TriCoMM Final Submission

Problem 2: Prescription Refusals

By: Ahbab Abeer, Dhruva Barua, & Ahmad Choudhary

November 12, 2023
Contents

1 Summary 3

2 Introduction 3

2.1 Background & Objective 3
2.2 Assumptions 4
2.3 Data Refinement 5

3 Which Counties Need the Most Attention? 5

3.1 People in Poverty 5
3.2 People of Color 6
3.3 Women Who Gave Birth Within The Past Year 6
3.4 People with Disabilities 7

4 Model & Analysis: Correlation Between Ratios and Income 7

4.1: Methodology 7
4.2 Pharmacies per People In Poverty 9
4.3 Pharmacies per Women Who Recently Gave Birth 10
4.4 Pharmacies per People of Color 11
4.5 Pharmacies per People with Disabilities 11

5 Conclusion 12

5.1 Strengths and Weaknesses 12
5.2 Further Study 14

6 References 15

7 Letter to North Carolina Governor 16
1 Summary

Overall, our goal for the governor was to lay out specific counties that would have the highest impact on specific minorities if a pharmacy were to become discriminatory. We also wanted to show that there was a significant difference between certain minority groups’ ability to get to a pharmacy in comparison to the general population. To do this, we looked separately at the impact on four specific minorities for each county: people in poverty, people of color, people with disabilities, and women who recently gave birth. We ranked each county based on the following ratio and returned the lowest 10 counties in each of the four minority groups.

\[
\frac{\text{number of pharmacies in the given county}}{\text{total people in the given minority group in the given county}}
\]

The intuition was that a low ratio indicated that a certain minority was more at risk if a pharmacy became discriminatory because there were not many alternate pharmacies to go to.

Furthermore, we tested for correlation between a given county's average family income and the above ratio in each of the four categories. We first plotted the ratio of (pharmacies) / (total people) against average family income as a base. Then, we plotted the ratio of (pharmacies) / (given minority) against income and compared the least squares regression line for each minority group to the base. We discovered that income has almost no correlation with the ratio of pharmacies to total people, but there was a noticeable \((r = \text{about 0.3})\) positive correlation between income and the ratio of pharmacies to a given minority group.

We used a t-test for the difference in slopes between the ratio of pharmacies per total people over income versus the ratio of pharmacies per given minority over income. We got \(p < 0.05\) for all but one minorities, suggesting that there is a statistically significant difference between the almost flat slope of the base and the slopes with the minority groups. We conclude that even though income does not correlate with the total population, minority groups were significantly more at risk if a pharmacy shut down in a lower-income county.

2 Introduction

2.1 Background & Objective

The refusal of prescriptions by pharmacists, often based on moral or religious grounds, poses a significant social justice concern, particularly impacting marginalized communities in states like North Carolina. Crucial medications like hormones for transgender individuals, contraceptives for those able to become pregnant, and HIV prophylaxis are commonly declined, but the lack of
tracked data makes it challenging to gauge the full extent of this issue. Developing a model to measure the impact of these refusals on marginalized groups within North Carolina can become crucial to comprehend the depth of this issue and its implications for access to necessary medications to especially people in need. The objective of this study is to create a model or framework for assessing the potential consequences on marginalized individuals when North Carolina pharmacies decline to dispense medications. Doing this will help call for more attention to be put to the issue of prescription refusals and predict which actions can be taken to minimize these discovered consequences on said marginalized individuals.

2.2 Assumptions

Our model holds the following assumptions:

1. A person who lives in a county goes to pharmacies within their respective county. This means that all of the pharmacies in a county serve the people in that county. This means that we are looking at entire counties as whole, homogenous counties rather than the smaller tracts within a county. This was done to minimize the number of observations with 0 pharmacies. Pharmacies are much more likely to exist in counties than in individual tracts.

2. The ratio of pharmacies per (group) of a given county represents how ‘safe’ it is for a given (group) to get pharmaceutical care in a county. For example, suppose the ratio of pharmacies per person in poverty is low in a given county. In that case, people in poverty in that county are highly at risk if a pharmacy refuses to serve that population. This is because a low ratio indicates that there are as many alternate pharmacies for that group to go to. A high ratio means there are many alternate pharmacies in the context of the population, so people in poverty are less at risk if a pharmacy becomes discriminatory.

3. One minority group does not weigh any more than another, establishing four distinct and independent minority groups to be analyzed. With this, the minority groups are independent of each other, fostering equal recognition and consideration for each group within the broader context. Thus, we cannot explicitly declare one county to be ‘worse off’ than another county due to a certain minority being more at risk than another.
2.3 Data Refinement

While analyzing the data set provided, we noticed that there were multiple tracts/entries of data for each county, so we decided to refine the raw data via the data set provided by creating a new data table that sorted each county by their “GEOID” (geographical id). With this, we took the sum of each of the entries of data for each of their respective counties to get generalized data for each county on the population, median household income, number of individuals with disabilities, those living in poverty, who gave birth, and who are people of color. We also took the entire list of all 2000 pharmacies in North Carolina and classified them by county, to get the number of pharmacies in each county. Finally, we created columns with the ratio of pharmacy to population and pharmacy to each of the four minorities.

We processed the data using Matplotlib in Python to store, sort, and graph the counties that have the lowest ratios. These counties need the most attention given to them to ensure that they don't become discriminatory.

3 Which Counties Need the Most Attention?

3.1 People in Poverty

The ten counties with the least pharmacies per person in poverty raise concerns about potential discrimination or prescription refusals for marginalized groups. Hyde and Camden counties stand out, having zero pharmacies for their populations exceeding 10,000. Additionally, Hoke, Caswell, and Chowan counties pose high risks due to extremely low pharmacy access for people in poverty.
3.2 People of Color

The graph depicts the lowest-ranking 10 counties for people of color, notably highlighting Hyde and Camden at the bottom due to their lack of pharmacies. Following closely are Hoke, Bertie, and Caswell. Caswell is a repeat of the previous data, while Bertie and Hoke are new additions. It remains uncertain whether priority should be given to counties in this graph or the previous one. Nevertheless, this data emphasizes the need for special attention and support in Hyde, Camden, and Caswell to ensure adequate alternative pharmacies for marginalized communities.

![Graph showing lowest counties for people of color](image)

3.3 Women Who Gave Birth Within The Past Year

Similarly, the graph below displays the 10 counties with the lowest ratios of pharmacies per woman who gave birth in the last 12 months, where Hyde, Camden, Currituck, and Hoke have the lowest ratios, followed by Onslow, Chowan, Johnston, Franklin, Wilkes, and Yadkin, respectively. This underscores the need for special attention and support in Hyde, Camden, and Hoke to ensure adequate alternative pharmacies for this marginalized community.

![Graph showing lowest counties for women giving birth](image)
3.4 People with Disabilities

Finally, the following graph illustrates the 10 counties with the lowest ratio of pharmacies per individual with disabilities, highlighting Hyde, Camden, Hoke, and Caswell as having the most limited ratios, followed by Gates, Wilkes, Harnett, Currituck, Franklin, and Graham. This emphasizes the necessity for focused assistance and support in regions like Hyde, Camden, and Hoke, to ensure accessible alternative pharmacies for people with disabilities.

4 Model & Analysis: Correlation Between Ratios and Income

4.1: Methodology

After discovering which countries have high and low pharmacy-to-minority ratios, we were interested in exploring which factors correlate to a county’s ratio. We wanted to determine if the average income in a county correlated with the pharmacies per capita in that state. We wanted to see if ‘richer’ counties had a higher concentration of pharmacies, so plotted the ratio of pharmacies to total people over average household income and got the following graph:
Not only did we get a negative trend line, which was the opposite of what we expected, but the r-squared value was 0.01, suggesting that there was a negligible correlation between income and the ratio of pharmacies to total people. Thus, we cannot conclude the average income of a county is correlated with the ratio of pharmacies per capita. This graph supports the claim that the availability of pharmacies to a given person stays constant regardless of the average income of the state. However, we can use this graph as a base to explore the correlation for minorities and see how it compares to the total population.

We then graphed other minority ratios over income, such as plotting the ratio of pharmacies to people in poverty over income to determine any trends for minorities. We could visually see that the trend line had a different slope than the graph above. Still, because the R-values were all in the moderate to low range, we need to explicitly test if the difference in slope is statistically significant. If they were statistically different, then we have evidence to claim that certain minority ratios correlate differently to income than the general population.

Our null and alternate hypothesis is as follows:
If the line modeling the ratio of pharmacies to total population to income is: \( \hat{y}_1 = \alpha_1 + \beta_1 x \)
and the line modeling the ratio of pharmacies to (minority group) to income is: \( \hat{y}_2 = \alpha_1 + \beta_1 x \)
where \( \alpha \) is the y-intercept and \( \beta \) is the slope, we can model our null and alternate hypothesis as follows:

\[
H_0 : \beta_2 - \beta_1 = 0 \\
H_A : \beta_2 - \beta_1 \neq 0
\]
To generally find the p-value for each comparison of the four different marginalized groups, we utilized the three equations as seen above to find the t-value and the standard error of the regression, where \( b_1 \) and \( b_2 \) are the slopes of the two ratios/regressions being compared, \( n \) (\( n_1 \) and \( n_2 \)) represents the total number of data points for each regression(100 and 100 respectively), and \( s_b \) (\( s_{b1} \) and \( s_{b2} \)) is the standard error of the regression of each slope, and within the standard error of each regression, \( y \) represents each of the 100 ratios and \( x \) represents each of the 100 incomes. Y-hat represents the predicted y-value from the regression at a given x-value. The first equation finds the standard error of slope.

The second equation finds the t-statistic by taking the difference of the slopes divided by the square root of the sum of the two variances calculated by equation 1. With the t-statistic, we can find the p-value by referencing the correct t-distribution with degrees of freedom = 196 (third equation). We use a 2-tailed p-value because we are interested in seeing if there is any difference.

### 4.2 Pharmacies per People In Poverty

The line for pharmacies per total is \( y = 0.00028351 + -1.62985E-09 \times \)

The line for pharmacies per people in poverty is \( y = 0.000365487 + 2.05285E-08 \times \)
After running a 2 tailed t-test for the difference between the two slopes, we got a p-value of 0.0031. This means we reject the null in favor of the alternate that the slopes differ. This means that while the overall population may not have a relationship with average income, the minority group of people in poverty may be more at risk if they happen to live in a county with a lower average family income. Thus special care should be given to pharmacies in areas of low income to make sure they do not discriminate against people in poverty;

4.3 Pharmacies per Women Who Recently Gave Birth

The equation for pharmacies per woman who recently gave birth is $y = 0.03058328 - 1.93573E-07$

This graph shows the relationship between pharmacies per woman who gave birth over income and pharmacies per total people over income. We can see a slight negative correlation with income. The t-test reveals a p-value of 0.14, and a 1-tailed test is 0.07, suggesting that even though there is a slight negative correlation, we do not have significant statistical evidence to say that the correlation of pharmacies per woman is different from that of the overall population. However, even if there is no relationship to income, section 3.2 reveals how certain counties are at the bottom of the list in terms of their ratio and how special care should be given to them. This test only proves that special care should not be given based on average income per county.
4.4 Pharmacies per People of Color

The equation for pharmacies per people of color over income is $y = 0.011600696 - 1.49491E-07x$

The two-tailed p-value is 0.07 but the one-tailed is 0.035, suggesting that we do not have enough evidence to say that the slopes are different, but we do have enough evidence to say that the slope of the purple line is less than the slope of the green line. The counties that have a higher average income may be more impactful to people of color if they shut down care to people of color more than if they shut down care to everyone. Thus, special care should be given to countries of high income to make sure they do not discriminate against people of color.

4.5 Pharmacies per People with Disabilities

The equation for pharmacies per people with disabilities over income is $y = 0.001442702 + 2.49471E-08x$
The p-value of a two-tailed test was 0.03, suggesting that we have significant evidence to say that the slopes are different. This means that our model predicts that on average, a person with disabilities will be more at risk in a county with a lower average family income. However, it is important to note the two counties with a ratio of 0 can skew the results. Thus, counties that are in the bottom half of the graph should be monitored, paying special attention to the counties with low average incomes to ensure that they stay fair to people with disabilities.

5 Conclusion

5.1 Strengths and Weaknesses

Our model heavily emphasizes the analysis of graphs compared to each other over relative ratios, representing the strength of pharmacies per marginalized group. This means we provide a more in-depth examination of specific groups and their county counterparts in drug refusals. The strength within the model lies in the tables, such as rankings on the worst counties for each issue, since it highlights the areas of most vulnerability. With these, we can then explore the specifics as seen in the scatterplots to compare them to other measures, such as family income, to notice further trends of significance. Finally, these graphs can be utilized to measure their variances and similarities in correlation to each other with t-tests and a final indicator of p-values to decide whether there is an underlying issue in the counties spanning our four different tests. Thus, one key success of our model is that we can hone in on each of the specific minorities who are most in danger in a specific state. We can tailor special care to each county.
There are weaknesses lying in the model as well, however. The first would be the substantial amount of outliers within the data we analyzed – the most blatant of which can be seen in the box and whisker plot for people of color. Including these in the model opened up the possibility of an inflated/deflated correlation between the respective groups analyzed. Secondly, the assumptions that we highlighted in 2.2 meant that all issues had equal weight in their relation to each other. Still, in a real-life scenario, it is highly unlikely that 50 pharmacies for 100 people of color are of the same concern as one pharmacy for two people with disabilities as issues such as factoring in the disability, the access they have for transportation to another pharmacy in case of emergencies is not taken into account. Gaps of unconsidered factors lead to successive errors that, in a realistic situation, might be significant enough for our model to be incorrect to a notable extent.

Additionally, our model was restricted to the borders of each county, meaning that since they were analyzed independently, travel time, geographic location, and neighboring counties were considered when gathering data on a specific county. For example, Hyde County consistently placed last along with Camden in each category since neither has a pharmacy. We could be wrong, however, in pushing for a pharmacy in each as an extreme issue since they could be extremely small in size as well as have numerous pharmacies in neighboring counties that are accessible without much issue in comparison to another county with one pharmacy but in an isolated location resulting in an unreasonable travel time to find another pharmacy nearby.
5.2 Further Study

Using our results and data analysis from this study, we can conduct further research and studies into several fields to understand the impact of limited pharmacies and prescription refusals on marginalized groups, such as possibly conducting policy and ethical examinations where one can explore the existing policies, their effectiveness, and ethical considerations regarding pharmacy service provision and prescription refusals, particularly in underserved areas. It would also be significant to analyze the intersectionality of race, socioeconomic status, and geographic location to understand how these factors compound the challenges faced by marginalized communities.
6 References

All code used can be found in the GitHub

The original raw data set can be found on Google Drive

The custom-designed processed data set can be found on Google Sheets


7 Letter to North Carolina Governor

November 12, 2023
Re: Analysis of Impact of Prescription Refusals on Marginalized Groups and Potential Solutions

Dear Governor,

In North Carolina, the contentious debate over pharmacists' freedom to refuse prescriptions due to personal beliefs is a significant concern. Our advocacy agency aims to mitigate the repercussions for marginalized communities affected by these refusals, examining their impact on individuals with disabilities and those in poverty.

Essentially, our approach included gathering a collection of parameters and data for each county in North Carolina, collecting thousands of data points for each parameter, such as the number of people in poverty, people with disabilities, women who recently gave birth, and people of color. Our results consisted of creating four separate linear regressions comparing the ratio of pharmacies to each marginalized group (number of people in poverty, people with disabilities, women who gave birth, and people of color), where we then analyzed the difference between the slopes of these regressions and the slope of the total population over income.

We found that although the average family income in a county does not affect one’s access to pharmacies, being a part of certain marginalized groups (as mentioned above) can affect one’s access to pharmacies, such as where people living in poverty do see a slight correlation and trend with access to pharmacies, where living in a county with a lower average family income (which is likely) limits their access to pharmacies, which can make the impact of prescription refusals much more significant. Though it could be assumed that the same people across North Carolina should have equal access to multiple pharmacies, it’s simply not the case for marginalized groups since there is a slight correlation in the data.

Specific counties within North Carolina where we recommend more detailed, on-the-ground work could be done (building pharmacies, greater access to prescriptions, monitoring customer reviews etc.) to help researchers and activists understand the scope of refusals and mitigate the impact on marginalized individuals would be Camden, Hyde, Hoke, and Caswell county. This is because Camden and Hyde do not have pharmacies, while Hoke and Caswell were observed in the context of our data as having very low ratios of pharmacies to people within these specified marginalized groups. We believe that looking at these regions of North Carolina in further detail will be a good initial step in learning and minimizing the effects of prescription refusals on marginalized groups.

We hope our findings prove helpful in your future work on this matter, and we would be happy to answer any questions you may have or to conduct any further analysis.

Sincerely,
Prescription Refusal Advocacy Group Modeling Team