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

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Racial Disparities of COVID-19 in NYC

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CDC Defined Risk Factors

- Old age, Underlying health conditions

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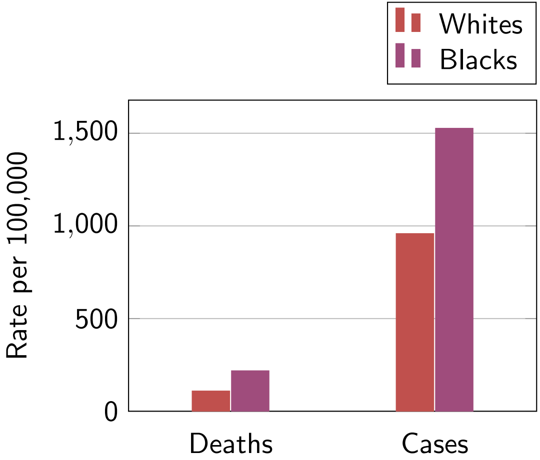

- Traditional risk factors alone do not explain the disparity.

Environmental Factors

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Natural Questions

- How does environment/neighborhood play a role?

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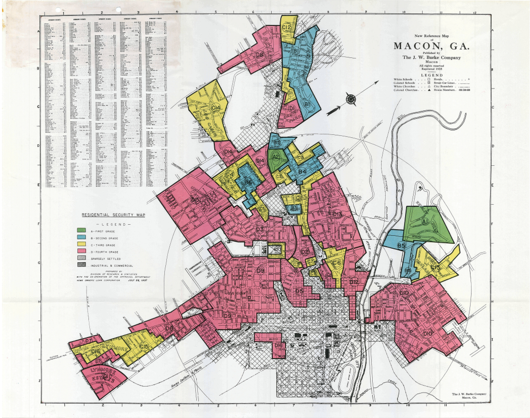
Natural Questions

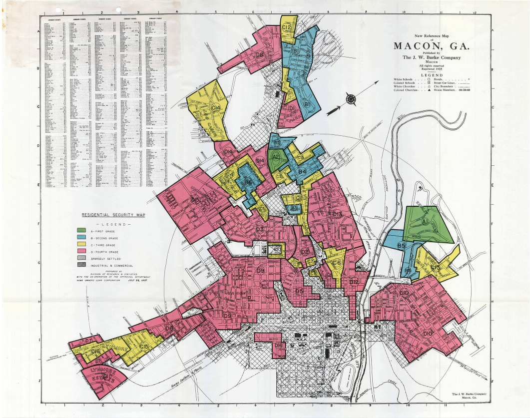
- How does environment/neighborhood play a role?
- How can we quantify and compare neighborhoods?

Residential Redlining



Source. Washington Post

Residential Redlining



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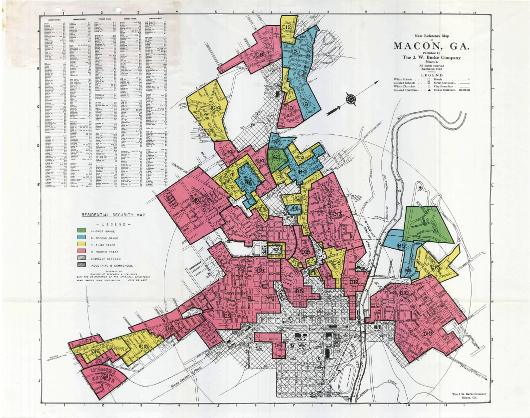

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- Barred Black individuals from entering White communities
- Transparency through Home Mortgage Disclosure Act (HMDA) in 1975

Current Efforts & 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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Importance of Our Work

- Provide a new measure to quantify the vulnerability of a community
- Ensure that racial differences are not what guarantee good healthcare 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 from 1 to 208,960 .

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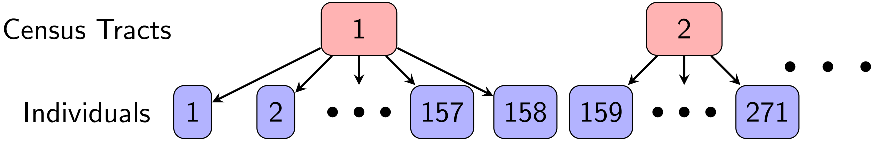

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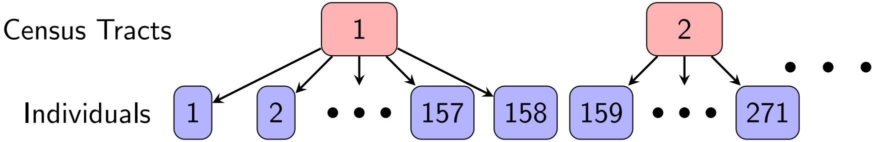

Multi-level

Level 1: NYC. Level 2: Census Tracts.

Multi-level Logistical Regression

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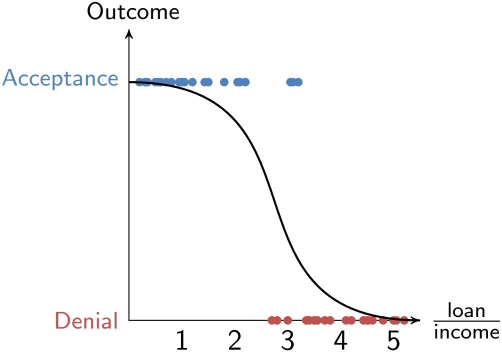
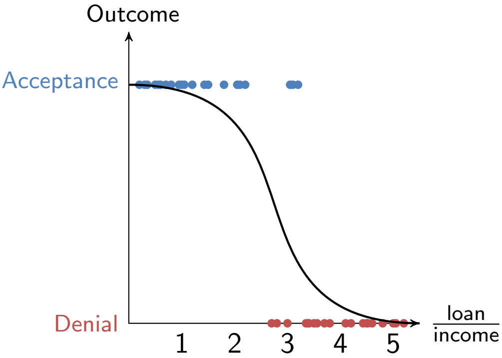


(Schematic)

Multi-level Logistical Regression



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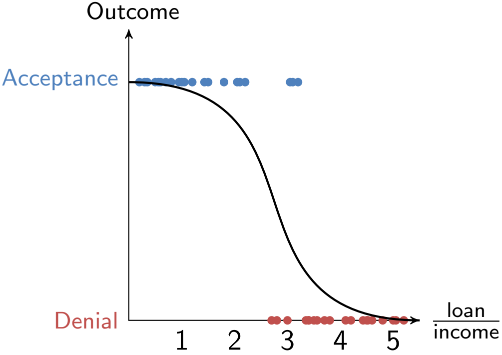
Curve of best fit

Multi-level Logistical Regression



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Curve of best fit

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

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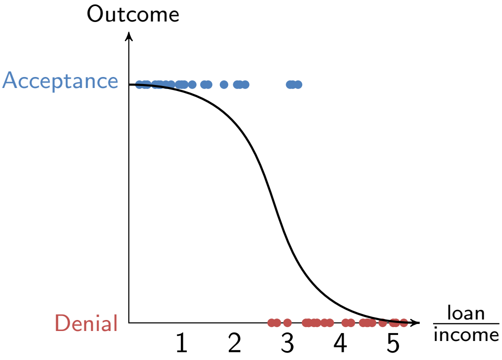

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Curve of best fit

- $\mathrm{P(y{=}1)} = \frac{e^{\alpha x+\beta}}{e^{\alpha x+\beta}+1}$
- $\log\left(\frac{\mathrm{P(y{=}1)}}{1-\mathrm{P(y{=}1)}}\right) = \alpha x + \beta$

Our Model

Our Model

Level 1 Equation

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

- r_{ij}: race of the applicant i in census tract j ($1 =$ white, $0=$black).
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Level 2 Equation

$$\beta_{kj} = \gamma_{k0} + u_{kj} \text{ for k} > 0.$$

- γ_{k0} is fixed over NYC.
- u_{kj} shows the variation across Census Tracts.

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Redlining Index Map

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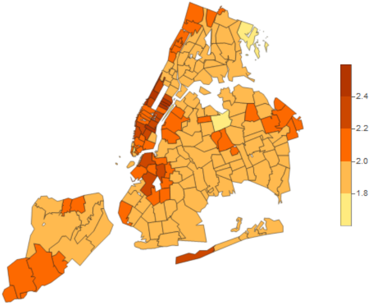

Fig. Redlining index

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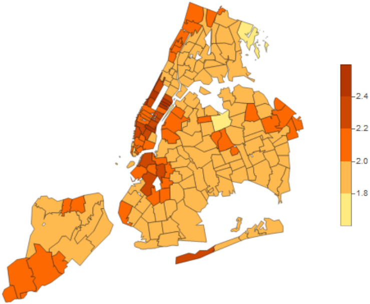

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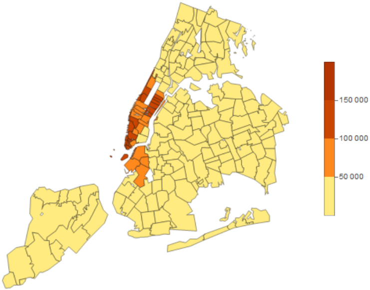

Fig. Per capita income

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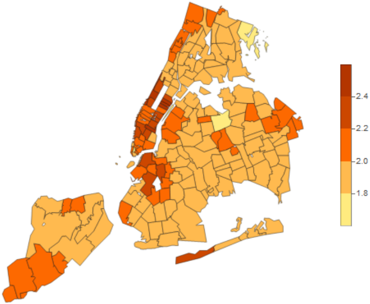

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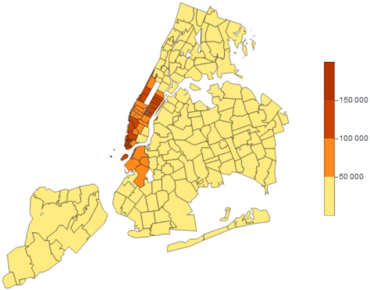

Fig. Per capita income

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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	Applicant Race				
	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)
2015	7487	34.8	32249	20.8	1.95 (1.83, 2.07)
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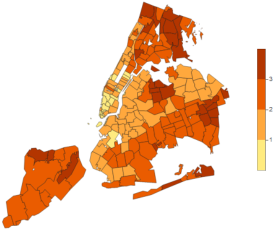

Fig. Rate of infection

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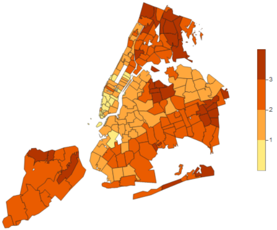

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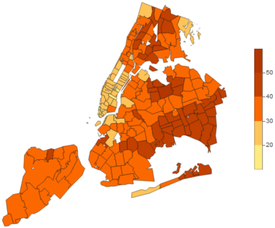

Fig. % of positive tests

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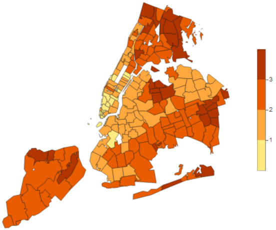

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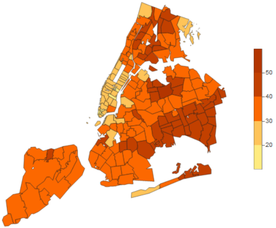

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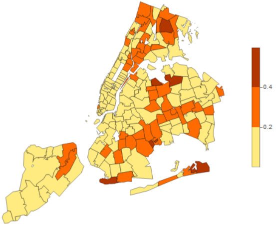

Fig. Rate of deaths

Scatterplots (May 20th)

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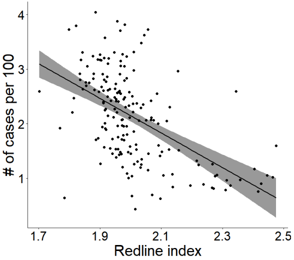

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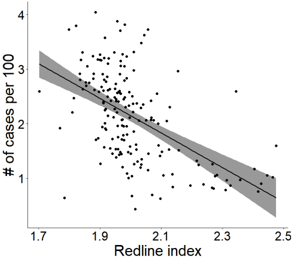

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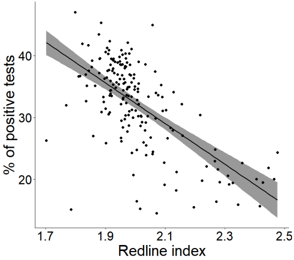

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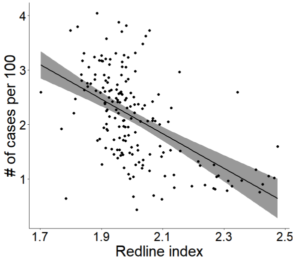

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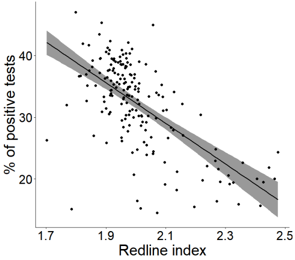

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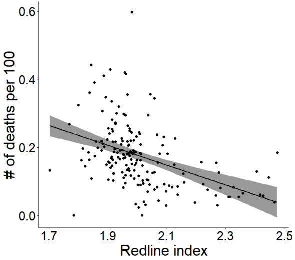

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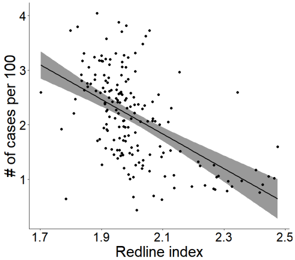

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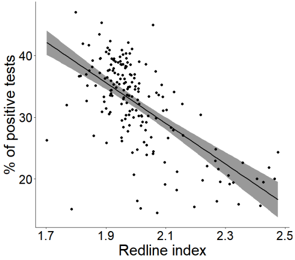

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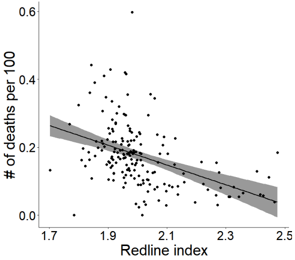

Fig. Rate of deaths

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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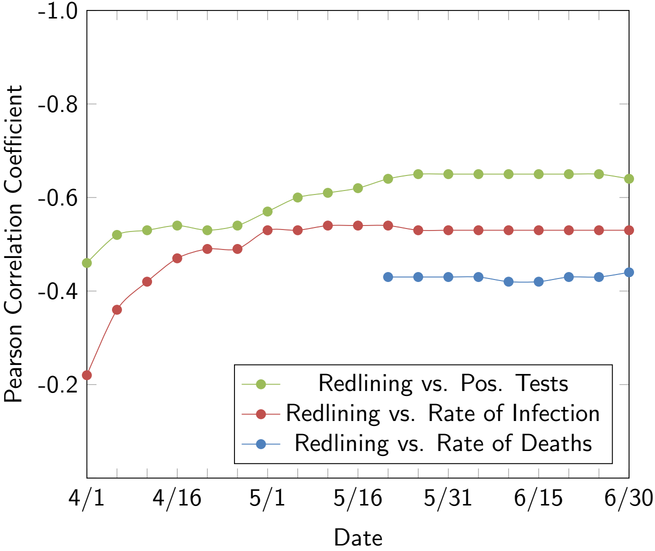

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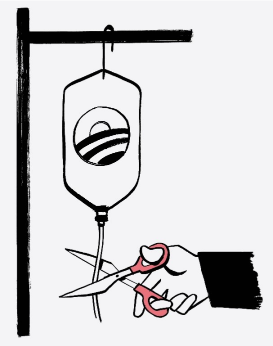
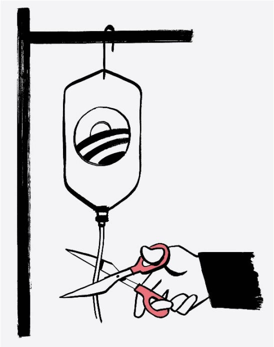


Source. The New Yorker

Possible explanations:

Conclusion



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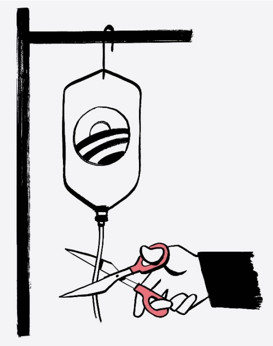

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Possible explanations:

- 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