TRICOMM PROJECT REPORT

RX MARKS THE SPOT: A GEO-SPATIAL MATHEMATICAL MODEL OF PRESCRIPTION REFUSAL AND PHARMACY AVAILABILITY IN NORTH CAROLINA

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Problem Chosen	2023 TriCoMM Summary Sheet
2	

0.1 Background:

In the state of North Carolina, it is legal for for pharmacists to refuse to fill prescriptions, with explicit protections allowing pharmacists to refuse to supply drugs used for terminating a pregnancy or any drug that the pharmacist deems not to be in the best interest of the patient [11]. In practice, this can result in pharmacists refusing to fill prescriptions including hormone therapy, contraceptives, abortifacients, and HIV prophylactic drugs. **The effects that pharmacy refusals can have on marginalized communities can be dire**, especially in situations where an individual may be unable to easily access another pharmacy. In some cases, individuals may be forced to live with medical and personal consequences resulting from their inability to obtain a prescribed medicine.

In order to evaluate the potential impact of pharmacy refusals on marginalized community, we first construct a three-part risk analysis model. We aim to (1) **determine the prevalence of groups at-risk for having a prescription refused**, allowing us to determine the magnitude and makeup of vulnerable communities. Then, we (2) **establish a model for pharmacy accessibility**, allowing us to identify "pharmacy deserts" in North Carolina where individuals may struggle to access another pharmacy after an initial refusal, and (3) **examine the availability of marginalized communities to find and travel to another pharmacy**.

0.2 Methods:

The impact of pharmacy prescription refusals is assessed through a **comprehensive tripartite analysis, modelling accessibility, availability, and vulnerability**. In terms of accessibility, we examine how easily individuals in the state of North Carolina can access pharmaceutical services. If the pharmaceutical network is widely accessible, individuals denied a prescription have the option to seek alternatives at other pharmacies. Availability, another key aspect, considers an individual's free time and flexibility. Higher-income individuals with shorter work hours have greater flexibility to explore alternative pharmacies in the event of rejection. Finally, vulnerability measures the likelihood of an individual requiring a prescription that is at risk of being rejected by pharmacists, adding an important dimension to the analysis since this probability is higher for certain marginalized groups.[1]

After taking into account these three factors, **we aggregate at the county level for ease of policy formulation** and then normalize the range of accessibility and availability metrics to [0,1] and then create a **final 'measure of impact' metric from the three major metrics**. From here we can easily identify counties where targeted healthcare investments or policy changes are most needed.

0.3 Results:

Counties from across the state show different patterns for the three main metrics, but overall **the three most impacted counties that require attention are Mecklenburg, Durham, and Pitt** counties

0.4 Conclusion:

Based on our model, we identify areas of vulnerability, inaccessibility, and unavailability for advocates to focus on education, accessibility, and individual support. Additionally, we suggest policy initiatives to mitigate the potential impacts of pharmacy refusals, as well as suggest areas of the state for researchers and activists to focus on to better understand the effects of refusals on marginalized communities throughout the state.

KEYWORDS: Geo-spatial modelling, pharmacy desert, accessibility, availability, vulnerability.

Contents

1 Introduction

In the state of North Carolina, **it is legal for for pharmacists to refuse to fill prescriptions**, with explicit protections allowing pharmacists to refuse to supply drugs used for terminating a pregnancy or any drug that the pharmacist deems not to be in the best interest of the patient. [11] The broad language of these protections allows for pharmacists to refuse to fill any drug that they have any religious, moral, or ideological objection against. In practice, the **drugs most often refused include abortifacients, emergency contraceptives and hormonal contraception pills for individuals who can get pregnant, hormone replacement therapy for transgender individuals, and HIV pre-exposure prophylaxis drugs** primarily for men who have sex with men.

Because pharmacies are not required to report refusals to fill prescriptions, most evidence surrounding refusals is anecdotal in nature, and **it is difficult to track how widespread the practice is, or the impact that it has on marginalized communities** when they are unable to fill prescriptions. However, the **potential impact of a pharmacy refusal is significant, especially in rural areas where individuals may be unable to access another pharmacy that would fill their prescription**. Impact can include unwanted and potentially dangerous pregnancies, mental and physical health detriment for transgender individuals unable to complete their transition, and an increase in HIV infection among men who have sex with men. These effects are harmful both to individuals and to their communities as a whole.

Given the uncertainty surrounding the prevalence of pharmacy refusals, we wish to understand the potential effects they may have on marginalized communities in North Carolina. To this end, **we seek to construct a model that identifies populations with the most vulnerability to a refusal and evaluates their ability to access another pharmacy**. Once this model is constructed, we look to analyze the possible impact on these communities when their prescriptions go unfilled and identify areas of the state most at-risk for harm. Due to the widespread availability of data and immediacy of impact, we focus on emergency contraceptives, but our model is also suitable to analyze a variety of other medication refusals.

2 Brief overview of our dynamic model

The central goal of this research is to predict the total impact of prescription refusal at a census tract level. To that end, we create a tripartite assessment of the potential comparative effect of prescription refusal, and the translate these comparative weights into tangible real-world consequences and their socioeconomic ramifications.

We simplified possible outcomes into a set of 4 progressively worse experiences, as follows:

1. The person easily obtains their medicine through the pharmacy system.
2. The person, through some sacrifice, obtains their medicine through the pharmacy system.
3. The person, despite sacrifices, is unable to obtain the desired medication through the pharmacy system, and opts for some alternative, but with few negative consequences.
4. The person, despite sacrifices, does not get the medicine, and any alternatives attempted end unsuccessfully. The person may then suffer serious negative impact.

Then, we considered what contextual and censual data would influence those outcomes. To facilitate interpretability, we decoupled explanatory variables into 3 main groups, each influencing the probability of each of the 4 outcome option in a distinct way:

- **Vulnerability**: How likely is an individual to seek medicine that has a risk of refusal?
- **Accessibility**: How much work is required of an individual when seeking the medicine?
- **Availability**: How much capacity does an individual have to obtain their medicine?

Here, an individual's capacity to obtain medicine is their ability to deviate from the usual requirements and responsibilities of their day-to-day lives. Factors such as long working hours, long commutes, poverty status, age, and disability status all have impacts on an individual's ability to find and access another pharmacy for their prescription.

An individual's physical location will dictate the amount of time and resources they will have to actually invest to obtain a prescription after an initial refusal. Individuals living near multiple pharmacies may find it feasible to visit several in a short period of time, whereas an individual living in a *pharmacy desert* may have to devote significantly more time and energy to visit multiple pharmacies.

Vulnerability is ultimately a measure of an individual's potential for refusal, and is based on demographic factors that contribute to individual needs for specific medications. These three factors therefore combine to predict the amount of people potentially facing a pharmacy refusal, the work they must do to find another way to get their prescription, and their capacity to actually do that work.

Ultimately, this model works at the level of granularity of census tracts. We may sample, considering density and area, of census tracts to simulate stochastic behavior, but fundamentally our outcomes treat each census tract as a monolithic entity with certain three-pronged dispositions. Then, from those dispositions and the census population data, we can estimate the number of people affected, how they are affected, and ensuing consequences.

3 Assumptions

3.1 Individual behavior

1. Individuals will not cross state lines to go to a pharmacy. We limit our analysis to the state of North Carolina, and therefore assume that patients will not access pharmacies across state lines. This has a slight impact on individuals living very close to state borders. However, some medications are more difficult to get out-of-state, so the impact of this assumption is minimal.

2. The commute transport mode of an individual (transit, carpooling or driving) informs their overall transport independence. Given North Carolina's precarious public transit options, it is assumed those who use it have no choice otherwise.

3.2 Pharmacies

1. We do not model the predisposition of a pharmacy to reject a prescription, and instead assume that all pharmacies are equally likely to fulfill or reject a prescription regardless of location or brand.

2. All pharmacies are created equal. We assume the probability of prescription rejection is some unknown constant on a per-drug basis. That is, the vulnerability metric is calculated depending on the demographic content of a census tract rather than specific pharmacies themselves. This is reasonable, as there is little data available on the difference in pharmacy policy between large chains and local stores.

3.3 Model values

1. We use county and census tract values instead of individual modeling
2. The vulnerability index does not explicitly model the likelihood of getting rejected at a pharmacy as a palpable event, but rather gauges the exposure of a county population to this possibility. Given some background probability of being

3.4 Accessibility

1. Individuals are spread uniformly across a census tract, based only on tract area and population.
2. Individuals with more pharmacy options have heightened accessibility due to increased number of options; that is, a refusal does not force them to divert from their usual plans as much.
3. During a chain of refusals, individuals may choose to go pharmacy hunting in succession or in a spread out interval, so we did not model any specific paths between pharmacies or pharmacies and homes. Rather, we gauged accessibility based only on local pharmacy gravity.
4. Given prior experiences, an individual is likely to prioritize pharmacies that rejected them less. So, over time, the amount of pharmacies an individual needs to visit to get a refill tends to decrease.

3.5 Availability

1. We included the following variables when considering what would allow an individual greater flexibility to go out of their way: income (with diminishing returns for larger incomes), mobility (given by age and disability, and modelled as a bell-shaped curve with a flat top, wherein younger and older people are disadvantaged), and work hours (given by weeks spent working, commute time and hours per week of work, and taken as a sigmoid where fewer total hours improves availability with diminishing returns, and more total hours decreases it similarly.
2. There is a positive correlation between income level and availability. However, it has diminishing returns: high earners do not experience a large change in availability through income change as much as low earners, mirroring the challenges of living paycheck to paycheck.
3. There is a negative correlation between the hours spent in a year doing work-related activities and one's availability. However, the relationship has diminishing returns in either extreme: those who work little remain fairly available even after somewhat increased workload, and those who work a lot remain generally unavailable even during a lighter week. The greatest availability change happens for those around the median work amount.
4. Age has a bell-shaped relationship with availability. Younger individuals will have decreased availability due to less personal autonomy (whether due to lack of car ownership or less formal income). Similarly, older individuals may not be able to drive or live alone. However, age does not generally affect availability during an individual's explicitly non-elderly adult years, so the top of the bell-curve ought to have a flat and wide plateau.
5. We assume that we can sample an individuals daily commute length independently from sampling their weekly hours worked.

3.6 Outcomes

1. Every individual who chooses prescription drugs and suffers a refusal will not immediately quit, but some may eventually quit and procure alternate options.

2. Vulnerability markers affect the likelihood of rejection, and therefore the extent of pharmacy hunting. So, they affect the probabilities of the first outcome primarily.

3. Accessibility and availability influence outcomes dually, where accessibility serves as the expected effort and availability as the possible power. If what is possible meets or exceeds what is expected, an individual will not seek alternate treatment. If, however, it does exceed, they will do so.

4 Building our model

To determine the impact of pharmacy prescription refusals we have taken a three-pronged analysis, approaching this problem through the lenses of accessibility, availability, and vulnerability.

In this case accessibility refers to how accessible the pharmaceutical network in the state of North Carolina is for an individual. If pharmacies are widely accessible and an individual gets denied a prescription, an option they have is to simply visit another pharmacy. Conversely, if the pharmaceutical network is wholly inaccessible, then an individual denied a prescription will be unable to find alternative locations to fulfill their medicinal needs.

Availability represents an individual's free time and flexibility. A high-income individual who works short hours is going to have far more flexibility to explore other pharmacy options in case of rejection, while an income-less teenager enrolled in school, a senior citizen who has to rely on somebody else for transportation, or somebody who works two full-time jobs is going to have a much more difficult time justifying trips to a far away pharmacy.

When discussing prescription rejection, vulnerability is a measure of how likely a certain individual is of requiring a prescription that is at risk of being rejected by pharmacist(s). We chose to focus on female population from 15 to 49 years old actively using contraceptives [1] with a primary focus on emergency contraceptive refusal.

After identifying appropriate measures for the three aforementioned key metrics, the objective is to synthesize a comprehensive, holistic metric that captures the overall impact of pharmacy prescription refusals. The final step involves creating an integrated measure of impact (MoI) metric, calculated as the sum of the normalized values for accessibility, availability, and vulnerability. Furthermore we streamline our analysis to the county level, facilitating the formulation of effective policies. The sum of the normalized key metric values therefore ranges from [0,3], with 3 indicating the least impacted county and 0 signifying the most impacted one. The rationale behind this approach is that it enables a nuanced assessment, allowing policymakers to pinpoint precise counties where targeted healthcare investments or policy changes are most urgently required.

4.1 Accessibility

The notion of pharmacy accessibility has been long discussed in literature and regions with the lack-thereof are often referred to as **'pharmacy deserts'**.[12] The goal of the accessibility part of the model is to then **create an objective metric of how accessible pharmacies are for any given individual**, or alternatively, how much of a 'pharmacy desert' any given region of the state is.

We looked to create a geo-spatial model utilizing the most granular possible population data, the census block, which provides the most precise possible map of population in the state of North Carolina.[9] It is common throughout literature to use distance as a heuristic for accessibility, but to determine the average accessibility level of a census block we need a point in space to calculate distance with. One possible option is to calculate the geographic center of each block, but this method is a very rough approximation of where people live and leads to all blocks being considered equal regardless of population. To overcome these two issues we decided to randomly sample n points within each block, where each point represents an individual. To determine the quantity of points n to sample, we simply divided the total block population by 100[1]. This method led to roughly 106 thousand samples across the state of North Carolina, or about 1% of the state's population. A notable drawback is that people may be allocated nonsensical locations, which is further discussed in Section 8.1.2.

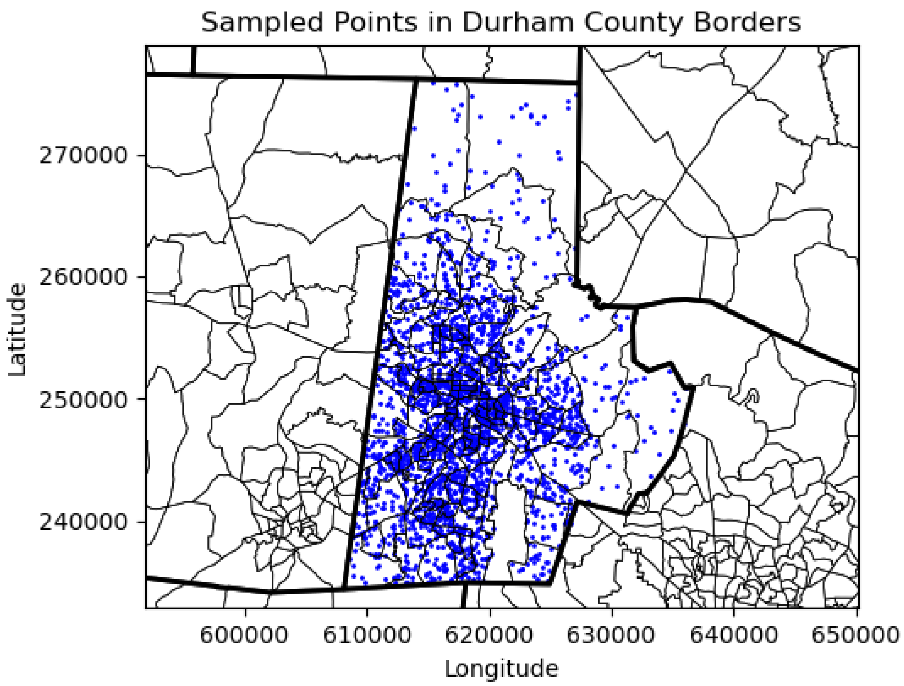

Figure 1: Randomly generated points selected from the census blocks in Durham County, note the lack of samples within the unpopulated Research Triangle Park block in the south of the county

The next step in calculating the 'pharmacy desert' effect in North Carolina is to locate all the pharmacies in the state, which was done using the given data-set. Then we identify the areas in which people at a considerable distance from a nearby pharmacy. Many existing models use minimum-distance-to-pharmacy thresholds to determine whether a region is in a pharmacy desert, but given the context of prescription refusals we found it important to also emphasize pharmacy diversity in a region.[12] For example, a small town with a single pharmacy may not be considered a pharmacy desert by the traditional definition, but if the sole pharmacy refuses to administer certain prescriptions, then the region is effectively within a pharmacy desert for those seeking specific treatments. To account for this in the model we chose to account for the distances to multiple pharmacies. We built the following formula to serve as a heuristic for how accessible the North Carolina pharmaceutical system is to an individual:

[1]Census blocks with less than 100 people were represented by a single randomly generated point

$$A_i = \sum_{p \in P} \max\left(\frac{1}{d(p,i)^n}, 1\right) \tag{4.1}$$

Where A_i represents the accessibility level of sample individual i, P is the set of all pharmacies in North Carolina where each element p represents an individual pharmacy, $d(\cdot\,,\cdot)$ represents the euclidean distance function which is being used to calculate the distance between a sample individual and a pharmacy in miles, and finally n represents a damping factor which can be adjusted to manipulate the effect of distance. Potential error *discuss later in errors section*

The sum of the inverse distances was used to emphasize the accessibility benefit of multiple nearby pharmacies, however we looked to represent some measure of distance decay. The parameter for n was chose after running the sampling process for values between 0.5-5 and determining that $n \sim 0.9$ results in an un-skewed unimodal distribution

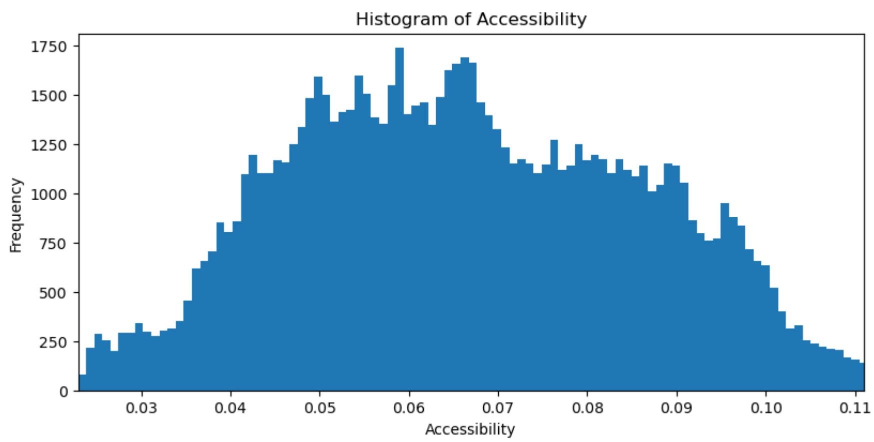

Figure 2: Distribution of calculated A_i levels across all generated sample individuals for $n = 0.9$

From this point we can then aggregate the samples at a county level to be able to formulate county-level policy decisions. Figure 3 reveals that the central Piedmont Crescent area of the state has the highest level of pharmacy accessibility in the state, while the Outer Banks and far west regions host the lowest accessibility levels. Notably, the counties with higher population densities tend to have higher accessibility metrics with a correlation coefficient of $\rho = 0.80$ observed between the accessibility score and the natural logarithm of population density.

4.2 Availability

The material conditions and socioeconomic autonomy of people varies throughout the state of North Carolina. This is evident in the difference between rural and urban environments, but also in the amount of time people work for in a year, the money they make, and even their geographical mobility.

These matters do not ostensibly influence whether someone is likely to be refused a prescription, nor are they necessarily related to someone's accessibility to pharmacy services. Rather, they impact a person's ability to diverge from the usual routines of their life to seek the required medication. Vulnerable individuals may need to search deeper and individuals without accessibility may need to search wider, but individuals without *availability* will have scarcer opportunities to search.

With that in mind, we located 3 vertices of effect from the census data:

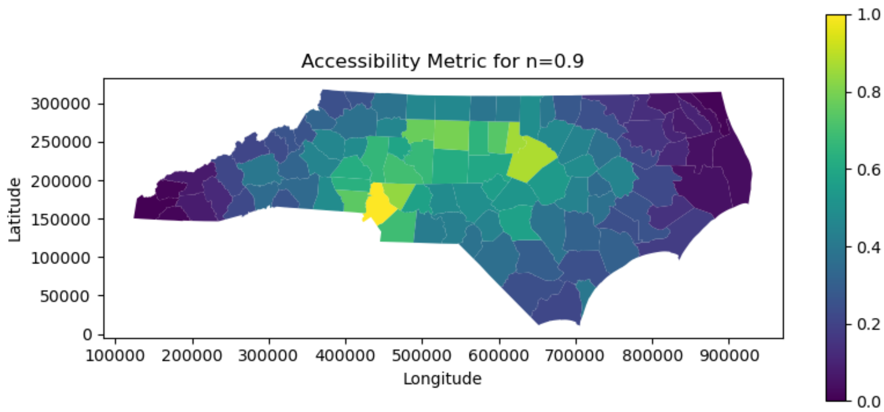

Figure 3: Accessibility metric averaged at the county level

- Income: a person's yearly salary. This will affect how money-strapped they are, how able they are to drop everything if needed, to pause their life.
- Work duties: the hours per week worked times the weeks per year for people. Those who spend a larger portion of their year working will, on average, have less free time to, quite simply, do maintenance chores. Similarly, they may put off medical needs more often and proportionately put off going to the pharmacy for one's needs. Even when they go, if they are refused, they may not be able to go pharmacy hunting immediately to resolve their issue.
- Mobility: The average adult generally has a stable level of mobility. However, young adults and teens may not yet have the means to move around freely. Perhaps they do not have a car or a budget capable of sustaining ride sharing. Similarly, the elderly may have driving impedance, or live in a retirement home, or otherwise simply lead a more sedentary life. Ultimately, at both ends of the cycle of life, people will have decreased mobility compared to the average adult. Also, mobility will be influenced, in a constant multiplicative factor way, by whether one is disabled or not.

With these ideas in mind, we notice that income is positively correlated with availability. However, it seems reasonable to assume diminishing returns: someone below the poverty line ought to have a drastic increase in availability with increased cash flows whereas someone making over $100,000$ USD a year might not functionally increase their availability much through increased salaries. Indeed, more money could still improve their quality of life, but it seems availability is qualitatively connected with the ability to stop your work or life, something those living paycheck to paycheck are drastically more affected by than those not doing so.

Then, work duties should affect availability negatively (the more work one has, the less availability). Additionally, the amount of work one does will not necessarily correlate with one's earnings, as there are many low-wage jobs that require long work hours. However, we also expect diminishing returns on either extreme. Someone who works 80 hours a week will not become drastically more available if they work 60 hours one given week. Similarly, someone who works 15 hours a week will likely not become substantially less available if they have to work 25 hours one week. So, we propose a sigmoid function to model this idea, such that those approximately at the median of work hours will have the biggest change in availability given a change in work hours.

Finally, as regards mobility, we see that either extreme in age will decrease availability, and it will be relatively flat otherwise. An obvious candidate function to use in modelling is the standard Gaussian.

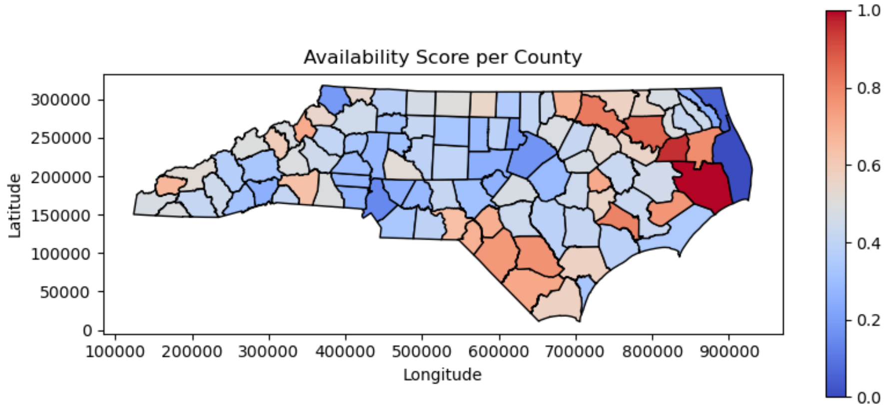

Figure 4: Availability data for each census tract

However, it is not sufficiently flat near the mean, so we can apply a transformation to the y^2 term, turning it instead into $\frac{1}{1-x^2}$. Essentially, we are trying to change the parabola into a semicircle. This function is called a bump function in academia. Moreover, we scale this by the percentage of people who are disabled, as disability should provide a constant factor influence on one's mobility.

Below is our resulting function. Notice we take the geometric mean of the three components (mobility, income and free time), as we want in some sense to compare these values together but in a dependent (multiplicative) way.

$$B_i = \left(\frac{1}{1 + \exp\left(\frac{W - W_m}{Y_h}\right)} \cdot \exp\left(-\frac{1}{D(1 - age^2)}\right) \cdot \log(I) \right)^{\frac{1}{3}} \tag{4.2}$$

Here, Y_h, the amount of waking hours in a year, was calculated as $8760 - 2920$, which is the total number of hours in a year minus the number of sleeping hours assuming 8 hours of sleep a night. We chose to divide the exponent of the sigmoid by this value, as this influences the steepness of the slope that changes availability to unavailability as the number of work hours grows. We also offset the value by 1137, as that was the median amount of hours worked, and we wanted the point of greatest slope in our function to be at that area.

Note: the census data was provided as histograms, not discrete data points. We decided to estimate quantities on a census-tract level of granularity, and found the values above by finding the expected value (mean) of the relevant histograms. Since gender was not predicted to influence one's availability, we usually simply summed the data for men and for women.

Upon calculating the preliminary results, we obtained a graph of census tracts based on availability, with values scaled to fit between 0 and 1.

One notes, at a glance, that the more urban counties in North Carolina seem to have decreased accessibility compared to most rural counties. This may indicate the importance of free time in influencing availability in our model, compared to the other factors, assuming urban environments often correlate with longer working hours. Similarly, higher-paying jobs would be generally in urban environments, but those should correlate positively with availability. This indicates that perhaps free time outweighs one's income level in predicting availability given our model. This makes sense, as we created the income chart specifically to penalize poverty a lot more than to benefit wealth.

4.3 Vulnerability

Due to the scarcity of data, it is difficult to accurately model pharmacy refusals of specific drugs. Instead, the vulnerability model seeks to measure the size of the population that is expected to need a potentially refused drug. Determining the amount of potentially vulnerable individuals in each census tract allows us to accurately analyze the magnitude of potential impact. By nature, the vulnerability analysis is specific to one particular drug; our primary analysis focuses on emergency contraceptives (ECs).

We looked to estimate the amount of individuals in a census tract that could expect to use an EC. Statistical information from the National Survey of Family Growth indicates that usage of ECs is widespread among women aged 15-49, and provides data on the age breakdown of women who report ever using an EC as a primary form of birth control. [1] [5]

Table 1: Emergency contraceptive usage reporting by age of women 15-49

Age range	Percentage of women reporting EC usage
15-19	20.5%
20-24	35.0%
25-29	35.8%
30-49	15.7%

We can use this data to analyze the demographics of each census tract and predict the amount of people potentially in need of an EC. The formula for the vulnerable population size in each census tract is a simple linear formula.

$$n_{\text{vulnerable}} = 0.205 * n_{\text{women 15-19}} + 0.350 * n_{\text{women 20-24}} + 0.358 * n_{\text{women 25-29}} + 0.157 * n_{\text{women 30-49}} \quad (4.3)$$

Using this formula, we can analyze the demographic data from the 2020 North Carolina Census to determine the magnitude of the vulnerable population.[9] Overall, we are able to determine that approximately 525300 individuals in North Carolina are in the population likely to need an EC, roughly 5.07% of the state's total population. Figure 5 demonstrates the percentage of the population of each county that is expected to need an EC.

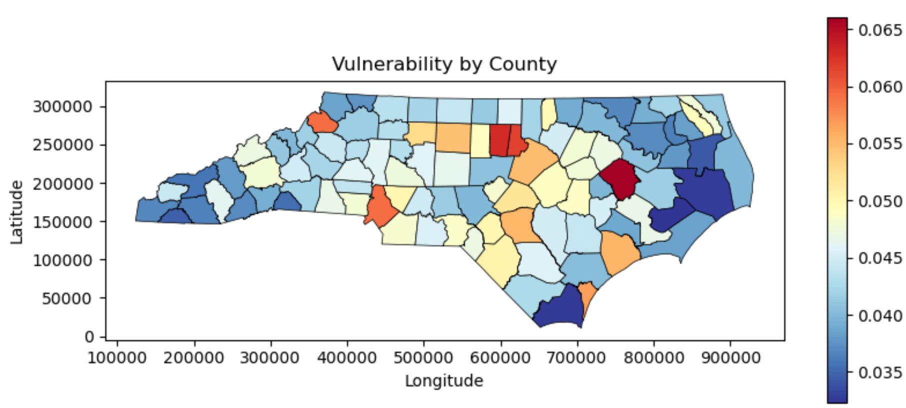

Figure 5: Percentage of individuals in each county expected to need an emergency contraceptive

The most vulnerable counties in the state are Durham County, Orange County, and Pitt County, with each expected to have over 6% of the population in need of an EC, while the least vulnerable counties, Pamlico County, Brunswick County, and Hyde County, still expect approximately 3.2% of the population to be in need of an EC.

4.4 Measure of Impact

As previously stated, we looked to combine the three key metrics into a holistic Measure of Impact (MoI) metric. The methodology is rather simple, first we normalize every county's accessibility and availability metrics using standard normalization methodology as show below:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{4.4}$$

And then we can achieve a holistic picture of the impact by multiplying by the determined vulnerability rate, leading to the following formula:

$$\mathrm{MoI}_i = \frac{V_i}{1 + z_{A_i} \cdot z_{B_i}} \tag{4.5}$$

Where MoI_i is county i's measure of impact metric, z_{A_i} and z_{B_i} represent the normalized accessibility and availability values of county i respectively, and V_i is the county's vulnerability rate. The reason behind the multiplicative interaction is because accessibility and availability rely on each other: there is no advantage to being fully available if there are no pharmacies available and vice-versa.

5 Results

The results of the accessibility-availability-vulnerability analysis can be seen in Figures 3, 5, 4, and in Table 3. The three plots all highlight different counties in different parts of North Carolina, not pointing towards any one definitive conclusion. For a broader view of all the counties, see Figure 6. The population density patterns observed in the accessibility calculations are no longer as apparent, while the influence of vulnerability is clearly seen in the bright spots of Durham and Pitt counties.

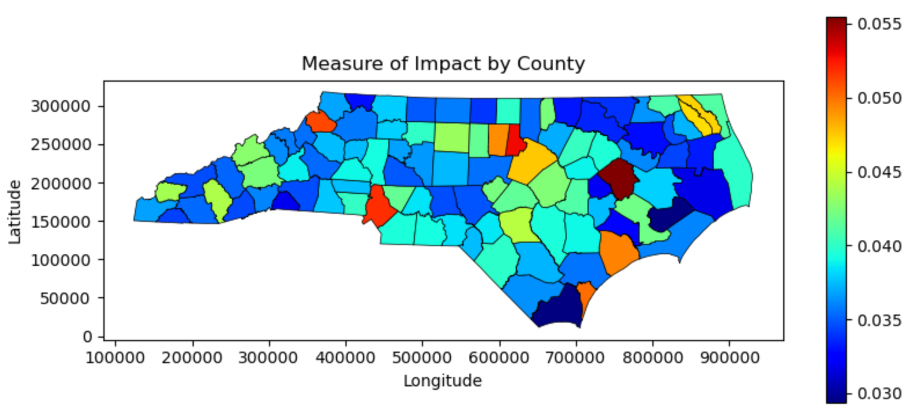

Figure 6: Measure of Impact by County, where the most impacte counties are clearly visible in deep red

Table 2: Variables used in Accessibility-Availability-Vulnerability model

Equation	Variable	Definition
(4.1): Accessibility	A	Metric for accessibility to pharmacies
	z_{A_i}	Normalized accessibility metric from [0,1]
	i	Randomly generated individual sample
	$d(\cdot\,,\cdot)$	Euclidean distance function
	P	Set of all pharmacies in North Carolina
	p	Element of P representing a single N.C. pharmacy
	n	Damping factor on pharmacy distance
(4.2): Availability	B	Calculated heuristic for availability
	z_{B_i}	Normalized availability metric from [0,1]
	Y_h	Awake hours in a year
	W	Quantity of weeks worked by the individual
	h	Quantity of hours per week worked by the individual
	c	Individual's commute length
	I	Individual's income
	D	Binary indicator of disability status
	age	Individual's age
	v_0	Availability of a car for ad hoc locomotion
(4.3): Vulnerability	V	Estimate rate of prescription denial vulnerability
	n_{category}	Quantity of people in category per tract in 2021 census
(4.5): Measure of Impact	MoI	Representation of negative impact of prescription denial

Table 3: Top 3 and bottom 3 counties for the three major metrics, note that high numbers are good for accessibility and availability while low numbers are good for vulnerability and MoI (normalized accessibility and availability values)

	N. Accessibility		**N. Availability**		**Vulnerability**		**Measure of Impact**	
Rank	County	z_{A_i}	County	z_{B_i}	County	% V	County	Value
1	Mecklenburg	1.000	Hyde	1.000	Pamlico	3.2%	Brunswick	0.029
2	Wake	0.877	Washington	0.954	Brunswick	3.3%	Pamlico	0.029
3	Durham	0.860	Bertie	0.867	Hyde	3.3%	Hyde	0.032
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
98	Graham	0.009	Mecklenburg	0.143	Pitt	6.2%	Mecklenburg	0.052
99	Currituck	0.008	Currituck	0.054	Orange	6.3%	Durham	0.053
100	Cherokee	0.000	Dare	0.000	Durham	6.6%	Pitt	0.055

6 Actionable Steps

It is our hope that our model's approach of analyzing vulnerability, accessibility, and availability can inform advocacy strategies. In order to reduce the impact of pharmacy refusals on the marginalized communities of North Carolina, we recommend a variety of possible actionable steps that address the areas of interest identified by our model. These action items include policy items for the North Carolina government to evaluate, as well as ways for researchers and activists to understand the scope of refusals and mitigate their impact on marginalized communities.

6.1 Statewide Policy

Presently, the North Carolina Board of Pharmacy allows for pharmacists to refuse to fill any prescription that they feel a moral, religious, or personal objection against.[11] However, the Board also notes that though a pharmacist may have a legal right to avoid ethical conflict, they do not have a right to obstruct legitimate prescriptions solely on the basis of conscientious objection. As such, pharmacists that refuse to fill a prescription for emergency contraception have an obligation to get the patient and the prescription to a pharmacist who will dispense that prescription in a timely manner.[10]

Although this initially seems like a reasonably compromise, the model's evaluation of accessibility and availability within the state indicate that simply being referred to another pharmacy may not always be sufficient. Residents living in pharmacy deserts may need to travel a significant distance to get to another pharmacy, and are often unable to do so. Refusals are also not reported to the Board of Pharmacy, which makes it difficult to track how often refusers actually assist the patient in procuring their prescriptions and whether this help is sufficient. As such, we recommend the following policies to mitigate the potential impact of pharmacy refusals.

1. (a) Require pharmacists to report refusals to the Board of Pharmacy
   (b) Require pharmacists to report how they help patients after refusing their prescription, and track the success rate of refused patients in procuring their prescription.
2. Obligate refusing pharmacists to help patients procure their prescription for **any** refused prescription, not just emergency contraceptives

3. Expand access to commonly refused prescriptions that are time-sensitive, like emergency contraceptives, by

    (a) removing the rights of pharmacists to refuse to fill time-sensitive prescriptions,

    (b) expanding access to these drugs by making them purchasable over-the-counter,

    (c) create programs to assist travel to distant pharmacies, and/or

    (d) stocking these drugs at mobile pharmacies at local government buildings like town halls.

These policies attempt to mitigate the impact of pharmacy refusals while remaining respectful of a pharmacist's right to refuse to dispense prescriptions they do not personally agree with. Policy 1 begins to record pharmacy refusal data, allowing for future interdisciplinary approaches to analyzing the impact of refusals, while also providing meaningful information on the efficacy of assistance finding another pharmacy. Policy 2 expands the existing code for emergency contraceptives to all drugs, increasing the range of options that refused individuals have. Finally, Policy 3 addresses the most pressing refusals, which are for time-sensitive drugs like emergency contraceptives that must be taken within a short period of time.

In order to further mitigate harm for refusals of emergency contraceptives specifically, the vulnerability model should be used to inform policy surrounding health interventions and family planning education. Vulnerable counties like Pitt County, Durham County, and Orange County are all ideal places to increase sex education, offer family planning resources, and create targeted public health campaigns and initiatives.

6.2 Activism and Advocacy

There are a variety of ways for individual activists, advocacy groups, and organizations to understand the scope of refusals and mitigate the impact on marginalized communities. By deconstructing the model of vulnerability, accessibility, and availability, advocates can identify areas that need assistance as well as next steps.

Vulnerability modeling suggests good places to start for education and prevention. In the specific case of emergency contraceptives, the most vulnerable counties are important places to offer education and family planning services, as well as provide outreach and support resources for individuals. The specific nature of emergency contraceptives, as well as abortion drugs, makes it so that advocates can work to prevent vulnerable populations from ever needing them. As such, we recommend that additional work of this nature be done in the most vulnerable counties, including Pitt County, Orange County, and Durham County. For other drugs, where their need cannot be prevented, vulnerability metrics still allow for pre-refusal education and preparation work with individuals. Teaching communities about the risks of pharmacy refusal can help them to plan for the worst and make a backup plan to get the medications they need.

Accessibility is arguably the most actionable area for advocates to make a difference. In pharmacy deserts, providing access to prescriptions can make a significant difference. Investing in mobile pharmacies, advocating for pharmacists to hire at least one employee who is comfortable dispensing commonly refused drugs, and increasing public transit access can make prescriptions significantly more accessible. We would suggest that advocates focus on the least accessible counties found by our model, including Cherokee County, Currituck County, and Graham County.

Availability is another actionable area, albeit potentially on a more individual level. Carpooling to pharmacies, running volunteer prescription delivery services, and providing childcare services can all increase someone's ability to make it to a distant pharmacy. We recommend that this work in the least available counties as found by our model, including Mecklenburg County, Currituck County, and Dare County.

Finally, in order to further understand the scope of the problem, we recommend that researchers and activists take on more detailed, on-the-ground work in the most intersectionally affected parts of the state to further understand the scope of refusals and the complicated interplay between the many factors that influence their impact on marginalized communities. These counties include Mecklenburg County, Durham County, and Pitt County.

7 Sensitivity analysis

The only part of the model privvy to sensitivity analysis would be the Accessibility section, since it extends beyond arithmetic manipulation. Since part of the process of determining accessibility includes generating random sample points to represent individuals, we can easily measure sensitivity by re-drawing the random sample multiple times and comparing the results. The differences are incredibly minor, likely due to the special care given for location-based sampling. Comparing two sets of points using point cloud-to-cloud Hausdorff distance results in negligible values across the data-set, see Table 4 for summary statistics of the Hausdorff distances calculated across 10 different point cloud generation processes.

Table 4: Hausdorff Distance between Accessibility Point Clouds

Statistic	**Value (miles)**
Mean	1.349
Median	0.871
Min	0.0002
Max	34.215
Standard Deviation	1.419

Since the county-level differences are aggregated from these sampled points, they are similarly insensitive.

8 Solution and results

8.1 Strengths and weaknesses

8.1.1 Strengths

1. Our model's accessibility formula takes into account the distance to multiple different pharmacies and doesn't have an arbitrary cutoff value, which allows for significantly more granular analysis than some literature.[12][13]

8.1.2 Weaknesses

1. Due to the model being

2. The accessibility model makes no differentiation regarding the rural or urban status of a county, as is commonly seen in literature.[12][13] This was done in part as a simplification effort on the

modelling part and in part due to the difficulty in accurately determining the urban/suburban/rural split geo-spatially.

3. The assumption that individuals cannot cross state lines to visit pharmacies is a significant weakness in the model and may be affecting the accessibility metric information on border counties.

4. The assumption that individuals are spatially uniformly distributed across a census block is incorrect and a different distribution which potentially takes into account varying density throughout a block may be more accurate.

5. Similarly, the spatially uniform random sampling of individuals within census blocks leads to individuals being assigned unrealistic home coordinates, such as on an interstate highway or in a body of water.

6. Furthermore, representing an individual as a static point is also unrealistic, as people dynamically move around their cities during commutes or while running errands. Representing an individual as a series of probabilities across an area in a similar manner to which electrons are modelled in an atom may be more accurate.

9 Discussion

Based on our model and analysis, we believe that there is a significant potential impact of pharmacy refusals on marginalized communities. Our model of emergency contraceptive refusals indicated a large population of North Carolinians vulnerable to a refusal, pharmacy deserts and accessibility concerns, and potential inabilities to travel to alternative pharmacies. We recommend an increase in education, healthcare planning and intervention, and policy changes in several areas across the state to mitigate the potential effects of refusals. Additionally, we identify methods to study the scope and impact of pharmacy refusals in greater detail, including counties best for researchers and activists to focus on.

Although our vulnerability analysis focuses primarily on emergency contraceptives, it is possible to construct similar demographic data for the size of other vulnerable populations. For example, the NSFG contains similar demographic data for usage of other contraceptives including hormonal birth control pills.[1] There is also a variety of robust demographic research on the population-wide prevalence of transgender individuals [8] [4], a vulnerable population for hormone replacement therapy refusal, and men who have sex with men [6] [2], a vulnerable population for HIV pre-exposure prophylaxis refusal. Vulnerability models for these populations could be relatively simple, such as applying the existing metric that 2.9% of men in North Carolina have sex with other men to the entire state [6], or they could take into account more sophisticated demographic data to create a county-level breakdown, as with the emergency contraceptive analysis.

This model did not take into consideration the actual likelihood of a pharmacy refusing to fill a prescription. Although the impact of a refusal is well-analyzed throughout this paper, it remains unknown what the actual likelihood of that refusal occurring is. Our policy recommendations include the tracking of this data, which would help contextualize the scope of the problem and inform next steps. In the absence of this data, there is some literature analyzing the propensity of pharmacists to refuse prescriptions. A 2010 survey in Nevada [3] found a significant correlation between a pharmacist's age and religious status and the likelihood of their refusal to provide certain drugs, as well as providing some rough estimates for refusal rates, such as about five percent for emergency contraceptives. Another study indicated a relationship between the race of the patient and the likelihood of a refusal [7], though that study focused on a different type of refusal. Based on this literature, it may be possible to construct a demographic model of refusal likelihood similar to our vulnerability model, but the data is sparse and circumstantial. As such, we strongly recommend an increase in data collection and further evaluation of refusal rates.

10 Conclusion

Based on our model, we propose that the government of North Carolina record pharmacy refusal rates as well as the rates of individuals later filling prescriptions, as well as expand access to time-sensitive prescriptions that are commonly refused and require pharmacists to help refused individuals fill their prescriptions elsewhere. Additionally, we identify areas of vulnerability, inaccessibility, and unavailability for advocates to focus on education and healthcare planning, accessibility and mobile pharmacies, and support for individuals who have had a prescription refused. Finally, we identify the most at-risk counties in the state as Durham County, Pitt County, and Mecklenburg County, and recommend that researchers and activists focus on these counties in order to further understand the potential impact that pharmacy refusals may have on marginalized communities in North Carolina.

11 Appendix

Code is viewable here.

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