Background

Many consequential policy decisions are multi-faceted and distributed over time.

- Policies often have to deal with both **allocation** and **scheduling**.
- Policies often happen along a **pipeline** consisting of a sequence of decisions [1, 2].
- Examples of such policies exist in many critical domains with equity concerns, including **education** and **criminal justice**.

Pipelines are difficult to study empirically.

- Pipelines can be **long and complex**, often spanning many years and multiple decision-makers
- There is **substantial unobserved confounding** between stages.

Domain: NYC Dept. of Parks and Recreation (DPR)

Cities use resident crowdsourcing.

- The public reports problems such as downed trees or power lines to the government.
- NYC's 311 system received over 2.6 million requests in 2021.

The Parks Department fields requests on street trees.

- Street Trees are important: NYC's 700,000 street trees provide life-saving temperature reductions, and when they fall they can cause significant damage, disruption and death.
- Requests trigger a pipeline of decisions: From 100,000 annual requests, DPR makes a sequence of bureaucratic decisions: an *inspection* involving an agency member visiting the incident location, and then a *work order* to fix the issue if necessary [3].
- Domain Advantages: Decision pipelines are centralized and short (weeks/months). There is arguably little unobserved confounding. Regular conversations with DPR officials provide us with vital context and an avenue to *change* operations.

References

[1] Eshwar Ram Arunachaleswaran, Sampath Kannan, Aaron Roth, and Juba Ziani. Pipeline interventions. arXiv preprint arXiv:2002.06592, 2020.

END-TO-END AUDITING OF DECISION PIPELINES Benjamin Laufer, Emma Pierson and Nikhil Garg

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Main Contributions

- We develop a method for auditing decision pipelines end-to-end with conditional parity tests at each stage.
- Using data on NYC DPR's decision pipeline, preliminary evidence suggests there are **socio-economic disparities in** allocation and scheduling decisions.

Parity Definitions

All definitions are provided for group attribute g and pipeline events report, insp, work order, and work completed.

Equity in Allocation Decisions

- Inspection Parity: Compare $\mathbb{P}(\operatorname{insp}|g, \operatorname{report})$ • Work Order Parity: Compare $\mathbb{P}(work order | g, insp)$ • Work Completion Parity: Compare $\mathbb{P}(work \text{ completed})$
- q, work order)

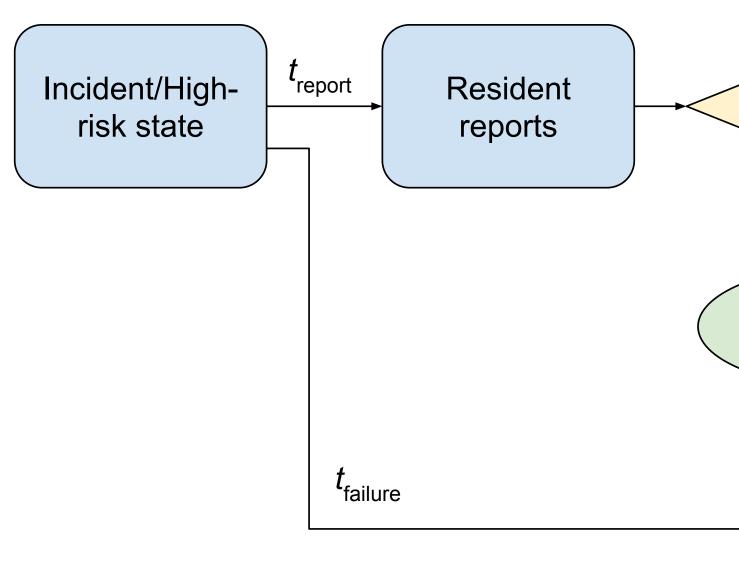
Equity in Scheduling Decisions

- Inspection Time Parity: Compare $\mathbb{E}[t_{report \to insp}|g]$
- Work Time Parity: Compare $\mathbb{E}[t_{insp \to work}|g]$

Risk-adjusted Regression Tests

In addition to demographic parity, we use risk-adjusted regression tests [4] in which we include the (predicted or observed) risk as a regressor in order to directly compare parity among reports that are of the same risk level

Figure 1 (below): Pipeline of NYC DPR Decisions

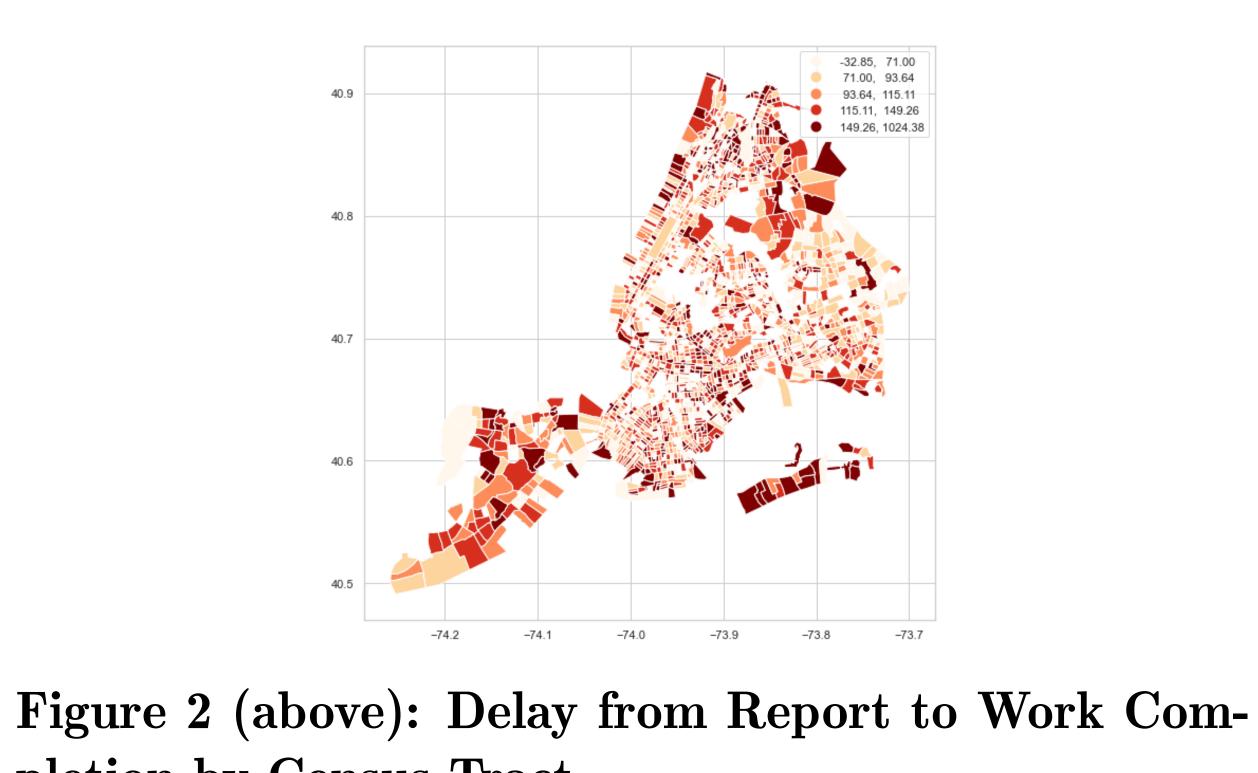


Preliminary Results

DPR inspection allocation benefits low-income neighborhoods.

- ing directed at the inspection stage.

However, each subsequent pipeline decision disadvantages low-income neighborhoods.



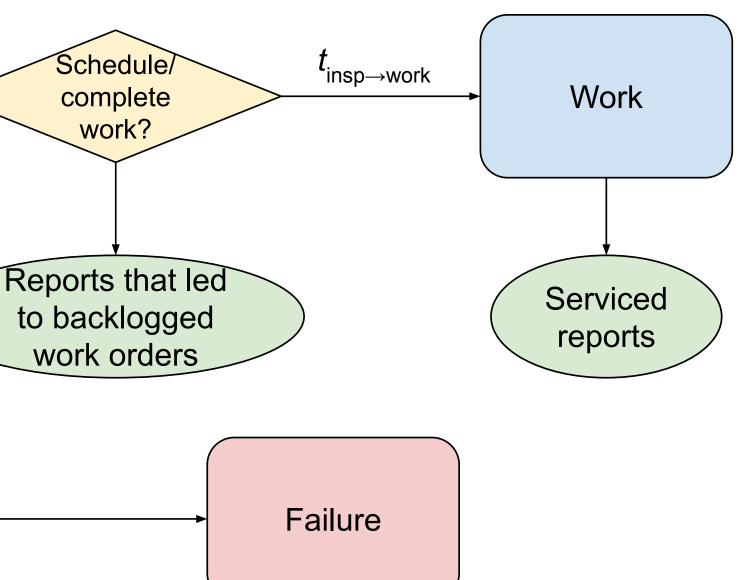
pletion by Census Tract ^ℓreport→insp Work inspect? Inspection order? Inspected Uninspected unserviced reports reports

• In regression tests with and without adjusting for risk, DPR's first decision of whether or not to inspect directs extra attention to low-income census tracts.

• This observation may be explained by existing audits be-

• In ordering work and completing work, the DPR is significantly less likely to allocate to low-income census tracts.

• In scheduling decisions, similar biases are observed. Reports from lower-income census tracts wait longer before being inspected and worked on, on average, compared to reports of the same risk from higher-income census tracts.



^[2] Lydia T Liu, Sarah Dean, Esther Rolf, Max Simchowitz, and Moritz Hardt. Delayed impact of fair machine learning. In International Conference on Machine Learning, pages 3150–3158. PMLR, 2018.

^[3] Zhi Liu and Nikhil Garg. Equity in resident crowdsourcing: Measuring under-reporting without ground truth data. arXiv preprint arXiv:2204.08620, 2022.

^[4] Jongbin Jung, Sam Corbett-Davies, Ravi Shroff, and Sharad Goel. Omitted and included variable bias in tests for disparate impact. arXiv preprint arXiv:1809.05651, 2018.