High Poverty Rates Correspond with Mental Health Rates in New York

Esenia Hernandez

2023-08-07

High Poverty Rates Correspond with Mental Health Rates

Abstract:

Mental health impacts people all throughout the world. During the Covid-19 pandemic, mental health rates rose significantly in New York, especially in low-income communities. To observe how poverty affects mental health, I used the 2020 New York Common Health Survey. This survey has over 8,000 responses and I focused specifically on the mental health and poverty group variables. Throughout my research, I discovered that there is a significant difference in mental health rates among the poverty groups, but some were also similar to each other. These findings proved my initial hypothesis and highlighted the gaps in mental health among poverty groups. Lastly, poverty groups two and three had the highest rates of mental health among all groups. These results can be used to further explore the impacts poverty has on mental health and treatment in these groups to take action for improvement.

Background:

In 2020, the Covid-19 pandemic had a big impact on health all over the world. Specifically on mental health in low-income communities. According to the New York Health Foundation, "low-income New Yorkers experienced the highest rates of poor mental health." Raising the question, to what extent do poverty rates affect mental health and treatment among New York residents in 2020?

Hypothesis: Poverty has a significant impact on mental health among New York residents.

Overall, poverty can affect the ability to be diagnosed and receive treatment for mental health illnesses. Through the first-hand experience of living in a low-income community, mental health issues are often overlooked and dismissed due to the unavailability to receive the treatment and care needed. In order to explore the effects of poverty, my research will be focused on studying the New York Common Health Survey from 2020. The Common Health Survey is a computer-assisted telephone interviewing system that is used to collect survey data from residents 18 years old and above. This data is useful in observing a variety of poverty groups and demographics regarding health.

Results:

Variable Definition Table

Variable	Definition
imputed_neighpovgroup4_1519	Rates of poverty (1-4)
mood2	Feeling of Nervousness
mood6	Feeling of hopelessness

I. Poverty Rate and Mental Health Correlation Plot

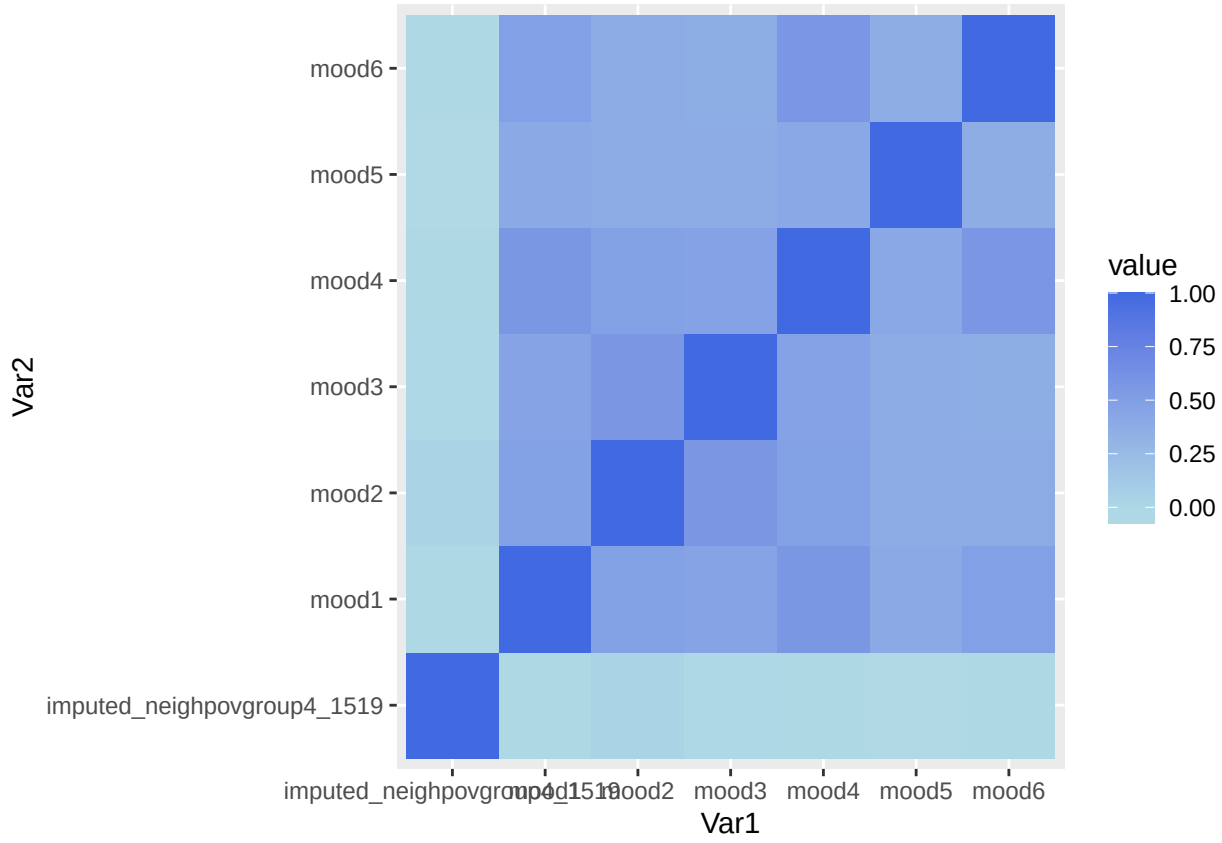
```
## [1] "C:/Users/lunar/OneDrive/Documents/DSRP 2023/DSRP-2023-Greenleaf"

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

## -- Attaching packages --------------------------------------- tidymodels 1.1.0 --

## v broom        1.0.5     v rsample      1.1.1
## v dials        1.2.0     v tibble       3.2.1
## v ggplot2      3.4.2     v tidyr        1.3.0
## v infer        1.0.4     v tune         1.1.1
## v modeldata    1.1.0     v workflows    1.1.3
## v parsnip      1.1.0     v workflowsets 1.0.1
## v purrr        1.0.1     v yardstick    1.2.0
## v recipes      1.0.6

## -- Conflicts ------------------------------------------ tidymodels_conflicts() --
## x purrr::discard() masks scales::discard()
## x dplyr::filter()  masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x recipes::step()  masks stats::step()
## * Search for functions across packages at https://www.tidymodels.org/find/

##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
## Warning: na_mean: No imputation performed for column 51 of the input dataset.
##                 Reason: Input x is not numeric.
```

```
##   [1] X                              cid
##   [3] strata                         survey
##   [5] wt21_dual                      wt21_dual_q1
##   [7] strata_q1                      qxvers
##   [9] mood1                          mood2
##  [11] mood3                          mood4
##  [13] mood5                          mood6
##  [15] mood9                          mood8
##  [17] mood11                         nutrition1
##  [19] newrace                        newrace6
##  [21] agegroup                       agegroup5
##  [23] agegroup6                      age21up
##  [25] age25up                        age40new
##  [27] age45up                        age50up
##  [29] age18_64                       birthsex
##  [31] imputed_neighpovgroup4_1519 imputed_povertygroup
##  [33] imputed_povgroup3              imputed_pov200
##  [35] generalhealth                  insuredgateway20
##  [37] insured                        insure5
##  [39] pcp20                          medplace
##  [41] didntgetcare20                 regularrx
##  [43] skiprxcost                     toldhighbp20
##  [45] toldprescription20             takingmeds20
##  [47] checkedbp20_q1                 diabetes20
##  [49] ageatdiabetes                  diabcntrlmeds
##  [51] toohighblsugar                 everasthma
##  [53] currentasthma20                stillasthmaall
##  [55] firsttoldasthma                k6
##  [57] nspd                           mhtreat20_all
##  [59] delaypayrent                   workingac_q1
##  [61] rodentsstreet                  helpneighbors20_q1
##  [63] discussissues                  helpcommproj
##  [65] didntcleandog                  trustkeys
##  [67] proudneigh                     smoker
##  [69] everyday                       numberperdaya
##  [71] cpd20a                         heavysmoker20a
##  [73] everydaycpda                   smokecat
##  [75] mentholcigs20                  sourcelastcig
##  [77] cost20cigarettes               cigpurchase20
##  [79] cigarillo20_q1                 smokeecig12m20_q1
##  [81] smokeecig30days20_q1           likedecigsflavs_q1
##  [83] smokehookah12m_q1              smellcigsmoke20_q1
##  [85] newrace6_b                     usborn
##  [87] maritalstatus20                sexualid20
##  [89] education                      employment20
##  [91] emp3                           bmi
##  [93] weightall                      weight20in4
```

```
##  [95] weight20in5                fluvaccineshot
##  [97] whereflu20                 fruitveg20
##  [99] avgsodaperday20            twoplussoda
## [101] nsugardrinkperday20        avgsugarperday20
## [103] nsodasugarperday20         avgsodasugarperday20
## [105] ssb                        exercise20
## [107] cyclingfreq                cycling20
## [109] swim                       difficultdailyact
## [111] assistdevice               evercolon20
## [113] colonoscopy10yr20          evercolon20_45
## [115] colonoscopy10yr_45         hiv12months20
## [117] everhivtest20              condom20
## [119] analsex                    analstdtest
## [121] analsexcondomuse20         sexbehav_active20
## [123] wsw                        wswexclusive
## [125] sexuallyactive20           sexpartner
## [127] everheardofprep            everusedprep20
## [129] msm                        msmexclusive
## [131] bthcontrollastsex20_q1     condomusetrend
## [133] drinker                    daysalc30
## [135] averagedrink20             heavydrink20
## [137] bingenew                   ipvphy
## [139] insultipv                  wt_compare
## [141] insure20r                  hhsize
## [143] child
## <0 rows> (or 0-length row.names)
```



This plot shows the correlation between poverty and mental health variables. Based on the plot, `mood2` and `mood6` have the highest positive correlation with poverty. These variables will be used to compare the rates of mental health among poverty groups.

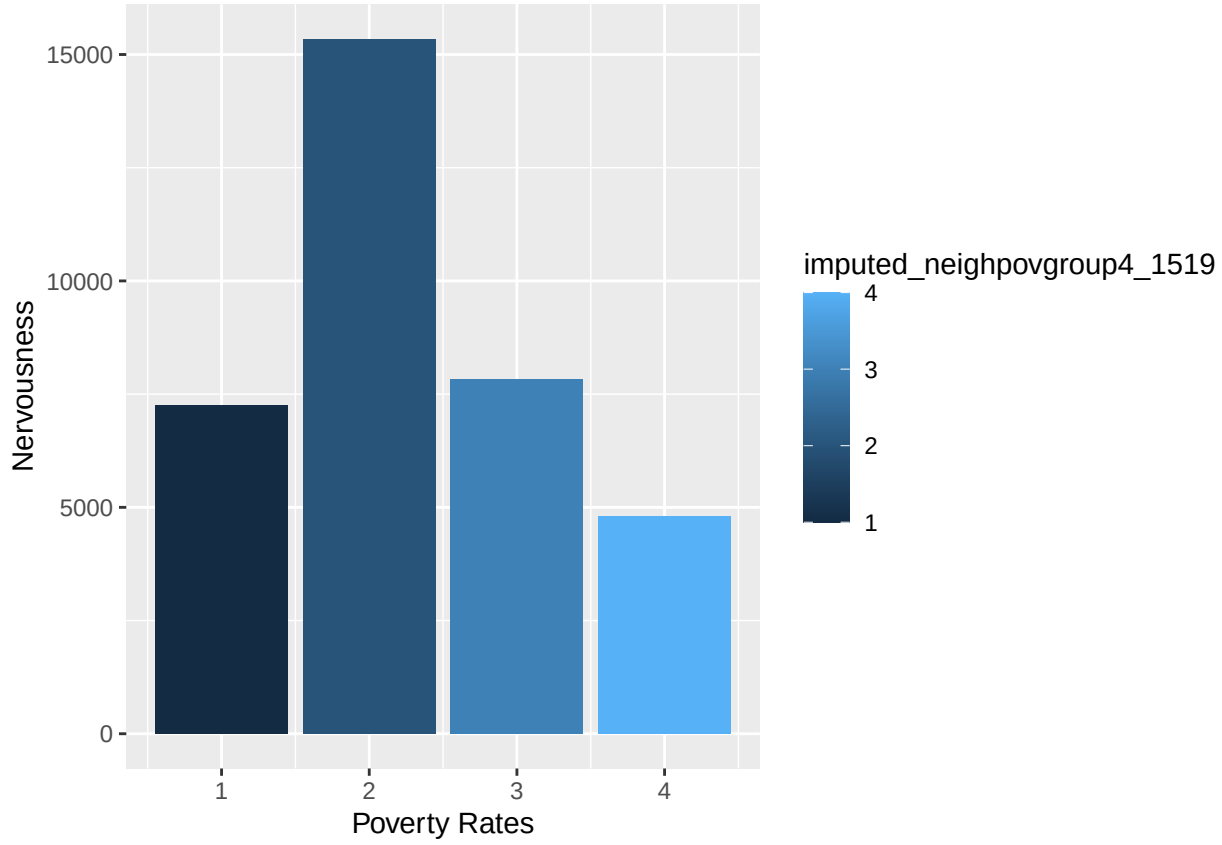
Hypothesis Testing

Apart from the correlation plot, t-testing, a statistical test used to compare means, was performed to compare the mental health rates among the wealthiest and poorest groups of residents. The t-test resulted in a p-value of **0.02012**, demonstrating a significant difference between the groups.

Additionally, machine learning models were developed, specifically regression models. A boosted tree and random forest model were used to observe any changes in poverty rate and mental health. The models demonstrated a high percentage of errors, showing room for improvement.

II. Frequency of Nervousness among Poverty Groups

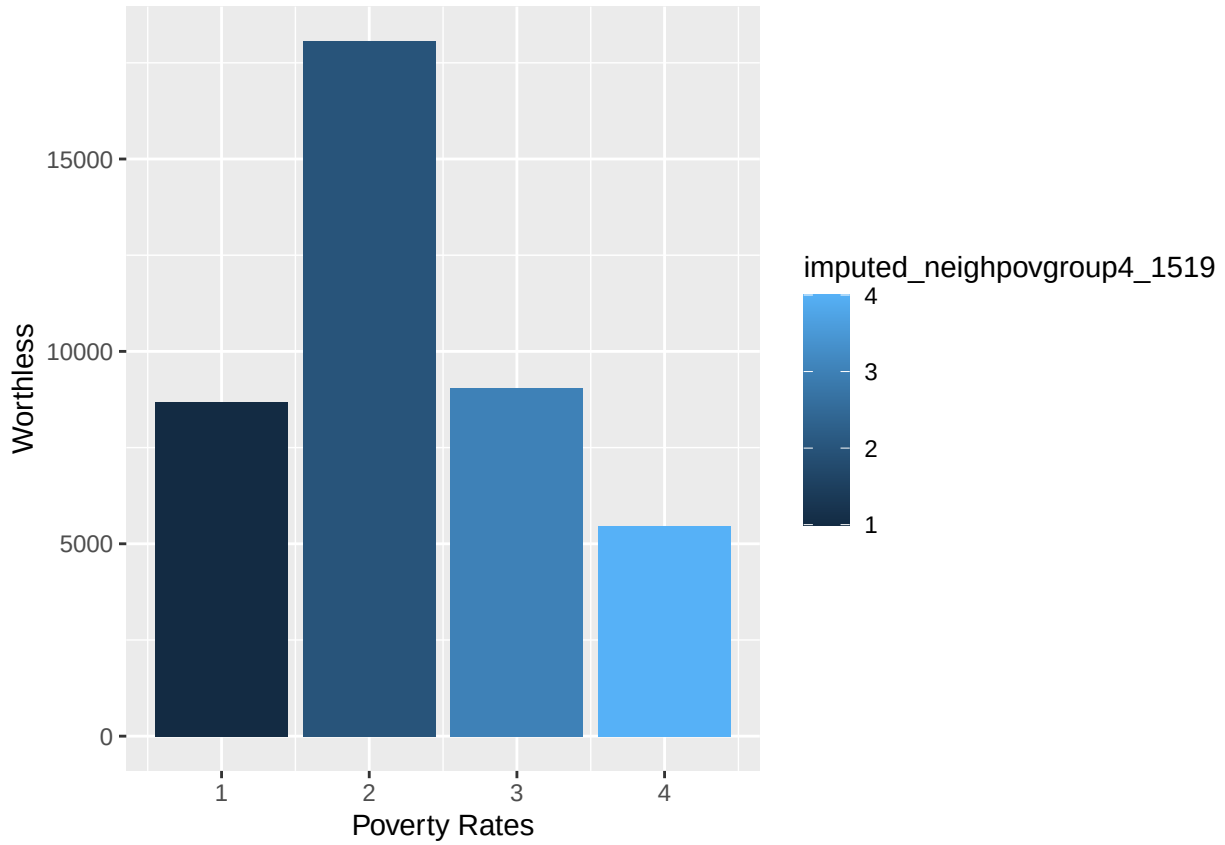
```
## Warning in geom_col(stat = "identity"): Ignoring unknown parameters: ‘stat‘
```



This bar graph shows how frequently feelings of nervousness were present among poverty groups. Based on the graph, poverty groups have different amounts of frequency.

III. Frequency of Worthlessness among Poverty Groups

```
## Warning in geom_col(stat = "stack"): Ignoring unknown parameters: ‘stat‘
```



This bar graph shows how frequent feelings of worthlessness were present among poverty groups. Similar to the previous figure, poverty groups varied in frequency.

Discussion:

Based on the results, poverty groups two and three have the highest rates of mental health. Demonstrating that poverty has a significant impact on mental health and proving the hypothesis. These results can help medical workers further research in low-income areas and create a plan of action to help residents get the treatment needed. At first, I expected the groups with the highest level of poverty to have the highest rates of mental health.

However, poverty group two has significantly spiked results due to a greater amount of people interviewed in that group. Additionally, many of the variables from the survey dataset were not available due to transferring issues which limited further exploration of variables.

Some next steps would be to explore the probability of substance abuse by including different variables. As well as the further development of machine learning models to observe changes. This research would help determine if mental health plays a big role in drinking alcohol and smoking in New York.

Code and Data Availability:

Coding can be found on GitHub. The New York Common Health Survey 2020 data can be found here.

Acknowledgments:

I would like to acknowledge Columbia University professor, Dr. Greenleaf for mentoring me throughout my research and for helping me learn more about public health. I would also like to acknowledge The Coding School for granting me a full scholarship to participate in the Data Science Research Program. Lastly, I would like to acknowledge Sarah Parker, Yijia Wang, and Mira Bell for helping me learn all about R and fixing bugs.