Racial Impact on Infections and Deaths due to COVID-19 in New York City

Forthcoming in *Harvard Technology Review*

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with Prof. James Unwin

MIT PRIMES

October 23, 2020

Racial Disparities of COVID-19 in NYC

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CDC Defined Risk Factors

- Old age, Underlying health conditions

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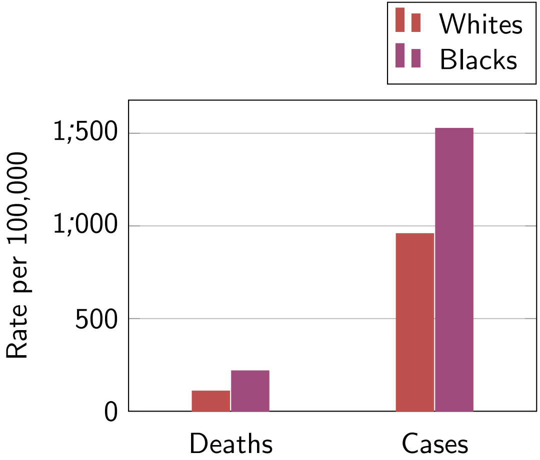

- Traditional risk factors alone do not explain the disparity.

Environmental Factors

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Natural Questions

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Natural Questions

- How does environment/neighborhood play a role?

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- Limited access to local healthcare (G. Gee, 2002)
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Natural Questions

- How does environment/neighborhood play a role?
- How can we quantify and compare neighborhoods?

Residential Redlining

Source. Washington Post

Residential Redlining

- Barred Black individuals from entering White communities

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- Transparency through Home Mortgage Disclosure Act (HMDA) in 1975

Current E orts & Importance

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Disease Modeling

Only a handful make use of the HMDA database

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COVID-19 Response

Identify individuals according traditional risk factors

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Disease Modeling

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COVID-19 Response

Identify individuals according traditional risk factors

Importance of Our Work

Provide a new measure to quantify the vulnerability of a community

Ensure that racial di erences are not what guarantee good healthca through policies

Multi-level Logistical Regression

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Data

Census Tracts were numbered from 1 to 2095.

Individuals were sorted into Census Tracts and were numbered fron
to 208,960 .

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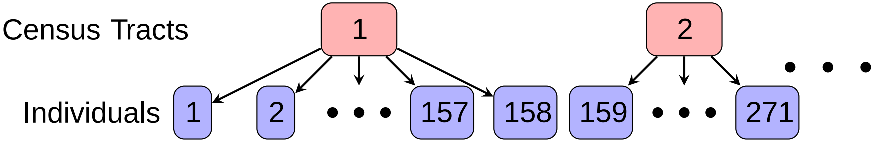

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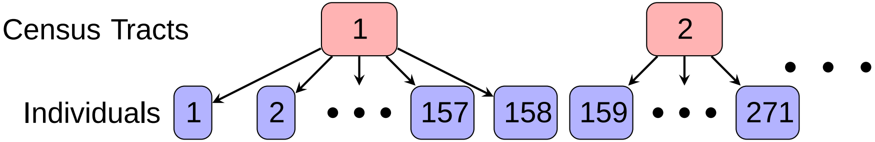

Multi-level

Level 1: NYC. Level 2: Census Tracts.

Multi-level Logistical Regression

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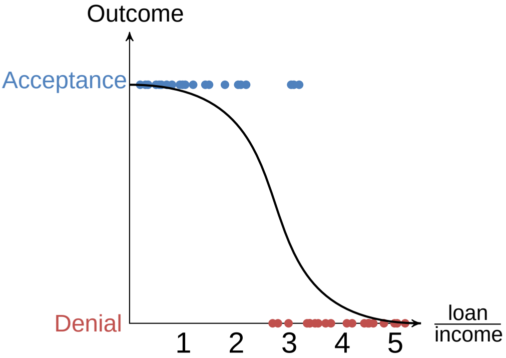
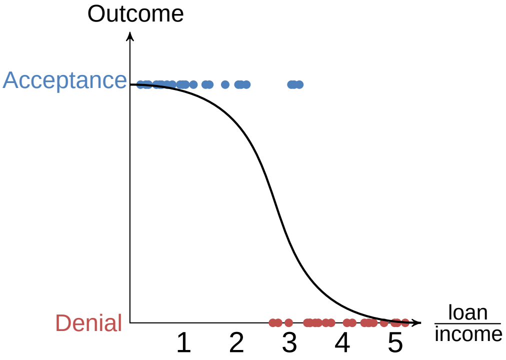


(Schematic)

Multi-level Logistical Regression



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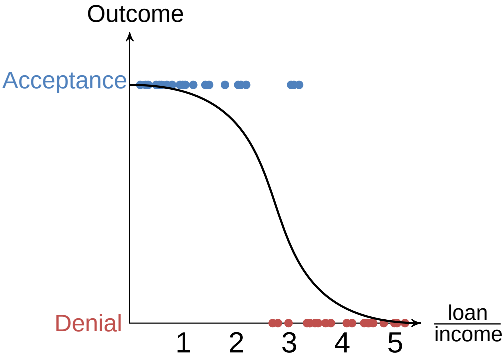
Curve of best t

Multi-level Logistical Regression



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Curve of best t

$$P(y=1) = \frac{e^{\ x+}}{e^{\ x+} \ \ +1}$$

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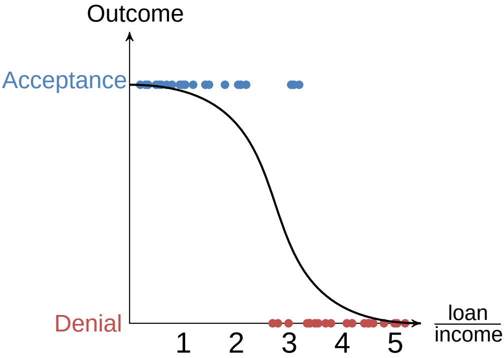

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Curve of best t

$$P(y=1) = \frac{e^{\ x+}}{e^{\ x+}\ \ +1}$$

$$\log\left(\frac{P(y=1)}{1\ \ P(y=1)}\right) = $$
$$x +$$

Our Model

Our Model

Level 1 Equation

$$\log[p_{ij} = (1 \quad p)_{ij}] = {}_{0j} + {}_{1j} r_{ij} + {}_{2j} s_{ij} + {}_{3j} l_{ij}$$

r_{ij} : race of the applicant i in census tract j (1 = white, 0=black).

s_{ij} : sex of the applicant (1 = male, 0=female).

l_{ij} : ratio of requested loan to income.

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${}_{k0}$ is xed over NYC.

u_{kj} shows the variation across Census Tracts.

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Redlining Index Map

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Fig. Redlining index

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Fig. Redlining index

Fig. Per capita income

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Fig. Per capita income

Redlining Index

Ranged from 1.70 to 2.48

A correlation of 0.68 with per capita income

Mortgage Discrimination in NYC 2013-17

Summary

Although mortgage discrimination is not institutionalized by the government, it is institutionalized in practice.

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	Black		White		
Year	N	Percent denied	N	Percent denied	Redlining Index (95 CI)
2013	9930	40.2	46475	23.8	1.88 (1.77, 1.99)
2014	7203	37.8	29848	23.4	1.93 (1.81, 2.01)
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Updated daily by the NYC Government for each ZCTA.

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Fig. Rate of infection

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Fig. % of positive tests

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Fig. Rate of deaths

Scatterplots (May 20th)

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Correlation with Index

Rate of infection: -0.54

% of positive tests: -0.64

Rate of deaths: -0.43

Correlation over time

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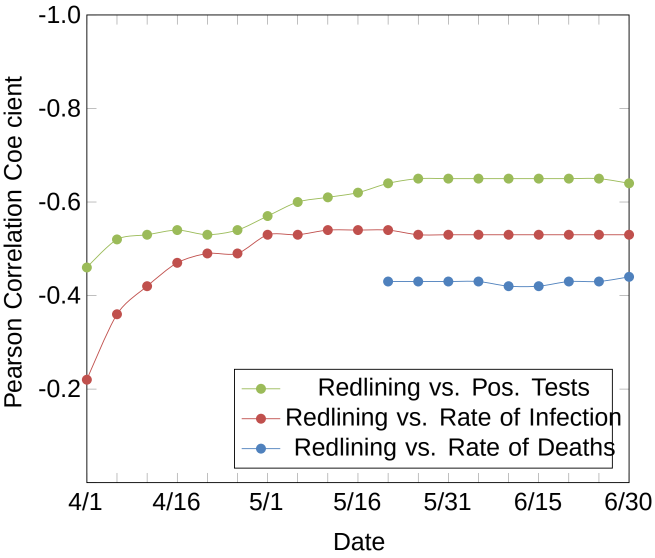

Conclusion

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Source. The New Yorker

Possible explanations:

Conclusion

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Medical resources are not distributed equally.

Conclusion

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Possible explanations:

- Medical resources are not distributed equally.
- Residents of redlined neighborhoods are less likely to seek medical assistance.

Acknowledgements

- Prof. James Unwin
- Dr. Slava Gerovitch
- Prof. Pavel Etingof
- Dr. Tanya Khovanova
- MIT PRIMES
- My sister, Yuji