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An Exploration of Social Determinants of Health (SDOH) Highlighting Transportation and Distance to Care Within Specific Disease States

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ABSTRACT

There are multiple factors that impact health outcomes as detailed within social determinants of health (SDOH) research. Disparities in care resulting from physical access to care, include quality of care providers, type of care offered, quality of community-v-urban care centers, and more. But access, the ability to physically navigate from Point A to Point B is an obstacle that can be addressed now that transportation beyond private and public options exist. Rideshare providers have launched dedicated health divisions though these programs have not been fully adopted by care providers such as hospitals, infusion centers, etc., insurance companies and payers, or the healthcare industry as part of patient support and adherence programs to improve outcomes. This research focuses on identifying health transportation markets where transportation and travel to physical care exacerbates the burden on patient populations using SDOH data, and CDC diagnosis and mortality data – among other data sets.

Keywords: Healthcare Industry, Transportation Barriers, Poorer Health Outcomes, Social Determinants Of Health, Ordinary Least Squares Regression, Regression.

1. INTRODUCTION

The effect of transportation barriers to healthcare access is huge. The barrier leads to rescheduling appointments or Missing appointments, or Delayed care or delayed medication. The consequences lead to poor management of illness and hospitalization, which result in high cost of treatment. "In total, 61 studies were reviewed. Overall, the evidence supports that transportation barriers are an important barrier to healthcare access, particularly for those with lower incomes or the under/uninsured" (Syed et al., 2013).

A survey which was conducted in 2017 suggested that 1.8% in the United States delayed medical care due to transportation barriers. They also found that Hispanic people, those living below the poverty threshold, Medicaid recipients, and people with a functional limitation had greater odds of reporting a transportation barrier after we controlled for other sociodemographic and health characteristics (Wolfe et al., 2020). Below diagram Figure 1 shows the impact of transportation on patient health. Transportation is impacting patient health by several aspects such as missing medical appointments or prescribed health management plans not covering transportation weaknesses.

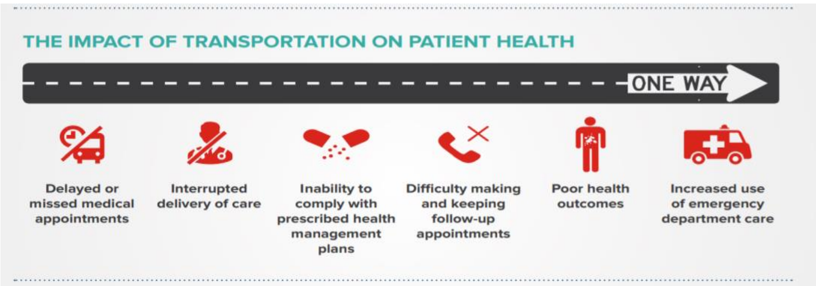

Figure 1: Show impact of transportation barriers to the health outcome for the patients.

The below diagram Figure 2 shows how the health outcome can change if we address the transportation barrier. Below flow suggests that timely availability of transportation would lead to timely medical care, timely medication access and improved health outcomes.

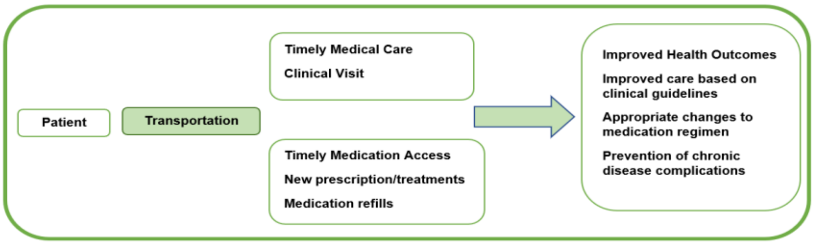

Figure 2: Health outcome for patients with proper transportation.

Steps are taken by some of the big hospitals and payers to collaborate with Uber and Lyft to provide transportation to patients, health plan members, and Medicaid and Medicare beneficiaries. Some managed care companies are testing rideshare services as an approach to providing transportation to health care for Medicaid enrollees. The objective of this study was to assess whether more rideshare transportation to health care was associated with improved self-reported ride experiences and fewer late/failed passenger pickups for Medicaid enrollees.

Recently Lyft announced the launch of Lyft Pass for Healthcare, a product that addresses one of the most frequent challenges. For the first time, eligible patients, health plan members, and Medicaid and Medicare beneficiaries can request a ride to and from their medical appointment or other destination via the Lyft app, giving them more flexibility and control over their healthcare journey. The sponsoring healthcare or social services organization still covers the cost of the ride, while having access to built-in controls for budget, location, compliance, and more (Lyft Pass, 2021).

In the past year more than 10 health care companies have teamed up with Lyft and Uber to provide rideshare to the patients. Lyft partnered with N.J.-based University Hospital, Florida Blue, Sacramento, Calif.-based Sutter Health, Chicago-based Common Spirit Health and LogistiCare Circulation, CVS Health's Aetna, Uber partnered with Cerner, Alignment Healthcare, Covig-19 Plasma Alliance NimbleRx (Drees, 2020b).

The transportation barriers are significant obstruction to healthcare access and people with lower income face difficulty in accessing healthcare facilities. This research inspects the current situation of regions based on the socio-economic factors, mortality rates and transportation connectivity in terms of number of trips. The aim of the study is to identify the regions having higher mortality rates and finding the dependency on the socio-economic factors. Then, it is aimed to illustrate the link between these socio-economic factors and transportation deserts.

2. METHODOLOGY

In order to evaluate the gaps in the transportation it is key to identify areas of prospect where use of Lyft or Uber can be expanded to help overcome patient transportation barriers. Areas for expansion, or on the gaps and potential areas for partnerships can be determined through a series of process steps that involves finding the correct data, analyzing the data that can be used in modeling, data pre-processing, identifying the model that can be used to run this analysis and finally, analyze the result from the model as shown in Figure 3:

Process Flow Diagram

Figure 3: Process of extraction the data from SDOC data, CDC diagnosis and mortality data

2.1 Dataset

For this research several datasets have been considered. The dataset "NYC trip" has been extracted from NYC Taxi and Limousine Commission (TLC Trip Record Data - TLC, 2021), "Mortality Rate" (FastStats, 2021) dataset from CDC official website and "Social determinants of health" (Social Determinants of Health Database (Beta Version), 2021) dataset from agency for healthcare, research, and quality.

Social Determinants of Health Dataset

The data set is for the full year 2018 and gives comprehensive information for all the states of the United States of America. The dataset contains 236 factors and 3225 rows of data. The factors are reduced as per the correlation to the objective of the research. Some of the important factors present in this dataset are median age, social vulnerability index, percentile ranking for socioeconomic theme etc. Ordinary least squares regression (multiple explanatory variables) analysis is performed on this dataset.

Mortality Rate Dataset

The dataset is for the full year of three years which are 2017, 2018 and 2019. The analysis is performed for the year 2018. This dataset contains 12 factors and 43,812 rows of data. Analysis is performed on state, county, year, place of deaths and deaths. Places of deaths available in this dataset are medical facility, inpatient, decedent's home, nursing home/long term care, hospice facility, medical facility, dead on arrival, medical facility, outpatient, or ER, other, and place of death unknown.

New York City (NYC) Trip Dataset

This dataset contains data of trips for months from January till December for the year 2018 for New York City (NYC). The dataset contains 6 columns to be analyzed. The analysis is performed on pickup location and drop off location. The location IDs are replaced with names of the region and borough using a lookup table present in NYC Taxi and Limousine Commission website (TLC Trip Record Data - TLC, 2021). The lookup table has 265 IDs for locations consisting of different pairs of Borough and Zones. Trip's pickup location and drop off location are identified by these location IDs.

2.2. Data Preprocessing

There were null values in social determinants of the health dataset. The columns with null values were identified and were replaced with the mean value of their respective columns. This was required to run the regression analysis of the factors. Location IDs in "NYC trip dataset" were replaced with names of boroughs and zones using inner join in python.

In the determination of data science models, the decision was taken to use the ordinary least squares regression model. The objective is to predict the value of mortality rate (dependent variable) based on socio economic factors (independent variables) therefore ordinary least squares regression model is considered. The model will help in finding out the factors which are responsible for higher mortality rate. Analyzing those socio-economic factors will help in identifying regions where transit access issues should be addressed.

The ordinary least squares regression model and result of the modeling is discussed further to understand the causation of higher mortality rate and its association with transit barriers.

2.3. Ordinary Least Squares Regression

Ordinary Least Squares Regression (OLS) is commonly known as linear regression. It can be simple or multiple depending on the number of explanatory variables. In the case of a model with p explanatory variables, the OLS regression model writes:

$Y = \beta 0 + \Sigma j=1..p\ \beta jXj + \varepsilon$

Here Y is the dependent variable, β0, is the intercept of the model, X j corresponds to the jth explanatory variable of the model (j= 1 to p), and e is the random error with expectation 0 and variance σ^2. When there are n observations, the estimate of the predicted value of Y (dependent variable) for the ith observation is given by:

$yi = \beta 0 + \Sigma j=1..p\ \beta jXij$

The OLS method corresponds to minimizing the sum of square differences between the observed and predicted values. This minimization leads to the following estimators of the parameters of the model:

[$\beta = (X'DX)\text{-}1\ X'\ Dy\ \sigma^2 = 1/(W - p^*)\ \Sigma i=1..n\ wi(yi - yi)$] where β is the vector of the estimators of the βi parameters, X is the matrix of the explanatory variables preceded by a vector of 1s, y is the vector of the n observed values of the dependent variable, p* is the number of explanatory variables to which we add 1 if the intercept is not fixed, wi is the weight of the its observation, and W is the sum of the wi weights, and D is a matrix with the wi weights on its diagonal.

The vector of the predicted values can be written as follows:

$y = X\ (X'\ DX)\text{-}1\ X'Dy$ (Ordinary Least Squares regression (OLS), 2021)

Results of the OLS regression analysis with multiple explanatory variables detailed in the next section in more detail.

3. RESULTS

Ordinary least squares regression analysis (multiple explanatory variables) is performed using python. Further analysis is performed using the result of regression to understand the effectiveness of the model using parameter analysis (R squared, adjusted R squared, F-statistics and correlation coefficients), interpreting the factors and their impact on mortality rate. Using the results of regression, datasets are analyzed to find out the region with higher transit barrier.

3.1 Ordinary Least Square Regression Analysis

Ordinary Least Squares regression method (multiple explanatory variables) is applied on social determinants factors dataset to understand the correlation between mortality rate and different socio-economic factors and the impact of these factors on the health or mortality with respect to a state/county/region. In this model, the dependent variable is CHR_PREMAT_DEATH_RATE which depicts age-adjusted deaths per 100,000 population aged 74 and under.

The summary of the result is as shown in Table 1a, 1b and 1c:

Table 1a: Model Parameters of Ordinary Least Squares Regression

Dependent Variable	CHR_PREMAT_DEATH_RATE	R-squared:	0.628
Model:	OLS	Adj. R-squared:	0.625
Method:	Least Squares	F-statistic:	207.4
Date:	Wed, 27 Oct 2021	Prob (F-statistic):	0
Time:	23:11:58	Log-Likelihood:	4366.3
No. Observations:	3224	AIC:	-8679
Df Residuals:	3197	BIC:	-8514
Df Model:	26		
Covariance Type:	Non robust		

Table 1b: Coefficient and P-value of independent variables of the OLS regression model

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-20.512	175.317	-0.117	0.907	-364.26	323.23
ACS_PCT_DISABLE	-0.109	0.027	-4.04	0	-0.162	-0.056
ACS_PCT_VA_DISABLE	-0.0321	0.012	-2.717	0.007	-0.055	-0.009
ACS_PCT_NONVA_DISABLE	0.3135	0.027	11.617	0	0.261	0.366
ACS_PCT_UNEMPLOY	0.032	0.015	2.119	0.034	0.002	0.062
ACS_MEDIAN_HH_INCOME	-0.2885	0.04	-7.279	0	-0.366	-0.211
ACS_VA_MEDIAN_INCOME	0.0207	0.02	1.027	0.305	-0.019	0.06
ACS_NONVA_MEDIAN_INCOME	0.2658	0.039	6.891	0	0.19	0.341
ACS_PER_CAPITA_INCOME	-0.1383	0.045	-3.072	0.002	-0.227	-0.05
ACS_GINI_INDEX	0.0574	0.023	2.501	0.012	0.012	0.102
ACS_PCT_PERSON_INC99	13.6454	118.969	0.115	0.909	-219.62	246.91
ACS_PCT_PERSON_INC124	4.8772	42.605	0.114	0.909	-78.658	88.413
ACS_PCT_INC137	0.2487	0.085	2.911	0.004	0.081	0.416
ACS_PCT_PERSON_INC199	8.295	71.361	0.116	0.907	-131.62	148.21
ACS_PCT_PERSON_INC200	19.8133	167.726	0.118	0.906	-309.05	348.67
ACS_PCT_INC400	0.0107	0.037	0.291	0.771	-0.061	0.083
ACS_PCT_VA_POOR	0.0947	0.016	6.04	0	0.064	0.125
ACS_PCT_NONVA_POOR	0.07	0.051	1.369	0.171	-0.03	0.17
ACS_PCT_INTERNET	-0.551	0.145	-3.795	0	-0.836	-0.266
ACS_PCT_NO_PC	0.0707	0.032	2.227	0.026	0.008	0.133
ACS_PCT_SMARTPHONE	0.0729	0.013	5.687	0	0.048	0.098
ACS_PCT_BROADBAND	0.5021	0.142	3.525	0	0.223	0.781
ACS_PCT_UNINSURED	0.0767	0.013	6.003	0	0.052	0.102
CCBP_RATE_CS_PER_1000	0.1106	0.018	6.283	0	0.076	0.145
SVI_RPL_THEME1_SOCIECO	0.1648	0.013	12.675	0	0.139	0.19
SVI_RPL_THEME4_HH_TRANS	-0.0074	0.008	-0.977	0.329	-0.022	0.007
SVI_RPL_THEMES_ALL	-0.0137	0.015	-0.909	0.364	-0.043	0.016

Table 1c: Statistics of Ordinary Least Squares Regression

Omnibus:	980.888	Durbin-Watson:	1.779
Prob (Omnibus):	0	Jarque-Bera (JB):	9302.153
Skew:	1.166	Prob(JB):	0
Kurtosis:	10.988	Cond. No.	5.65E+05

After the regression model is applied on the dataset, parameter analysis is done to determine efficiency of the model and to identify which variables impact the most.

3.2. Parameter Analysis

OLS Regression result shows the statistical measure R-squared value as 62.8%. This implies the linear regression model explains 62.9% of changes in dependent variables (mortality rate) by changes in independent variables (socio economic factors).

The model parameter "Adjusted R-squared" value is 62.5%. This means that the model's multiple dependent variables' efficacy is 62.5%.

The overall significance "Prob (F- statistics)" is 0.00. The F-statistic compares linear models for variables against a model with variables' effect zero, to find out if the group of explanatory variables are statistically significant. Prob(F-statistics) is used to check the hypothesis. Since P- value is 0, we reject the null hypothesis of all regression coefficients being zero. This means that there is evidence that suggests a linear relationship between mortality rate and independent variables (socio economic indicators). In other words, the given regression is logical.

Correlation Coefficients SVI_RPL_THEME1_SOCIECO (Social Vulnerability Index: Percentile ranking for socioeconomic theme) has the highest correlation with CHR_PREMAT_DEATH_RATE (r = 0.7232) shown in Figure 4 (X axis represents independent variables and Y axis represents correlation coefficient).

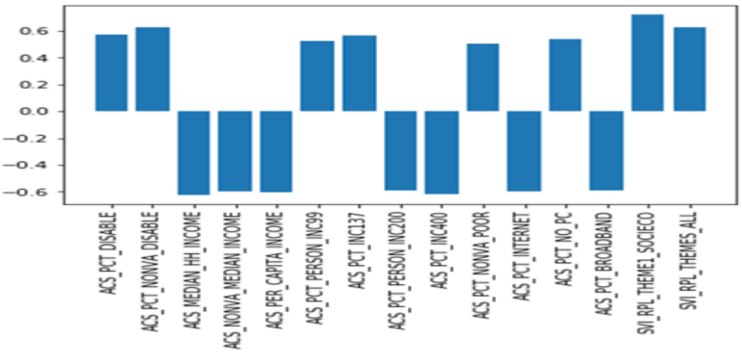

Figure 4: Correlation plot of correlation between mortality rate and explanatory variables

After parameter analysis has been done, it is found that the model is efficient in predicting mortality rate and the interpretation of factors is necessary to find the factors that are significant to have an impact on dependent variable.

3.3 Interpretation of Factors

Listed below are the factors that are significant (P value < 0.05) to explain the changes in dependent variable which is mortality rate (CHR_PREMAT_DEATH_RATE):

1. ACS_PCT_NONVA_DISABLE: Percentage of nonveterans with a disability (ages 18-64)

2. ACS_PCT_UNEMPLOY: Percentage of population that was unemployed (ages 16 years and over)

3. ACS_MEDIAN_HH_INCOME: Median household income (in dollars, inflation-adjusted to file data year)

4. ACS_NONVA_MEDIAN_INCOME: Median income of civilian nonveteran population (in dollars, inflation-adjusted to file data year; ages 18 and over)

5. ACS_PER_CAPITA_INCOME: Per capita income (in dollars, inflation-adjusted to file data year)

6. ACS_GINI_INDEX: Gini index of income inequality

7. ACS_PCT_INC137: Percentage of population with income to poverty ratio of 1.00–1.37

8. ACS_PCT_VA_POOR: Percentage of civilian veterans with income below the poverty level in past 12 months (ages 18–64)

9. ACS_PCT_INTERNET: Percentage of households with any internet connection

10. ACS_PCT_NO_PC: Percentage of households without a computer

11. ACS_PCT_SMARTPHONE: Percentage of households with a smartphone with no other type of computing device

12. ACS_PCT_BROADBAND: Percentage of households with any type of broadband internet subscription

13. ACS_PCT_UNINSURED: Percentage of population with no health insurance coverage

14. CCBP_RATE_CS_PER_1000: Convenience stores per 1,000 people

15. SVI_RPL_THEME1_SOCIECO: Social Vulnerability Index: Percentile ranking for socioeconomic theme

If the above factors can be determined for any region, then the mortality rate for that region can be estimated. Transit barriers should be analyzed in the area where the estimated value of mortality rate is higher.

3.4 Data Analysis

Tableau data visualization software was used to further analyze the result generated from the linear regression model. Next steps to analyze the data for mortality rate by state-wise, New York City trip dataset and focusing into details at borough level.

Mortality Rate Dataset

Mortality rate dataset is analyzed for identifying states with maximum number of deaths and the place of deaths for seven states with highest number of deaths. The bar graph is filtered for top ten states and these top 10 states with maximum number of deaths are California, Florida, Texas, New York, Pennsylvania, Ohio, Illinois, Michigan, North Carolina, and Georgia. On analyzing Figure 5, California has the highest number of deaths followed by Florida, Texas, New York, Pennsylvania, and Ohio.

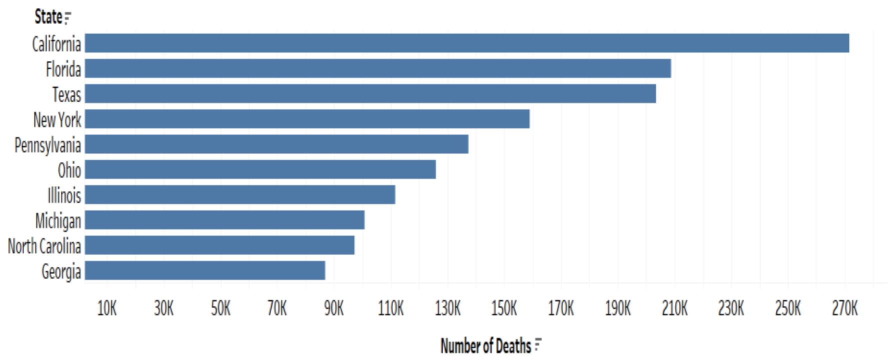

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Figure 5: Top 10 states with maximum number of deaths between years 2017-2019

Place of deaths for seven states with highest mortality rates are analyzed as shown in Figure 6. These seven states are California, Texas, Florida, New York, Pennsylvania, Illinois, and California. California has the maximum number of deaths for Place - Decedent's home, Medical Facility- Outpatient or ER, Nursing home/long term care, and Medical Facility - Inpatient. The exceptions are observed in place of deaths "hospice facility" and "Medical Facility - Dead on Arrival". Florida has the maximum number of deaths where the place of death is Hospice Facility and New York has the highest number of deaths for the place – "Medical Facility- Dead on Arrival".

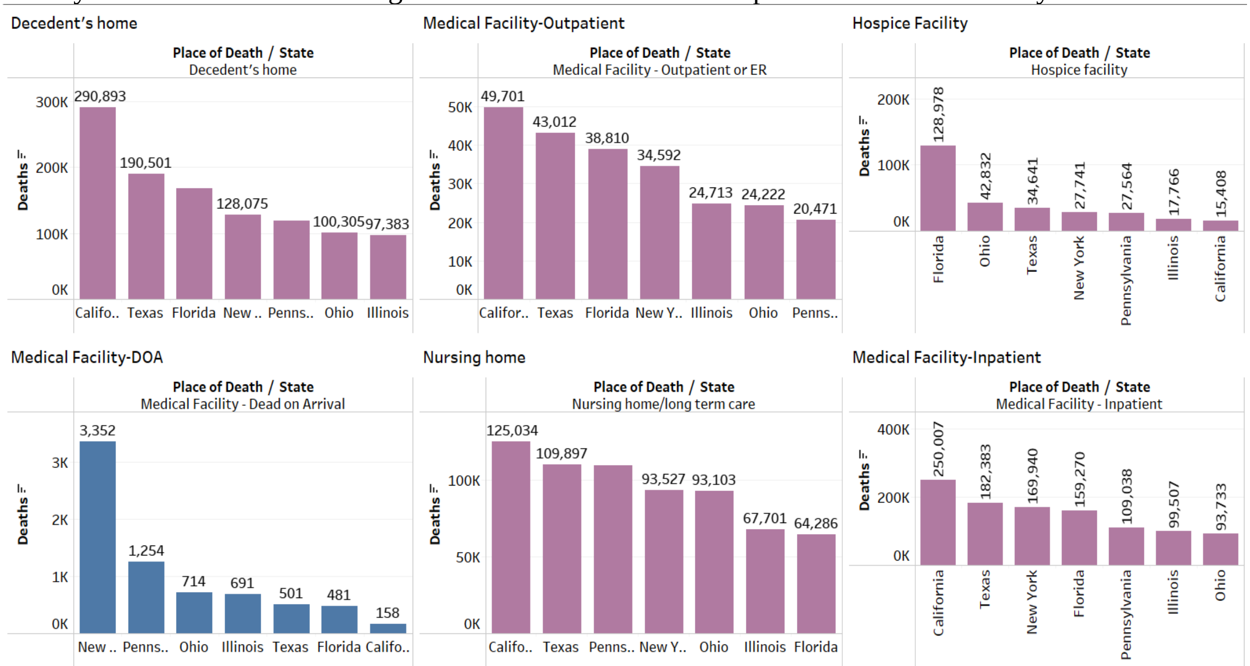

Figure 6: Place of Deaths Analysis

California has maximum deaths for all the places of deaths except Medical Facility - Dead on Arrival. Therefore New York state is analyzed further to determine if the cause of this anomaly is transit barriers.

Social Vulnerability Index (SVI_RPL_THEME1_SOCIECO) has the highest impact on mortality rate (Its coefficient in linear multiple regression is maximum and correlation is also the highest). So, on analyzing this factor in social determinants of health dataset for New York state as shown in Figure 7, and limiting the result to show the top ten counties (Bronx County, Montgomery County, Franklin County, St. Lawrence County, Kings County, Chautauqua County, Oswego County, Allegany County, Cattaraugus County and Sullivan County), it is found that "Bronx County" has the highest social vulnerability index which implies that it would be having higher mortality rate and transit barriers.

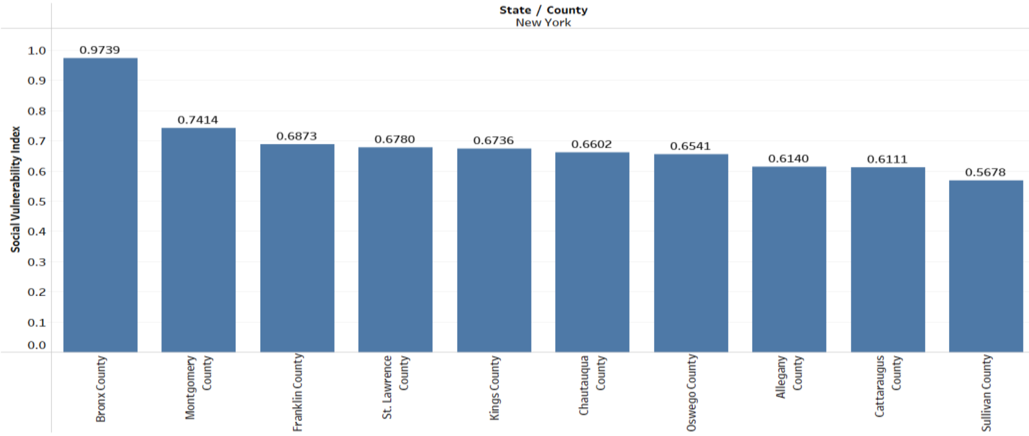

Figure 7: New York's County vs Social Vulnerability Index Analysis (Top 10 counties)

New York City (NYC) Trip Data

Trips data for New York City (NYC) is analyzed further to determine the areas where there is a minimum number of trips and hence highest transit barriers. Figure 8 shows the number of trips between pickup boroughs (Bronx, Brooklyn, EWR, Manhattan, Queens, Staten Island, Unknown) and drop off boroughs (Bronx, Manhattan, Queens and Unknown) for January 2018. The minimum number of trips has happened in the Bronx in comparison to Queens, Manhattan, and Brooklyn. Same analysis was found for the rest of the months in 2018.

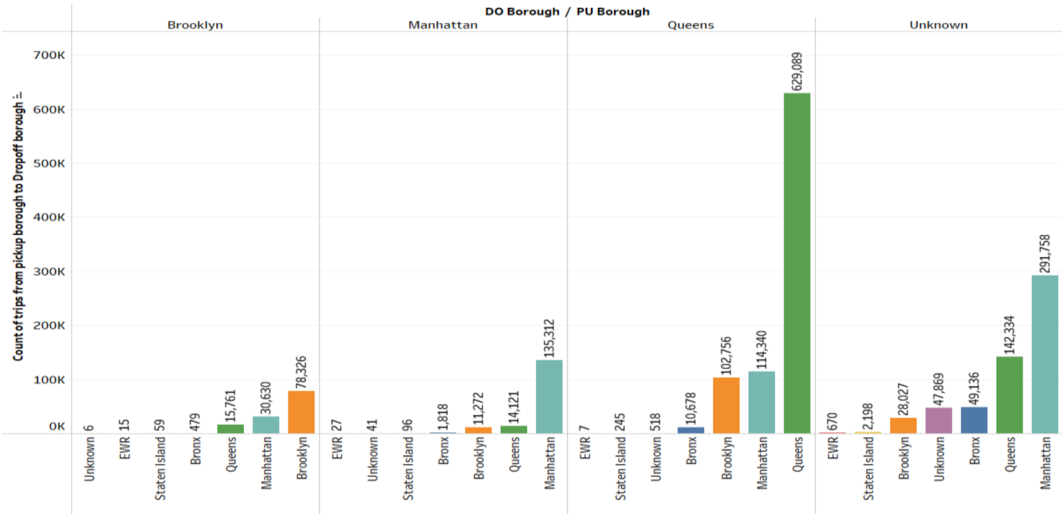

Figure 8: Count of trips between Pickup Borough and Dropoff Borough in New York City

This is also illustrated in Figure 9 which shows the total number of pickups in a particular borough. Figure 9 shows the number of pickups in each borough of NYC (Queens, Manhattan, Brooklyn, Bronx, Unknown, Staten Island, and EWR) for January 2018 and the analysis is the same for the rest of the months of 2018. Bronx has the lowest number of Pickups as compared to Queens, Manhattan, and Brooklyn.

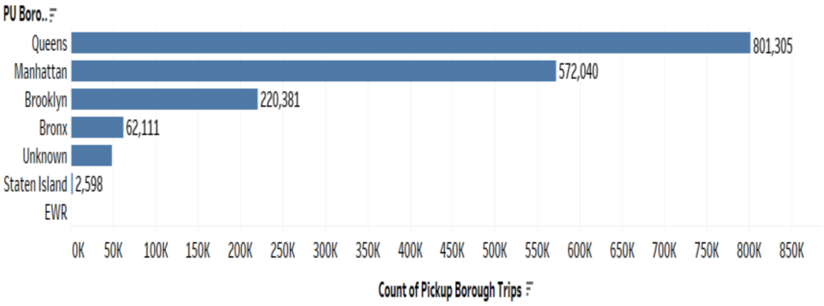

Figure 9: Count of trips from Pickup Boroughs

Bronx County has the least number of trips as compared to Queens, Manhattan, and Brooklyn. Zones are determined further to analyze the regions with maximum transit barriers (minimum number of trips) and the eight zones with least number of trips is shown in Figure 10 for Year 2018. Figure 10 shows that Rikers Island, Cortana Park, City Island, Country Club and Pelham Bay Park zones have minimum number trips which implies higher transit barriers.

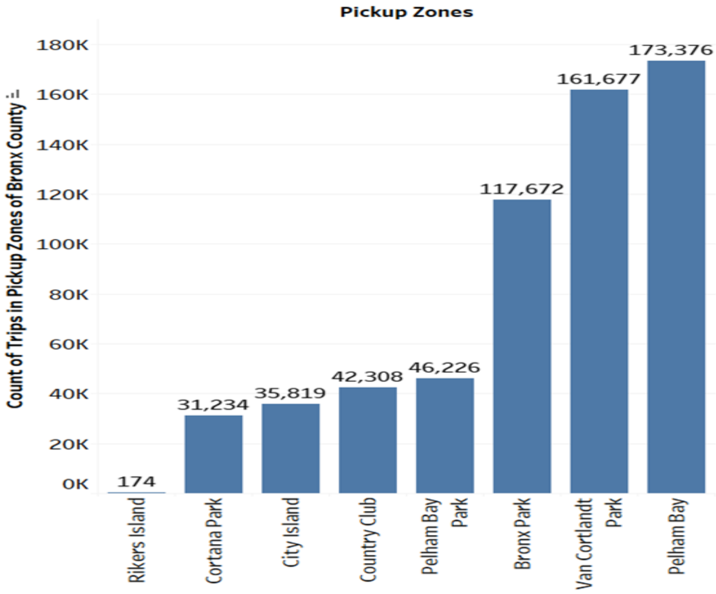

Figure 10: Trips in Pickup Zones of Bronx County in Year 2018

This analysis also supports the interpretation of the regression model that the region with higher Social Vulnerability Index has higher mortality rate and one of the reasons is transit barriers. Health care access requires analyzing the areas based on socio economic indicators and linking it with the trips data for determining the areas where ride sourcing companies can expand their services. Transportation barriers to healthcare access are common, and greater for vulnerable populations. The studies reviewed may help guide both the design of interventions that address transportation barriers and the choice of measures used in assessing their effectiveness.

4. CONCLUSION

It is likely that the population of aging baby boomers who are reliant on external transportation provision to health care facilities will grow. Conclusively, transit barriers all come down to more emergency rooms appearances and the care that is available. Since most transportation barriers affect people who are low income and elderly, help should be offered. No matter about the location, cost and distance, there should be free, no cost, transportation for these patients in their neighborhood. For elderly people, there is more of a transportation issue because of the fact that they are older and more prone to have a sickness due to their age. But before there can be a definite answer, we can only assume because there needs to be additional research before a truthful conclusion is made.

Though this research was restricted in scope and had several limitations. Studies with an exclusive focus on screening, prevention, and prenatal and pregnancy care were not evaluated and may have different findings. But at the end of the day, transportation barriers are a topic that needs strong attention to make changes for people who are struggling. People aren't getting any younger, just older. This needs to be handled as soon as possible to make a change in the world we live in today. Millions of Americans face transportation barriers to healthcare access and addressing these barriers may help transport them to improved health care access and a better chance at improved health.

This research was focused on New York City as a base location to do the analysis due to the highest number of deaths that happened in that place for 'Dead on Arrival'. The similar research could be done for other states as well with the same procedure as a suggestion to the future researchers. In order to make a conclusion, the studies reviewed may help guide both the design of interventions that address transportation barriers and the choice of measures used in assessing their effectiveness. Future studies should focus on both the details that make transportation a barrier (e.g., cost, mode of travel, public transit safety, vehicle access) and objective outcome measures such as missed appointments, rescheduled appointments, delayed medication fills, and changes in clinical outcomes. Such studies would help clarify both the impact of transportation barriers and the types of transportation interventions needed. Millions of Americans face transportation barriers to healthcare access and addressing these barriers may help transport them to improved health care access and a better chance at improved health (Richard Wallace, Paul Hughes-Cromwick, Snehamay Khasnabis, 2005).

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Conflict of interests

The authors declare that there is no conflict of interest.

REFERENCES

Syed, S. T., Gerber, B. S., & Sharp, L. K. (2013, October). *Traveling towards disease: Transportation Barriers to Health Care Access*. Journal of community health. Retrieved October 31, 2021, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4265215/.

Wolfe, M. K., McDonald, N. C., & Holmes, G. M. (2020). *Transportation Barriers to Health Care in the United States: Findings from the National Health Interview Survey*, 1997–2017. American Journal of Public Health, 110(6), 815–822. https://doi.org/10.2105/ajph.2020.305579

Drees, J. (2020, September 4). *10 healthcare organizations that have teamed up with Lyft, Uber*

in the past year. Https://Www.Beckershospitalreview.Com/. https://www.beckershospitalreview.com /consumerism/10-healthcare-organizations-that-have-teamed-up-with-lyft-uber-in-the-past-year.html?oly_enc_id=6611D5548989F5K

Ordinary least squares regression (OLS). XLSTAT, Your data analysis solution. (n.d.). Retrieved November 12, 2021, from https://www.xlstat.com/en/solutions/features/ordinary-least-squares-regression-ols.

Social Determinants of Health Database (beta version). AHRQ. (n.d.). Retrieved November 10, 2021, from https://www.ahrq.gov/sdoh/data-analytics/sdoh-data.html.

Taxi & Limousine Commission. (n.d.). Retrieved November 10, 2021, from https://www1.nyc.gov/site/tlc/index.page.

Centers for Disease Control and Prevention. (2021, October 19). FASTSTATS - deaths and mortality. Centers for Disease Control and Prevention. Retrieved November 10, 2021, from https://www.cdc.gov/nchs/fastats/deaths.htm.

Bambra C, Gibson M, Sowden A, Wright K, Whitehead M, Petticrew M. (2010) Tackling the wider social determinants of health and health inequalities: Evidence from systematic reviews. Journal of Epidemiology and Community health. 64(4):284–291. https://pubmed.ncbi.nlm.nih.gov/13130112/

Chronic diseases and health promotion. 2012b Retrieved May 15, 2012, from http://www.who.int/chp/en/

World Health Organization. (2017). Social determinants of health. Retrieved from https://www.who.int/health-topics/social-determinants-of-health

TLC Trip Record Data. TLC Trip Record Data - TLC. (n.d.). Retrieved November 12, 2021, from https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page.

Grant, R., Gracy, D., Goldsmith, G., Sobelson, M. & Johnson, D. (2014). Transportation barriers to child health care access remain after health reform. JAMA Pediatrics, 168(4): 385- 386. Retrieved from http://jamanetwork.com/journals/jamapediatrics/fullarticle/1819645

Dickersin-Prokopp, C. (2014, January 9). See how housing and transportation costs hold the poor back. Retrieved from https://ggwash.org/view/33421/see-how-housing-andtransportation-costs-hold-the-poor-back

Wallace, R. R. Paratransit Customer: Modeling Elements of Satisfaction with Service. In Transportation Research Record 1571, TRB, National Research Council, Washington, D.C., 1997 https://journals.sagepub.com/doi/10.1177/0361198105192400110