-list]
      set no-pay? temp-no-pay?
      set OTP-docs providers-here
    ]
  ]
  [
    let num-doc 1 + random 2
    hatch-providers num-doc
    [
      set specialist? true
      set onList? false
      set Rxing? false
      set CapHigh? false
      set willAdd? false
      set provider-type "MTH-doc"
      set do-telemedicine? false
      set BUP-patients turtle-set nobody
      set tele-patients turtle-set nobody
      set MTH-patients turtle-set nobody
      set patients-per-provider 0
      set capped-patients-per-provider 0
      set MTH-spots round (temp-MTH-spots / num-doc)
      set total-capacity MTH-spots
    ]
  ]

```

```

        set accepted-insurance-list (list)
        foreach temp-list[x -> set accepted-insurance-list fput x
accepted-insurance-list]
            set visit-cost 40 + random 60
            set OTP-doc? true
            set colleagues other providers in-radius colleague-radius
            if not any? colleagues [let other-guys min-n-of 2 providers
[distance myself] set other-guys other other-guys set colleagues other-
guys ]
                set no-pay? temp-no-pay?
            ]
            set OTP-docs providers-here with [provider-type = "MTH-doc"]
        ]
    end

```

B.2.7 PtSetup.nls

```

to setup-patients
    ask n-of (number-patients) deps [init-patient]
    ask patients[set-initial-intreatment]
    ask patients with [getting-bup-weeks > -1][get-provider]
end

to init-patient
    set pt? true
    set-dose
    set monthly-medication-cost dose * medication-cost-base
    set-provider-groups
    set color blue
    st
end

to set-dose
    ifelse random 100 < dose-sixteen [set dose 16]
    [ifelse random 100 < dose-eight [set dose 8]
    [ifelse random 100 < dose-tfour [set dose 24]
    [set dose 32]
    ]
    ]
    if dose = 0 [set dose 16]
end

to set-provider-groups
    let inradius-OTP-docs providers with [provider-type = "MTH-doc" and
member? [insurance] of myself accepted-insurance-list and distance
myself < [my-travel-distance] of myself]
    let inradius-providers providers with [onList? and member?
[insurance] of myself accepted-insurance-list and distance myself <
[my-travel-distance] of myself]
    set inradius-providers (turtle-set inradius-OTP-docs inradius-
providers)

```



```

    let ref-OTP-provider min-one-of inradius-providers with [otp-
doc?][distance myself]
    let ref-provider min-one-of inradius-providers with [otp-doc? =
false][distance myself]
    if ref-OTP-provider != nobody
    [
      set my-provider ref-OTP-provider
      set indexprovider 0
      set too-far? FALSE
      set provider-group (turtle-set my-provider provider-group)
    ]
    ifelse ref-provider != nobody
    [
      if my-provider = nobody or ref-OTP-provider = nobody or
distance ref-provider < distance ref-OTP-provider [set my-provider ref-
provider]
      set indexprovider 0
      set too-far? FALSE
      set provider-group (turtle-set ref-provider ref-OTP-provider)
    ]
    [
      if telemedicine?[ set provider-group turtle-set providers with
[do-telemedicine? and onList? and member? [insurance] of myself
accepted-insurance-list = TRUE]]
      ifelse provider-group = nobody [set my-provider dummy-doc ]
      [set my-provider one-of
provider-group]
      if my-provider = nobody [set my-provider dummy-doc]
    ]
    set seeking-BUP? true
    set sought? TRUE
end

to set-initial-intreatment
  if random-float 1 < initial-pct-patients-in-tx
  [
    set seeking-BUP? false
    set sought? false
    set getting-BUP-weeks ceiling random-exponential 10
    if my-provider != dummy-doc[
      set provider-group
      (turtle-set my-provider
        ([colleagues] of my-provider) with [member? [insurance] of
myself accepted-insurance-list = TRUE]
        providers with [do-telemedicine? and member? [insurance] of
myself accepted-insurance-list = TRUE])
    ]
  ]
end

to set-distance ;; plug for data on willingness to travel.
  if [pop-den] of patch-here > 5000 [draw-5000]

```

```

    if [pop-den] of patch-here < 5000 and [pop-den] of patch-here > 2500
[draw-2500]
    if [pop-den] of patch-here < 2500 and [pop-den] of patch-here > 1000
[draw-1000]
    if [pop-den] of patch-here < 1000 and [pop-den] of patch-here > 500
[draw-500]
    if [pop-den] of patch-here < 500 and [pop-den] of patch-here > 250
[draw-250]
    if [pop-den] of patch-here < 250 and [pop-den] of patch-here > 100
[draw-100]
    if [pop-den] of patch-here < 100 and [pop-den] of patch-here > 50
[draw-50]
    if [pop-den] of patch-here < 50 and [pop-den] of patch-here > 25
[draw-25]
    if [pop-den] of patch-here < 25 and [pop-den] of patch-here > 10
[draw-10]
    if [pop-den] of patch-here < 10 and [pop-den] of patch-here > 0
[draw-0]
    if my-travel-distance = 0 [set my-travel-distance 5]
end

```

```

to draw-5000
  let nn random-float 1
  if nn < 1 [set my-travel-distance 100]
  if nn < .985085 [set my-travel-distance 95]
  if nn < .9849 [set my-travel-distance 90]
  if nn < .9843 [set my-travel-distance 85]
  if nn < .9841 [set my-travel-distance 80]
  if nn < .9835 [set my-travel-distance 75]
  if nn < .9820 [set my-travel-distance 70]
  if nn < .9813 [set my-travel-distance 65]
  if nn < .9808 [set my-travel-distance 60]
  if nn < .9757 [set my-travel-distance 55]
  if nn < .9749 [set my-travel-distance 50]
  if nn < .9567 [set my-travel-distance 45]
  if nn < .9525 [set my-travel-distance 40]
  if nn < .94012 [set my-travel-distance 35]
  if nn < .931733 [set my-travel-distance 30]
  if nn < .8922 [set my-travel-distance 25]
  if nn < .85049 [set my-travel-distance 20]
  if nn < .7391 [set my-travel-distance 15]
  if nn < .5769 [set my-travel-distance 10 ]
  if nn < .218 [set my-travel-distance 5]
end

```

```

to draw-2500
  let nn random-float 1
  if nn < 1 [set my-travel-distance 100]
  if nn < .97884343 [set my-travel-distance 95]
  if nn < 0.978667137
[set my-travel-distance 90]
  if nn < 0.977697461
[set my-travel-distance 85]

```

```

    if nn < 0.977433004
[set my-travel-distance 80]
    if nn < 0.975141044
[set my-travel-distance 75]
    if nn < 0.97196756
[set my-travel-distance 70]
    if nn < 0.969851904
[set my-travel-distance 65]
    if nn < 0.967295487
[set my-travel-distance 60]
    if nn < 0.954777856
[set my-travel-distance 55]
    if nn < 0.951428068
[set my-travel-distance 50]
    if nn < 0.91969323
[set my-travel-distance 45]
    if nn < 0.911583216
[set my-travel-distance 40]
    if nn < 0.888751763
[set my-travel-distance 35]
    if nn < 0.871385755
[set my-travel-distance 30]
    if nn < 0.79698519
[set my-travel-distance 25]
    if nn < 0.719058533
[set my-travel-distance 20]
    if nn < 0.527062764
[set my-travel-distance 15]
    if nn < 0.298748237
[set my-travel-distance 10 ]
    if nn < 0.052803244
    [set my-travel-distance 5]

end

to draw-1000
    let nn random-float 1
    if nn < 1 [set my-travel-distance 100]
    if nn < 0.980004957
[set my-travel-distance 95]
    if nn < 0.979426588
[set my-travel-distance 90]
    if nn < 0.977939354
[set my-travel-distance 85]
    if nn < 0.977360985
[set my-travel-distance 80]
    if nn < 0.974221267
[set my-travel-distance 75]
    if nn < 0.968602826
[set my-travel-distance 70]
    if nn < 0.963480129
[set my-travel-distance 65]
    if nn < 0.959431546
[set my-travel-distance 60]

```

```

    if nn < 0.941832603
[set my-travel-distance 55]
    if nn < 0.936296786
[set my-travel-distance 50]
    if nn < 0.896554573
[set my-travel-distance 45]
    if nn < 0.884491448
[set my-travel-distance 40]
    if nn < 0.849458812
[set my-travel-distance 35]
    if nn < 0.820457738
[set my-travel-distance 30]
    if nn < 0.71759068
[set my-travel-distance 25]
    if nn < 0.603734611
[set my-travel-distance 20]
    if nn < 0.387341981
[set my-travel-distance 15]
    if nn < 0.175989424
[set my-travel-distance 10 ]
    if nn < 0.025448236
[set my-travel-distance 5]

end

to draw-500
  let nn random-float 1
  if nn < 1 [set my-travel-distance 100]
  if nn < 0.970779221
[set my-travel-distance 95]
  if nn < 0.97038961
[set my-travel-distance 90]
  if nn < 0.967662338
[set my-travel-distance 85]
  if nn < 0.965844156
[set my-travel-distance 80]
  if nn < 0.961038961
[set my-travel-distance 75]
  if nn < 0.954415584
[set my-travel-distance 70]
  if nn < 0.947922078
[set my-travel-distance 65]
  if nn < 0.93974026
[set my-travel-distance 60]
  if nn < 0.916753247
[set my-travel-distance 55]
  if nn < 0.906363636
[set my-travel-distance 50]
  if nn < 0.843766234
[set my-travel-distance 45]
  if nn < 0.820649351
[set my-travel-distance 40]
  if nn < 0.76987013
[set my-travel-distance 35]

```

```

    if nn < 0.717012987
[set my-travel-distance 30]
    if nn < 0.578961039
[set my-travel-distance 25]
    if nn < 0.436103896
[set my-travel-distance 20]
    if nn < 0.231688312
[set my-travel-distance 15]
    if nn < 0.09012987
[set my-travel-distance 10 ]
    if nn < 0.015064935
[set my-travel-distance 5]

end

to draw-250
  let nn random-float 1
  if nn < 1 [set my-travel-distance 100]
  if nn < 0.952435312
[set my-travel-distance 95]
  if nn < 0.951674277
[set my-travel-distance 90]
  if nn < 0.945459158
[set my-travel-distance 85]
  if nn < 0.941146626
[set my-travel-distance 80]
  if nn < 0.932648402
[set my-travel-distance 75]
  if nn < 0.917047184
[set my-travel-distance 70]
  if nn < 0.900431253
[set my-travel-distance 65]
  if nn < 0.887747336
[set my-travel-distance 60]
  if nn < 0.846905124
[set my-travel-distance 55]
  if nn < 0.829020802
[set my-travel-distance 50]
  if nn < 0.745560629
[set my-travel-distance 45]
  if nn < 0.70890411
[set my-travel-distance 40]
  if nn < 0.643708777
[set my-travel-distance 35]
  if nn < 0.581557585
[set my-travel-distance 30]
  if nn < 0.428589548
[set my-travel-distance 25]
  if nn < 0.297945205
[set my-travel-distance 20]
  if nn < 0.14028412
[set my-travel-distance 15]
  if nn < 0.063926941
[set my-travel-distance 10 ]

```

```

    if nn < 0.013191273
    [set my-travel-distance 5]

end

to draw-100
  let nn random-float 1
  if nn < 1 [set my-travel-distance 100 ]
  if nn < 0.925048411
  [set my-travel-distance 95]
  if nn < 0.92322588
  [set my-travel-distance 90]
  if nn < 0.916733113
  [set my-travel-distance 85]
  if nn < 0.912632418
  [set my-travel-distance 80]
  if nn < 0.898849527
  [set my-travel-distance 75]
  if nn < 0.877206971
  [set my-travel-distance 70]
  if nn < 0.855222691
  [set my-travel-distance 65]
  if nn < 0.832896685
  [set my-travel-distance 60]
  if nn < 0.770816722
  [set my-travel-distance 55]
  if nn < 0.74074496
  [set my-travel-distance 50]
  if nn < 0.612826062
  [set my-travel-distance 45]
  if nn < 0.56133956
  [set my-travel-distance 40]
  if nn < 0.47385807
  [set my-travel-distance 35]
  if nn < 0.402323727
  [set my-travel-distance 30]
  if nn < 0.256065611
  [set my-travel-distance 25]
  if nn < 0.163116528
  [set my-travel-distance 20]
  if nn < 0.071989976
  [set my-travel-distance 15]
  if nn < 0.032577742
  [set my-travel-distance 10 ]
  if nn < 0.009112655
  [set my-travel-distance 5]

end

to draw-50
  let nn random-float 1
  if nn < 1
  [set my-travel-distance 100]
  if nn < 0.952435312

```

```

[set my-travel-distance 95]
  if nn < 0.951674277
[set my-travel-distance 90]
  if nn < 0.945459158
[set my-travel-distance 85]
  if nn < 0.941146626
[set my-travel-distance 80]
  if nn < 0.932648402
[set my-travel-distance 75]
  if nn < 0.917047184
[set my-travel-distance 70]
  if nn < 0.900431253
[set my-travel-distance 65]
  if nn < 0.887747336
[set my-travel-distance 60]
  if nn < 0.846905124
[set my-travel-distance 55]
  if nn < 0.829020802
[set my-travel-distance 50]
  if nn < 0.745560629
[set my-travel-distance 45]
  if nn < 0.70890411
[set my-travel-distance 40]
  if nn < 0.643708777
[set my-travel-distance 35]
  if nn < 0.581557585
[set my-travel-distance 30]
  if nn < 0.428589548
[set my-travel-distance 25]
  if nn < 0.297945205
[set my-travel-distance 20]
  if nn < 0.14028412
[set my-travel-distance 15]
  if nn < 0.063926941
[set my-travel-distance 10 ]
  if nn < 0.013191273
[set my-travel-distance 5]

end

to draw-25
  let nn random-float 1
  if nn < 1
    [set my-travel-distance 100]
    if nn < 0.842581661
    [set my-travel-distance 95]
    if nn < 0.839433294
    [set my-travel-distance 90]
    if nn < 0.826446281
    [set my-travel-distance 85]
    if nn < 0.807949626
    [set my-travel-distance 80]
    if nn < 0.780401417
    [set my-travel-distance 75]

```

```

    if nn < 0.733175915
[set my-travel-distance 70]
    if nn < 0.690279418
[set my-travel-distance 65]
    if nn < 0.662337662
[set my-travel-distance 60]
    if nn < 0.556080283
[set my-travel-distance 55]
    if nn < 0.50806769
[set my-travel-distance 50]
    if nn < 0.346713892
[set my-travel-distance 45]
    if nn < 0.303423849
[set my-travel-distance 40]
    if nn < 0.225108225
[set my-travel-distance 35]
    if nn < 0.174734357
[set my-travel-distance 30]
    if nn < 0.093663912
[set my-travel-distance 25]
    if nn < 0.058638331
[set my-travel-distance 20]
    if nn < 0.029515939
[set my-travel-distance 15]
    if nn < 0.018103109
[set my-travel-distance 10 ]
    if nn < 0.008658009
[set my-travel-distance 5]

```

end

```

to draw-10
    let nn random-float 1
    if nn < 1
    [set my-travel-distance 100]
    if nn < 0.72
[set my-travel-distance 95]
    if nn < 0.714545455
[set my-travel-distance 90]
    if nn < 0.691818182
[set my-travel-distance 85]
    if nn < 0.680909091
[set my-travel-distance 80]
    if nn < 0.647272727
[set my-travel-distance 75]
    if nn < 0.595454545
[set my-travel-distance 70]
    if nn < 0.551818182
[set my-travel-distance 65]
    if nn < 0.515454545
[set my-travel-distance 60]
    if nn < 0.431818182
[set my-travel-distance 55]
    if nn < 0.394545455

```



```

[set my-travel-distance 50]
  if nn < 0.26
[set my-travel-distance 45]
  if nn < 0.222727273
[set my-travel-distance 40]
  if nn < 0.166363636
[set my-travel-distance 35]
  if nn < 0.132727273
[set my-travel-distance 30]
  if nn < 0.072727273
[set my-travel-distance 25]
  if nn < 0.054545455
[set my-travel-distance 20]
  if nn < 0.023636364
[set my-travel-distance 15]
  if nn < 0.015454545
[set my-travel-distance 10 ]
  if nn < 0.008181818
[set my-travel-distance 5]

end

to draw-0
  let nn random-float 1
  if nn < 1
    [set my-travel-distance 100]
    if nn < 0.48372093
[set my-travel-distance 95]
    if nn < 0.479069767
[set my-travel-distance 90]
    if nn < 0.460465116
[set my-travel-distance 85]
    if nn < 0.446511628
[set my-travel-distance 80]
    if nn < 0.41627907
[set my-travel-distance 75]
    if nn < 0.381395349
[set my-travel-distance 70]
    if nn < 0.360465116
[set my-travel-distance 65]
    if nn < 0.334883721
[set my-travel-distance 60]
    if nn < 0.272093023
[set my-travel-distance 55]
    if nn < 0.255813953
[set my-travel-distance 50]
    if nn < 0.202325581
[set my-travel-distance 45]
    if nn < 0.186046512
[set my-travel-distance 40]
    if nn < 0.16744186
[set my-travel-distance 35]
    if nn < 0.162790698
[set my-travel-distance 30]

```

```

    if nn < 0.125581395
[set my-travel-distance 25]
    if nn < 0.104651163
[set my-travel-distance 20]
    if nn < 0.072093023
[set my-travel-distance 15]
    if nn < 0.06744186
[set my-travel-distance 10 ]
    if nn < 0.034883721
[set my-travel-distance 5]

```

```
end
```

B.2.8 ProviderGo.nls

```

to age-providers
  let short-tick 1 / 52
  add-docs
  ask providers [
    set BUP-years BUP-years + short-tick
    if BUP-years > 1 AND BUP-years < 2 and willAdd?
    [
      set capped-patients-per-provider patients-per-provider
      if patients-per-provider > high-cap [set capped-patients-per-
provider high-cap]
    ]
  ]
end

```

```

to add-docs
  let weekrate 0
  let randomizer weekly-add-docs - floor weekly-add-docs
  ifelse random-float 1 < randomizer [set weekrate floor weekly-add-
docs + 1][set weekrate floor weekly-add-docs]
  create-providers weekrate [
    set color black
    set-initial-doc-location
    set BUP-years 0
    set provider-type "doc"
    set OTP-doc? FALSE
    set do-telemedicine? FALSE
    set BUP-patients turtle-set nobody
    set tele-patients turtle-set nobody
    set MTH-patients turtle-set nobody
    set-practice-characteristics
    set-doc-characteristics
    set-capacity
    set colleagues other providers in-radius colleague-radius
    if not any? colleagues [let other-guys min-n-of 2 providers
[distance myself] set other-guys other other-guys set colleagues other-
guys ]
  ]
  set number-docs count providers with [provider-type = "doc"]

```

```
end
```

B.2.9 GoCommands.nls

```
to do-street-market
  diffuse pills-here (8 / 9)
  set patches-with-pills patches with [pills-here > 0]
  if show-street-market? [
    ask turtles [ht]
    ask patches [set pcolor scale-color green pills-here 0 20]
  ]
end

to grow-deps
  let num-new-deps ((pts-dependent * dep-incidence * total-pop / (total-
population * 52)))
  create-deps num-new-deps [set-initial-dep-stats]
end

to chance-OD
  ask nonpats [
    let m random-float 1
    ifelse weeks-of-pills >= 1 [
      set weeks-of-pills weeks-of-pills - 1
      if m < (ods-pts-in-tx / (1000 * 52 ))[
        set ods-deps ods-deps + 1 die
      ]
    ]
    [
      if weeks-of-pills > 0
      [
        set weeks-of-pills 0
      ]
      if m < (od-deps-CMR / (1000 * 52))[
        set ods-deps ods-deps + 1 die
      ]
    ]
  ]
end

to reset-flagged-vars
  if ticks mod 52 - 8 = 0
  [
    ask deps with [no-access-flag? and recipient-flag? = FALSE][ht]
    ask deps with [seeking-bup? = false and getting-bup-weeks = -1][ht]
    ask deps with [recipient-flag?][set recipient-flag? FALSE]
    ask deps with [got-any-tx-flag?][set got-any-tx-flag? FALSE]
    ask deps with [getting-BUP-weeks >= 0][set recipient-flag? TRUE set
got-any-tx-flag? TRUE]
    ask deps with [getting-BUP-weeks = -200][set got-any-tx-flag? TRUE
]
    ask deps with [getting-BUP-weeks = -1] [set recipient-flag? FALSE
set got-any-tx-flag? FALSE]
```

```

    ask deps [set no-access-flag? FALSE]
    ask deps [set sought? FALSE]
  ]
  reset-counters
end

to reset-counters
  if ticks mod 52 - 8 = 0 [
    set ODs-pats 0
    set ODs-deps 0
    set diverted-medicine 0
  ]
end

```

B.2.10 PtGo.nls

```

to age-patients
let current-patients patients

ask current-patients with [(getting-BUP-weeks != -1 or stable-
abstinence?) ][if random-float 1 < (ods-pts-in-tx / (1000 * 52 ))
[stop-provider-link set-dead]]
ask current-patients with [weeks-waiting > my-wait-threshold ][do-
relapse];;
ask current-patients with [getting-bup-weeks = -200][do-methadone]
ask current-patients with [getting-bup-weeks >= 0][do-buprenorphine]
ask current-patients with [waitlisted? and getting-bup-weeks = -
1][initiate-tx]
ask current-patients with [waitlisted? = false and getting-bup-weeks =
-1][initiate-tx]
start-seeking-tx
end

to stop-provider-link
  ifelse getting-bup-weeks = -200 [
    let local-mth-set [MTH-patients] of my-provider
    set local-mth-set other local-mth-set
    ask my-provider [
      set MTH-patients local-mth-set
    ]
  ]
  [
    let local-BUP-set [BUP-patients] of my-provider
    let local-TELE-set [tele-patients] of my-provider
    if member? self local-BUP-set [
      set local-BUP-set other local-BUP-set
      ask my-provider [
        set BUP-patients local-BUP-set
      ]
    ]
  ]
  if member? self local-TELE-set [
    set local-TELE-set other local-TELE-set
  ]
end

```

```

        ask my-provider [
            set tele-patients local-TELE-set
        ]
    ]
end

to set-dead
    ifelse getting-bup-weeks = -1 and stable-abstinence? = false
        [set ods-deps ods-deps + 1]
        [set ods-pats ods-pats + 1]
    die
end

to do-relapse
    set relapse? true
    set pt? false
    set getting-bup-weeks -1
    set seeking-bup? false
    set indexprovider 0
    set color white

    if weeks-of-pills > 0 and getting-bup-weeks > 4
        [ask patch-here [set pills-here pills-here + [weeks-of-pills] of
myself * [dose] of myself]]
    if weeks-of-pills > 0 and getting-bup-weeks < 4
        [ask patch-here [set pills-here pills-here + ([weeks-of-pills] of
myself * [dose] of myself) / 4]]

end

to do-methadone
    if random-float 1 < mth-weekly-quit-rate [
        stop-provider-link
        if random-float 1 < (post-tx-die / (1000 * 52 )) [set getting-bup-
weeks -1 set-dead]
        do-relapse
    ]
end

to do-buprenorphine
    ifelse (getting-BUP-weeks = 0 AND random 100 < first-week-bup-quit)
        or (getting-BUP-weeks = 1 AND random 100 < second-week-bup-quit)
        or (getting-BUP-weeks >= 2 AND random 500 < (100 / getting-BUP-
weeks))
    [
        stop-provider-link
        if random-float 1 < (post-tx-die / (1000 * 52 )) [set getting-
bup-weeks -1 set-dead]
        do-relapse
    ]
    [

```

```

    ifelse getting-BUP-weeks >= abstinence-threshold
    [
      stop-provider-link
      set getting-BUP-weeks -1
      set relapse? false
      set stable-abstinence? true
      set color pink
    ]
    [
      get-pills
      divert-pills
      use-pills
      set getting-BUP-weeks getting-BUP-weeks + 1
      set relapse? false
    ]
  ]
end

to get-pills
  if getting-BUP-weeks mod 4 = 0
  [
    set weeks-of-pills 4
    ifelse getting-BUP-weeks != 0
    [
      ifelse [accepted-insurance-list] of my-provider = ["none"]
      [set monthly-out-of-pocket-payment [visit-cost] of my-provider +
monthly-medication-cost * (100 - coinsurance) / 100 ]
      [set monthly-out-of-pocket-payment [visit-cost] of my-provider *
(100 - coinsurance) / 100 + monthly-medication-cost * (100 -
coinsurance) / 100 ]
      set total-tx-cost total-tx-cost + [visit-cost] of my-provider +
monthly-medication-cost
    ]
    [
      ifelse [accepted-insurance-list] of my-provider = ["none"]
      [set monthly-out-of-pocket-payment [visit-cost] of my-provider *
2 + monthly-medication-cost * (100 - coinsurance) / 100 ]
      [set monthly-out-of-pocket-payment [visit-cost] of my-provider *
2 * (100 - coinsurance) / 100 + monthly-medication-cost * (100 -
coinsurance) / 100 ]
      set total-tx-cost total-tx-cost + [visit-cost] of my-provider * 2
+ monthly-medication-cost
    ]
    ifelse monthly-out-of-pocket-payment > income * pct-of-income [set
cantAfford? TRUE][set cantAfford? FALSE]
  ]
end

to divert-pills

  let need-money false

  if poverty < 3 and wanted$ > random 5200 [set need-money true]
  ifelse cantAfford? = true and random 5200 < divertAfford

```

```

[
  let m one-of [ .14 .28 .35]
  if weeks-of-pills - m > 0[
    set weeks-of-pills weeks-of-pills - m
    set diverted-medicine diverted-medicine + (m * dose)
    set have-diverted? True
    set divert-reason lput "afford" divert-reason
    ask patch-here [set pills-here m * [dose] of myself ]
  ]
]
[
  if need-money = true
  [
    let m one-of [ .14 .28 .35]
    if weeks-of-pills - m > 0[
      set weeks-of-pills weeks-of-pills - m
      set diverted-medicine diverted-medicine + (m * dose)
      set have-diverted? True
      set divert-reason lput "money" divert-reason
      ask patch-here [set pills-here m * [dose] of myself ]
    ]
  ]
]
end

to use-pills
  set weeks-of-pills weeks-of-pills - 1
  if weeks-of-pills <= 0 [set weeks-of-pills 0]
end

to initiate-tx
  if seeking-BUP?
  [
    get-provider
  ]
end

to get-provider ;;
  ifelse [provider-type] of my-provider = "dummy"
  [
    ifelse any? insurance-not-dummies with [distance myself < [my-
travel-distance] of myself]
    [set-provider-groups]
    [
      set no-access-flag? TRUE
      set too-far? true
      set getting-BUP-weeks -1
      set seeking-BUP? true
      set sought? true
      set got-any-tx-flag? false
      set recipient-flag? false
      set color yellow
    ]
  ]

```

```

        st
        set size 1
        get-diverted-bup
    ]
]
[
    ifelse provider-group != nobody and (indexprovider < count
provider-group)
    [
        if indexprovider = 1 or waitlisted?[set provider-list sort-on
[distance myself] provider-group]
        if indexprovider != 0 [set my-provider item indexprovider
provider-list]
        ifelse my-travel-distance < distance my-provider
        [
            set no-access-flag? TRUE
            set getting-BUP-weeks -1
            set seeking-BUP? true
            set sought? true
            set got-any-tx-flag? false
            set color orange + 2
            set waitlisted? true
            st
            set size 1
            try-telemedicine
            if getting-BUP-weeks = -1 [    get-diverted-bup    ]
        ]
        [
            ifelse ([provider-type] of my-provider = "MTH-doc" and
([count MTH-patients] of my-provider < ([total-capacity] of my-
provider) ))    ;
            [
                try-to-start-mth-tx
                if getting-bup-weeks = -200
                [
                    set color red
                    add-to-MTH-list
                ]
            ]
        ]
        [
            ifelse(getting-bup-weeks != -200 and ([count tele-patients]
of my-provider + [count BUP-patients] of my-provider) < ([total-
capacity] of my-provider))
            [
                set color black
                start-tx
                if getting-bup-weeks >= 0 and recipient-flag? [
                    add-to-BUP-list
                ]
                if getting-bup-weeks = -200
                [
                    set color red
                    add-to-MTH-list
                ]
            ]
        ]
    ]
]

```



```

    ]
    [
        set indexprovider indexprovider + 1
        get-provider
    ]
]
]
[
    if getting-bup-weeks = -1
    [set color orange
        st
        set size 1
        set no-access-flag? TRUE
        set waitlisted? true
        set provider-group
        (turtle-set my-provider
            ([colleagues] of my-provider) with [member? [insurance] of
myself accepted-insurance-list = TRUE]
            providers with [do-telemedicine? and member? [insurance] of
myself accepted-insurance-list = TRUE]
        )
        set indexprovider 0
        get-diverted-bup
        set seeking-BUP? true set sought? true
        set getting-BUP-weeks -1
        set my-provider min-one-of provider-group [distance myself]
    ]
]
]
end

```

```

to try-telemedicine
    let teledocs turtle-set provider-group with [do-telemedicine? and
capped-patients-per-provider - (count BUP-patients + count tele-
patients) > 0]
    if any? teledocs
    [
        set my-provider one-of teledocs
        start-tx
        ifelse getting-bup-weeks >= 0 and seeking-bup? = FALSE
        [
            add-to-tele-list
        ]
        [set getting-bup-weeks -1 set waitlisted? true]
    ]
end

```

```

to get-diverted-bup
    if random-float 5200 < percentSayYes [
        if ask-friends-for-pills = true

```

```

    [set have-purchased-pills? true set pill-source lput "friends"
pill-source ]
  ]
  ifelse weeks-of-pills >= 1 [set relapse? false ]
  [
    let street-market patches-with-pills with [distance myself < [my-
travel-distance] of myself]

    let pills-on-street sum [pills-here] of street-market
    if pills-on-street > 0[
      ifelse pills-on-street <= dose * 7 * (1 - weeks-of-pills)
      [
        set weeks-waiting weeks-waiting + 1
        set weeks-of-pills weeks-of-pills + (pills-on-street / (dose
* 7))
      ]
      [
        set weeks-of-pills 1
        set relapse? false
      ]
      buy-street-pills street-market pills-on-street
      set have-purchased-pills? true
      set pill-source lput "street" pill-source
    ]
  ]
  if have-purchased-pills? = false [set weeks-waiting weeks-waiting +
1]
end

```

```

to-report ask-friends-for-pills
  let purchased-pills? false
  let my-radius min list 5 my-travel-distance
  let candidate-friends other patients with [weeks-of-pills > 0 and
distance myself < my-radius ]
  let friends n-of min list 5 count candidate-friends candidate-friends
  let total-pills sum [weeks-of-pills] of friends

  while [any? friends and purchased-pills? = FALSE and total-pills >
0][
    ask one-of friends [
      let m ([dose] of myself / dose)
      if m > 1 [set m 1]
      if weeks-of-pills - m > 0
      [
        set weeks-of-pills weeks-of-pills - m
        set diverted-medicine diverted-medicine + (m * dose)
        set have-diverted? true
        set divert-reason lput "friends" divert-reason
        set purchased-pills? true
        ask myself [set weeks-of-pills m]
      ]
    ]
  ]

```

```

        set friends turtle-set other friends
    ]
]
ifelse purchased-pills? [report TRUE]
[report FALSE]
end

to buy-street-pills [street-market pills-on-street]
let purchased-pills 0
let pill-need dose * 7 * (1 - weeks-of-pills)

ifelse pills-on-street > pill-need
[
    while [purchased-pills < pill-need]
    [
        if any? street-market with [pills-here > 0] [
            ask one-of street-market with [pills-here > 0]
            [
                ifelse pills-here < ([pill-need] of myself - purchased-pills)
                [ set purchased-pills purchased-pills + pills-here set pills-
here 0 set street-market other street-market ]
                [ set pills-here pills-here - purchased-pills set purchased-
pills [pill-need] of myself ]
            ]
        ]
    ]
]
[set purchased-pills pills-on-street ask street-market [set pills-here
0 ]]
end

to start-tx
    ifelse [OTP-doc?] of my-provider = true ;
    [
        ifelse [provider-type] of my-provider = "MTH-doc"
        [try-to-start-mth-tx]
        [try-to-start-bup-or-mth-tx]
    ]
    [start-bup-tx]
end

to try-to-start-mth-tx
    let temp-no-pay? [no-pay?] of my-provider
    let cantAffordMTH? FALSE
    let have-MTH-spots [MTH-spots] of my-provider
    let number-MTH-pts [count MTH-patients] of my-provider

    ifelse [accepted-insurance-list] of my-provider = ["none"]
    [set monthly-out-of-pocket-payment mth-cost ]
    [set monthly-out-of-pocket-payment mth-cost * (100 - coinsurance) /
100]

```

```

    if monthly-out-of-pocket-payment > income * pct-of-income [set
cantAffordMTH? TRUE]

    ifelse ((cantAffordMTH? = FALSE or (cantAffordMTH? and temp-no-pay?))
and ((have-MTH-spots - number-MTH-pts) > 0))
    [
      ifelse [otp-doc?] of my-provider = false
      [error "methadone error here" start-mth-tx]
      [start-mth-tx]
    ]
    [
      set getting-bup-weeks -1
      set waitlisted? TRUE
      set cantAfford? TRUE
      set provider-group
      (turtle-set my-provider
        ([colleagues] of my-provider) with [member? [insurance] of
myself accepted-insurance-list = TRUE]
        providers with [do-telemedicine? and member? [insurance] of
myself accepted-insurance-list = TRUE]
      )
      set indexprovider indexprovider + 1
      get-provider
    ]
  end
end

```

```

to start-mth-tx
  set recipient-flag? false
  set getting-BUP-weeks -200
  set got-any-tx-flag? TRUE
  set seeking-BUP? false
  set relapse? false
  set stable-abstinence? false
  set cantAfford? false
  set waitlisted? FALSE
  set color green - 2
  set too-far? FALSE
  set weeks-waiting 0
end

```

```

to try-to-start-bup-or-mth-tx
  let number-bup-pts (count ([BUP-patients ] of my-provider) + count
([tele-patients] of my-provider))

  ifelse [accepted-insurance-list] of my-provider = ["none"]
  [set monthly-out-of-pocket-payment [visit-cost] of my-provider +
monthly-medication-cost * (100 - coinsurance) / 100]
  [set monthly-out-of-pocket-payment [visit-cost] of my-provider *
(100 - coinsurance) / 100 + monthly-medication-cost * (100 -
coinsurance) / 100]

```

```

    if monthly-out-of-pocket-payment > income * pct-of-income [set
cantAfford? TRUE]
    ifelse number-bup-pts < [capped-patients-per-provider] of my-provider
and cantAfford? = FALSE and random 100 < pct-try-bup-first
        [start-bup-tx]
        [if [otp-doc?] of my-provider = TRUE[try-to-start-mth-tx]]
    end

to start-bup-tx
    set recipient-flag? TRUE
    set getting-BUP-weeks getting-BUP-weeks + 1
    set got-any-tx-flag? TRUE
    set seeking-BUP? false
    set relapse? false
    set stable-abstinence? false
    st
    set color green
    set size 1
    set waitlisted? FALSE
    set weeks-waiting 0

    ifelse [accepted-insurance-list] of my-provider = ["none"]
        [set monthly-out-of-pocket-payment [visit-cost] of my-provider +
monthly-medication-cost * (100 - coinsurance) / 100]
        [set monthly-out-of-pocket-payment [visit-cost] of my-provider *
(100 - coinsurance) / 100 + monthly-medication-cost * (100 -
coinsurance) / 100]
    set total-tx-cost total-tx-cost + [visit-cost] of my-provider +
monthly-medication-cost
    if monthly-out-of-pocket-payment > income * pct-of-income [set
cantAfford? TRUE]
    end

to start-seeking-tx
    ask n-of (round (count deps * seeking-incidence / 52)) deps [
        init-patient
        set sought? true
    ]

end

to add-to-BUP-list
    ask my-provider[set BUP-patients (turtle-set BUP-patients myself)]
end

to add-to-MTH-list
    ask my-provider[set MTH-patients (turtle-set MTH-patients myself)]
end

to add-to-tele-list
    ask my-provider[set tele-patients (turtle-set tele-patients myself)]
end

```

B.2.11 Reporters.nls

```

to-report random-lognormal[densd denmean]
  let sigmaden sqrt (ln (((densd * densd) / (denmean * denmean)) + 1))
  let mu ln (denmean) - (sigmaden / 2)
  report (exp (random-normal mu sigmaden) )
; show mu
; show sigmaden
end

to-report patients
  report deps with [pt?]
end

to-report nonpats
  report deps with [pt? = false]
end

to-report not-dummies
  report providers with [provider-type != "dummy"]
end

to-report insurance-not-dummies
  report providers with [provider-type != "dummy" and member?
[insurance] of myself accepted-insurance-list = TRUE]
end

to-report real-providers
  report providers with [provider-type != "dummy"]
end

to-report total-pop
  report sum [pop-den] of patches
end

```