Machine Learning for Proactive Rights Enforcement: The Case of Labor and Housing Rights

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Shaping the Digital Future: August 2024

Slides

https://github.com/rebeccajohnson88/talks/blob/master/rjohnson_shapingdigitalfutures_mlrights_august2024.pdf

Acknowledging collaborators on both projects

Tenant rights (funder: Data Science for Social Good fellowship):

- Teng Ye, University of Michigan School of Information (at time); Currently, University of Minnesota Carlson School of Management
- Samantha Fu, California Policy Lab
- Jerica Copeny, Nextdoor
- Bridgit Donnelly, Mayor's Public Engagement Unit (at time)
- Alex Freeman, Mayor's Public Engagement Unit (at time)
- Joe Walsh, CMU Center for Data Science and Public Policy (at time)
- Rayid Ghani, CMU Center for Data Science and Public Policy

Agricultural guestworker rights (funder: Department of Labor):

- Cameron Guage, Dartmouth College '22
- Eunice Liu, Dartmouth College '23
- Helen Ma, Dartmouth College '23
- Grant Anapolle, Dartmouth College '21
- Data science students in Dartmouth QSS20
- Elizabeth Shackney, Texas Riogrande Legal Aid (TRLA)
- Cassie Davis, Texas Appleseed foundation

Organization of talk

- General challenge: reactive rights enforcement (help people who complain about a rights violations) creates biases in who gets help
- Project 1 (majority of talk): outreach to tenants at risk of rights violations by their landlords
- Project 2 (brief preview): outreach to temporary agricultural guestworkers at risk of rights violations by their employers/visa-holders
- Conclusion

Where we are

- **General challenge: reactive rights enforcement (help people who complain about a rights violations) can lead to biases in who gets help**
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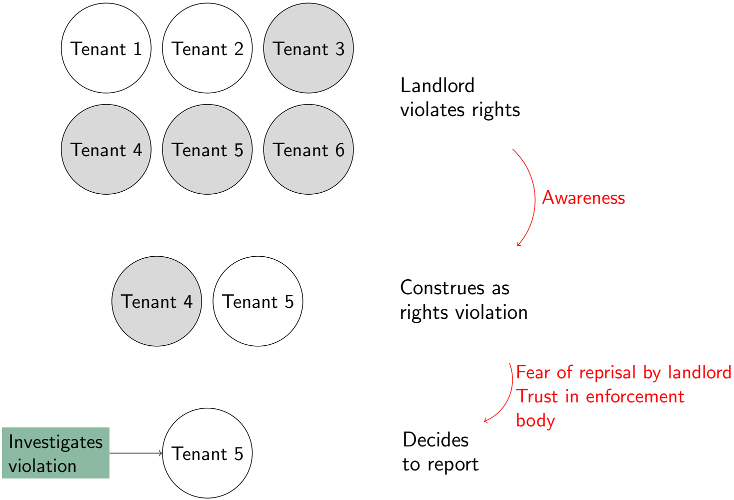
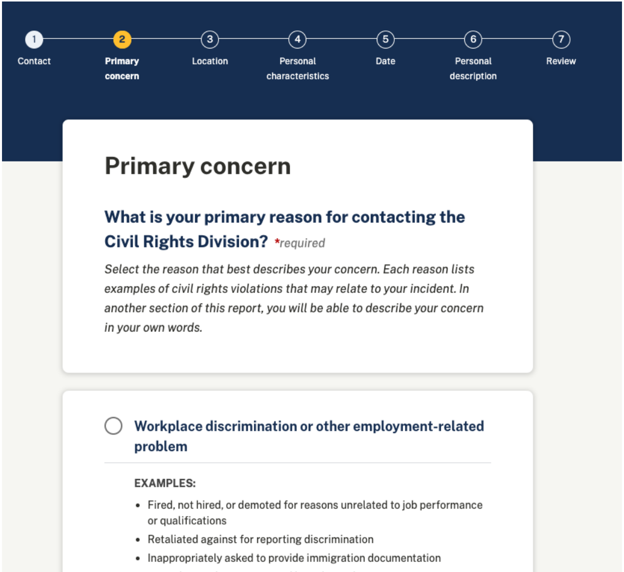
Perennial issue in law and inequality: attrition through "naming, blaming, and claiming" of rights violations



Example of federal civil rights reporting process

https://civilrights.justice.gov/report/



Multiple avenues to try to reduce differential underreporting

1. Still rely on complaint-driven enforcement but try to make reporting less logistically difficult and/or less worrisome from perspective of retaliation
2. **Focus here:** shift, in part, from complaint-driven enforcement—waiting for people to complain—to more proactive enforcement: actively canvass a sample of at-risk individuals to learn about rights violations and use that to target oversight
3. Bypass asking people about issues and conduct inspections/random audits

What role can data science and supervised machine learning play in proactive enforcement?

Annual Review of Law and Social Science

Tool for Surveillance or Spotlight on Inequality? Big Data and the Law

Rebecca A. Johnson[1] and Tanina Rostain[2]

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https://www.annualreviews.org/doi/pdf/10.1146/annurev-lawsocsci-061020-050543

- If canvassing to learn about potential issues, can (1) randomly select where to canvas, (2) learn relationship between predictors and issues, and (3) use that relationship on a larger pool of data to generate lists of high-risk entities
- If doing random inspections, can similarly use the results to gain less biased insight into where issues are occurring
- Examples from other areas: U.S. Occupational Safety and Health Administration (OSHA) inspections for worker safety (Levine, Toffel, and Johnson (not me!), 2012, 2019); food safety inspections (Stanford RegLab)

Discussion Break

Questions:

1. Can you think of examples from your organization of "reactive" policy decisions? Beyond the enforcement of rights, this could be things like code enforcement, policing, and other topics
2. What do you see as the background reasons why the organization uses that mode of oversight?
3. What do you see as pros and cons of that mode of oversight compared to more proactive forms of oversight?

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More details on project

- **Paper:** https://dl.acm.org/doi/10.1145/3314344.3332484
- **Code:** Repository is private but I made public-facing version with 1) all our `utils` (Python helper functions we wrote to help make various ETL, preprocessing, and model estimation tasks more efficient), and 2) example code from some of the pipeline steps: https://github.com/rebeccajohnson88/sharing_ml_landlord

Background: policy levers to increase housing affordability

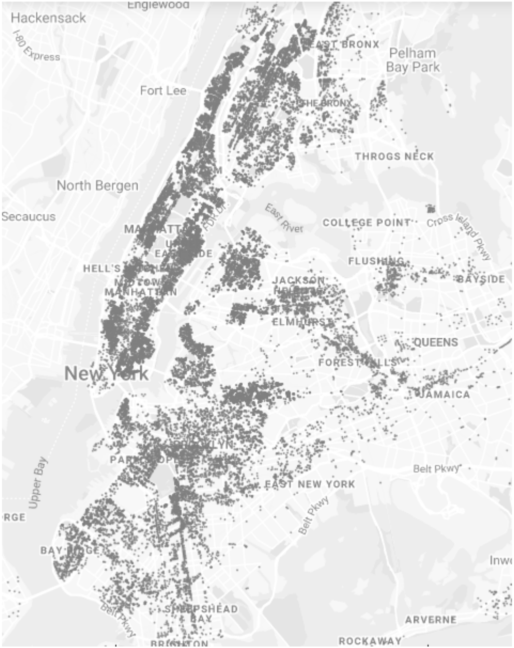
$$\frac{\text{Monthly rent}}{\text{Monthly income}}$$

Rent stabilization:
Acts on: numerator;
Attaches to: a housing unit

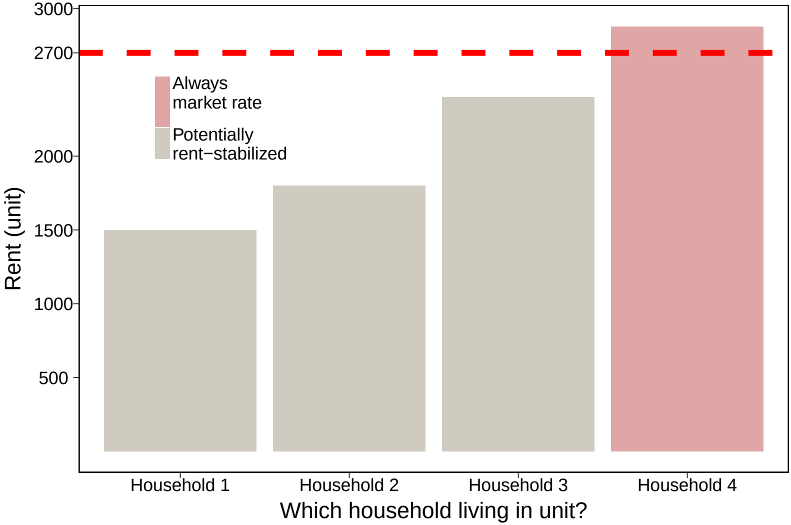
Housing vouchers:
Acts on: entire ratio;
Attaches to: individuals

Rent control:
Acts on: numerator;
Attaches to: individuals + a housing unit

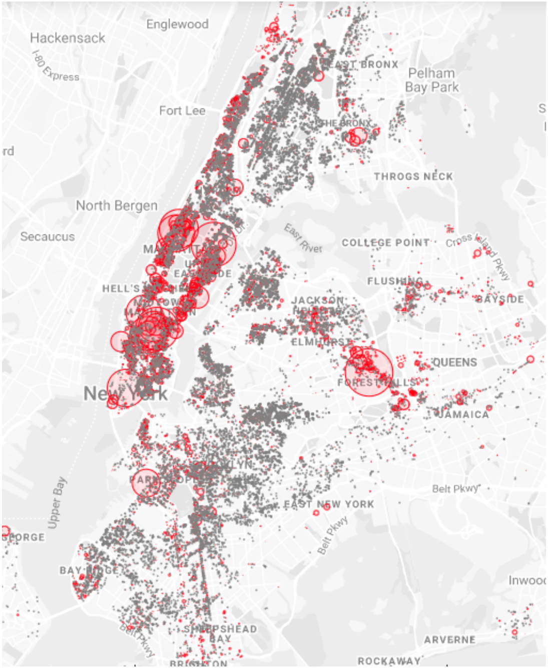
In New York City (NYC), rent stabilization is an important policy lever against housing instability...



...But some landlords exploit legal loopholes to convert rent-stabilized apartments to market-rate ones



Contributing to conversion of over 38,000 rent-stabilized apartments to market-rate ones (2007-2015)



Mayor Bloomberg set up a "right against landlord harassment" as part of local housing code

New Law Lets Tenants Sue Over Harassment

By Manny Fernandez

March 14, 2008

Mayor Michael R. Bloomberg signed a bill into law on Thursday that for the first time gives tenants the right to sue their landlords in Housing Court for using threats and other forms of harassment to force them out.

The new law was passed by the City Council last month with overwhelming support from tenant groups, housing activists and legal advocates who said landlord harassment of tenants had increased in recent years.

Previously, the city's Housing Maintenance Code had not classified harassment as a violation, so tenants were restricted in taking landlords to Housing Court for problems with services or the physical condition of units. The new law makes harassment a housing code violation and allows a judge to impose civil penalties from $1,000 to $5,000. It takes effect immediately.

Harassment is defined in the new law as the use of force or threats, repeated interruptions of essential services, the frequent filing of baseless court actions and other tactics that "substantially interfere with or disturb the comfort, repose, peace or quiet" of any unit's lawful occupant.

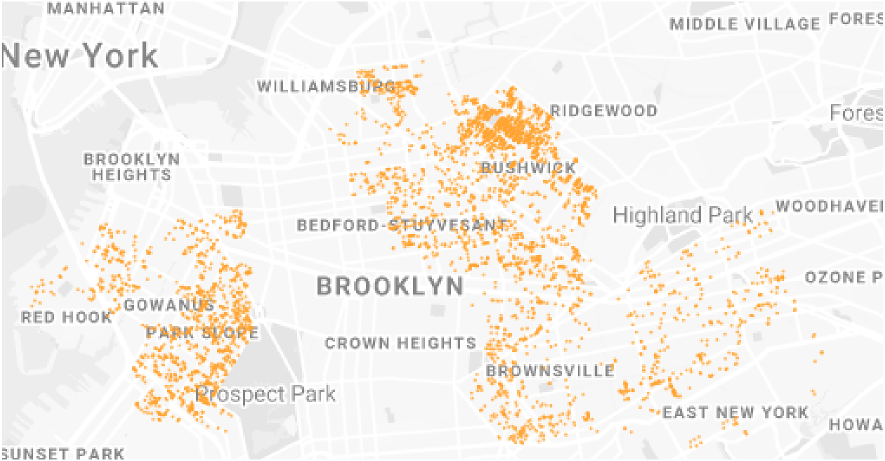
Potential way to ameliorate biases from reactive rights enforcement: *proactive* rights enforcement

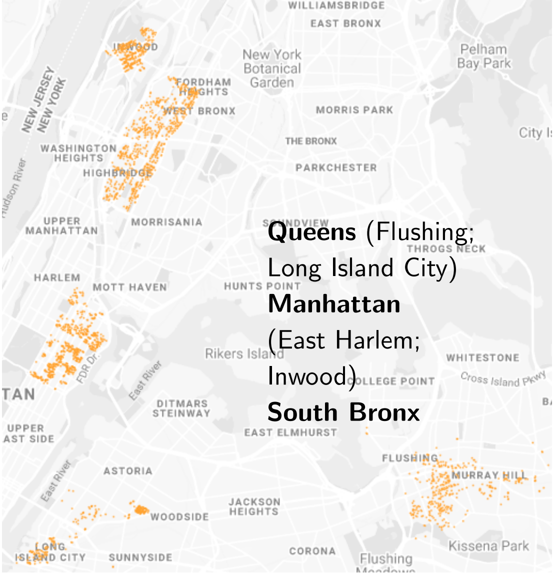
When it comes to protecting tenants and affordable housing, we don't wait for a 311 call to come in.

We have teams [Tenant Support Unit (TSU)] knocking on doors in fast-changing neighborhoods to solve problems then and there. (Mayor Bill de Blasio, 2016)

How should the Tenant Support Unit prioritize visits among ~ 6500 buildings containing $\sim 142{,}000$ residential units?

Brooklyn (Bushwick; Gowanus; East New York)





Queens (Flushing; Long Island City)
Manhattan (East Harlem; Inwood)
South Bronx

Have thus far gone block by block generating monthly lists for proactive engagement

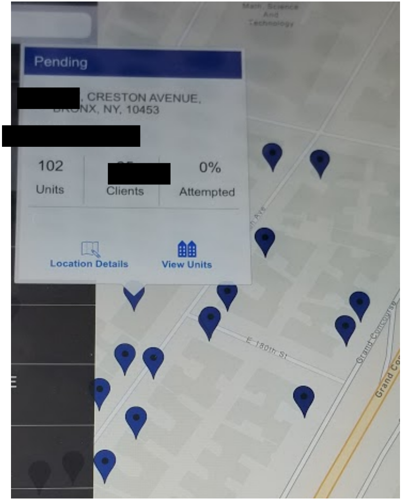
Outreach list: Bushwick Sub-Team
June 2016

Address	*Borough*	Sub-*team*
a5243	Brooklyn	Bushwick
a2110	Brooklyn	Bushwick
⋮		
a0052	Brooklyn	Bushwick

Outreach list: Flushing Sub-Team
June 2016

Address	*Borough*	Sub-*team*
a0031	Queens	Flushing
a1947	Queens	Flushing
⋮		
a6042	Queens	Flushing

Using large-scale data to improve prioritization

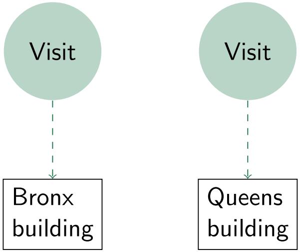


k: knocks; o: door opens; c: harassment cases

ID	Date	k	o	c
a1	06-01-2016	18	5	1
a1	06-02-2016	0	NA	NA
a2	06-01-2016	20	7	0
a2	06-02-2016	30	10	2
⋮	⋮	⋮	⋮	⋮
a_n	06-01-2016	10	0	0

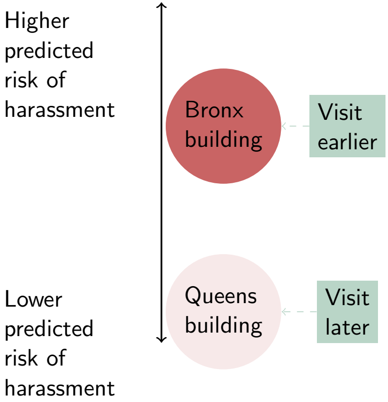
Applying machine learning to that large-scale data to improve prioritization

Current outreach:

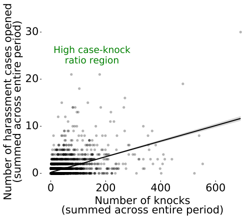


vs.

Machine learning (ML)-guided prioritization:



Steps in ML-guided prioritization: (1) define label



1. Labels to model (for building b in month m):

- Any new case in next month
- New cases/units $>$ threshold

Modeling any case in building versus ratio of cases/units

- *Reasons to use any case label*:
  - Landlord typically use tactics against all tenants in rent-stabilized units in a building
  - Fear of reprisal means only one speaks out
- *Reasons to use case /units label:*
  - Landlords typically use tactics against some proportion of more vulnerable tenants in rent-stabilized units in a building
  - Variation in that proportion is relevant
  - From legal aid perspective, need critical mass of tenants to build a "building"-wide or "cluster of properties"-wide case against a landlord

Discussion Break

Questions:

1. Is the choice of label a technical decision that we as data scientists should make alone?
2. If not, what is a fair and appropriate process of stakeholder engagement around which label/outcome variable definition is most consistent with the policy goals behind the outreach program?
3. Should the definition of the stakeholders include the tenants themselves and if so, how can make them feel included in the policy process?
4. In the case of conflicting opinions, which stakeholders' opinions should be given the greatest weight in these decisions?

Steps in ML-guided prioritization: (1) define label; (2) choose features

1. Define label

2. Choose features:
Internal (e.g., "which specialists visit?")
Building (e.g., "who is landlord?"(use fuzzy string matching to match
BAINBRIDGE CLASTER AS;
BAINBRIDGE CLUSTER AS;
BAINRIDGE CLUSTER ASS))
Violations (e.g., "how many violations found by code enforcement agency?")
Neighborhoods (ACS tract) (e.g., "what's the demographic composition? When are people home?")

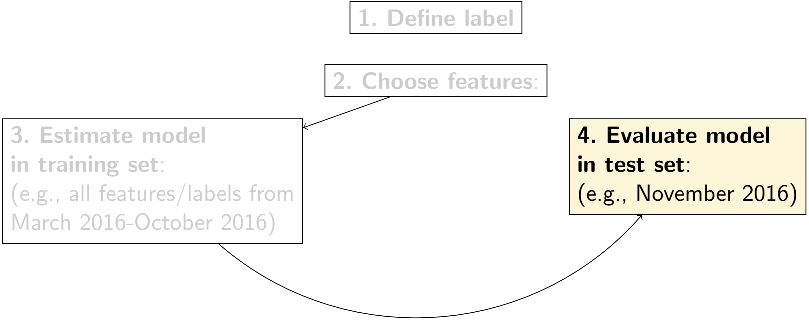
Steps in ML-guided prioritization: (1) define label; (2) choose features; (3) split data temporally and estimate model in training set

1. Define label

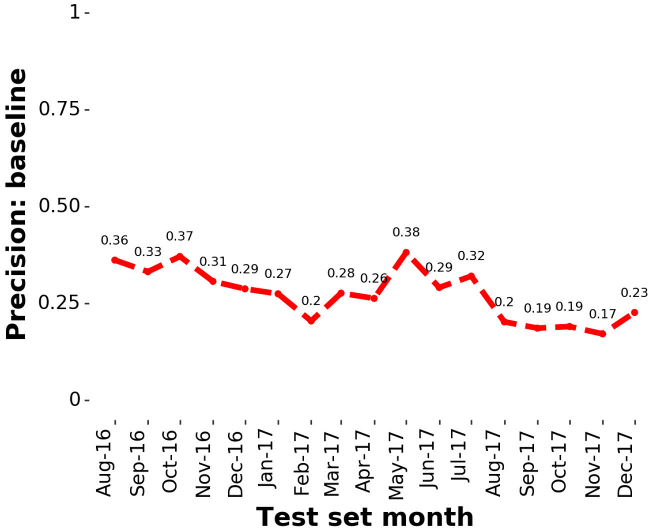
2. Choose features:

3. Estimate model in training set:
(e.g., all features/labels from March 2016-October 2016)

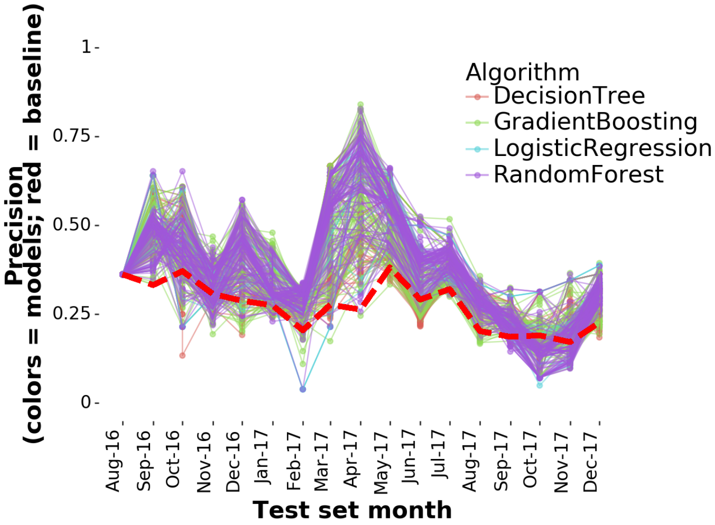
Steps in ML-guided prioritization: (1) define label; (2) choose features; (3) split data temporally and estimate model in training set, (4) evaluate performance in test set



What we want to outperform: TSU's existing prioritization

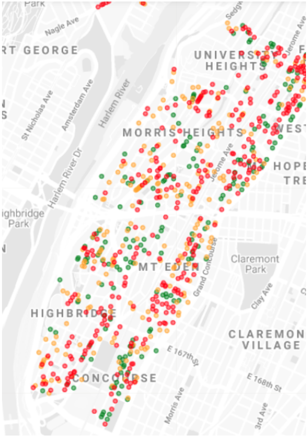


Nearly all models ($N \sim 800$) outperform that existing prioritization



Focusing on best-performing model (gradient boosting with 10,000 estimators)

Risk tertiles in South Bronx (any case):



Staying at their same capacity to visit ∼ 60,000 residential units each year, 40-80% increase in performance:

- *Before ML-guided prioritization:* TSU finds ∼ **1800 possible cases** of landlord harassment
- *Using ML-guided prioritization:* TSU finds ∼ **2500-3300 possible cases** of landlord harassment

Does this increase in efficiency come at the expense of equity?

- Critics of social service organizations using machine learning to prioritize argues that increased efficiency may come at the expense of fairness (e.g., O'Neil, 2017; Eubanks, 2018; Bakalar and Zevenbergen, 2017; Bakalar and Zevenbergen, 2017)
- Suggests that, in addition to examining *aggregate* improvements, should ensure that buildings flagged as highest-risk align with substantive notions of need and vulnerability

Evaluating fairness: ability to capture different forms of vulnerability to harassment

- Mayor De Blasio: "We have teams knocking on doors in fast-changing neighborhoods"
- Theory (e.g., Sharkey, 2013; Hwang and Sampson, 2014; Desmond, 2016) highlights different potential pathways into high harassment risk:

Buildings in 20 target zip codes with at least 1 rent-stabilized unit

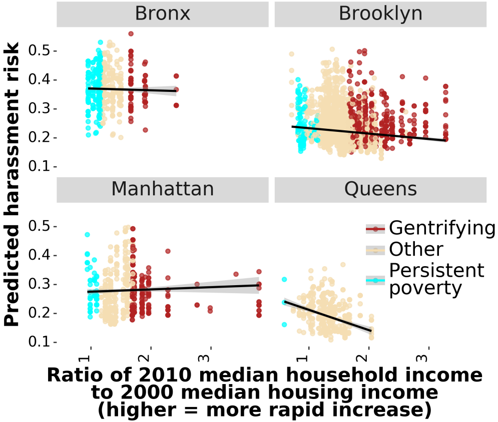
Type of neighborhood: "gentrifying" (poverty + large increase in median income (2000-2010))

Reason for harassment: strong financial incentives to convert units to market rate

Type of neighborhood: "persistent poverty" (poverty + little increase in median income (2000-2010))

Reason for harassment: persistent landlord-tenant power asymmetries

High predicted harassment risk in both gentrifying and persistent poverty neighborhoods



Use LTDB (Logan et al., 2012); similar to Ellen and Torrats-Espinosa (2018), use large change in median household income as a measure of gentrification

Broader lessons and takeaways from tenant rights project

- **All measures of rights violations have their own biases:**
  - **In the case of 311 calls**: which tenants are aware of the reporting process and can navigate steps to report
  - **In the case of canvassing**: TSU did its best to hire from the relevant communities so that outreach workers were those that residents might know/were more likely to trust; still variation in who's home during canvassing periods (10am-2pm M-Friday and Saturday) and either answers the door or calls back from a flier
- **Unit of analysis:** tenants/residential units (those who have issues) nested in buildings (site of visits) nested in landlords (target of oversight); for data/operational reasons, used buildings
- **Academic project/prototype versus deployed model:** TSU used some of the data and code we shared (e.g., to identify entities with many HPD violations), but ultimately no continuous model deployment
- **Value in taking what an organization is doing already (canvassing) and turning that into systematic data:** many civil legal aid organizations do outreach/canvassing but do not keep individual-level, timestamped data on: (1) visits, (2) conversations, and (3) results of those conversations

Discussion Break

Questions:

1. What challenges does your organization confront in incorporating data-driven decisions into its workflow?
2. How does your organization weigh the pros and cons of (1) relying on internal technical capacity to drive these decisions versus (2) bringing in outside technical expertise (either in the form of contractors; academic researchers; and so on)?
3. Can you think of similar cases of data your organization already collects that could be used by data scientists to build useful predictive models?

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Motivation: equitable oversight of agricultural employers

- H-2A guestworkers, who are granted temporary work visas tied to a specific employer, can be vulnerable to violations of their rights (e.g., unsafe housing conditions; wage theft; and other issues)
- DOL's Wage and Hour Division (WHD) collects complaints from workers about issues, but there are barriers to submission of complaints (language; fear of retaliation; distrust in federal government) that mean those are likely a biased measure of violations of worker rights
- Our project is aimed at two questions related to equity in DOL oversight of H-2A employers:
  1. **Can we use local data to identify false negatives in federal complaints?:** We partner with Texas RioGrande Legal Aid (TRLA), which conducts proactive outreach to workers at risk of issues in six states (TX; MS; LA; KY; AL; TN)
  2. **Can we use supervised machine learning to predict employers that will go on to have a high likelihood of violations (either flagged through DOL enforcement or local intake)?**

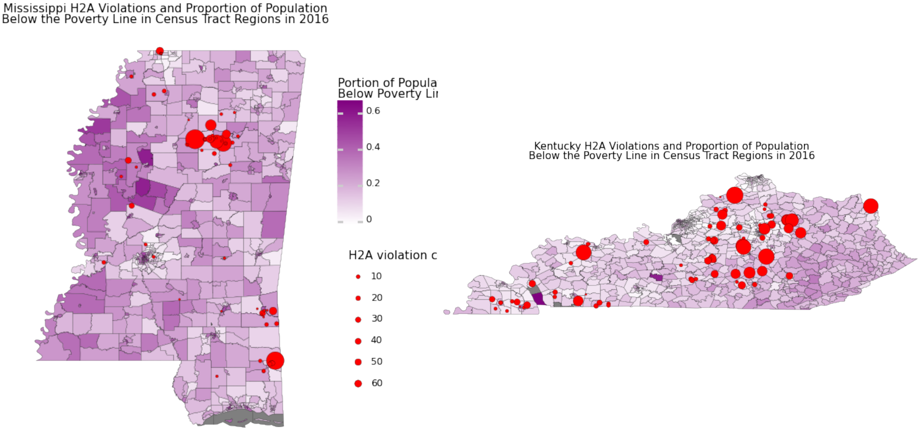
Data sources and methodology

Universe of employers: H-2A certificate dataset (OFLC ETA) from FY 2014-Q2 FY2021. Key fields:
- Employer name (unit of analysis is employer across approved certificates)
- Employer address

Define binary outcomes of (1) any investigation and (2) violation conditional on investigation:
- **Federal enforcement:** fuzzy match to WHD compliance action data based on employer name/address to find any investigation and, if investigation, any violations
- **Local enforcement:** fuzzy match to TRLA intake data

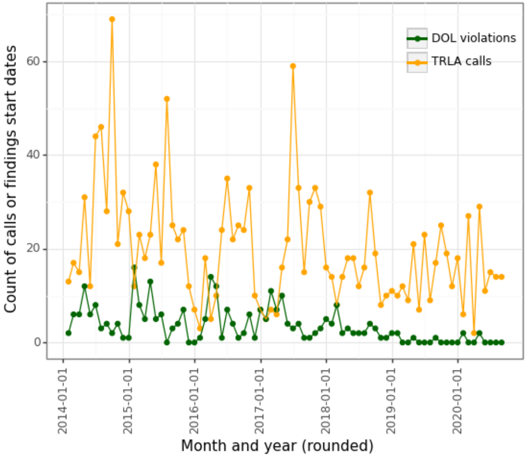
Predictors at employer or tract-level:
- **Geocode** employer addresses to lat/long $\Longrightarrow$ census tract; ACS contextual variables related to migration patterns, unemployment, and poverty
- **Example predictors from H-2A certificate data:** attorney representation; crop type; job characteristics
- **For FY 20 and 21, text features from work contracts:** bag-of-words features; topic modeling; deliberate coding of red flag keywords (eg strict oversight of phone use)

Initial trends 1: geographic concentration versus dispersion in locations of issues (WHD violations)



Notes: dots represent worksite locations with > 0 counts of H-2A violations in the WHD complaints data between 2016-2020; shapes represent census tracts shaded by ACS 2016 poverty values

Initial trends 2: TRLA local outreach-based issues versus complaints submitted to federal government



Points of commonality and difference with project 1

- **Points of commonality:**
  - The legal aid organization, similar to the tenant outreach organization, does active outreach to at-risk guestworkers; see whether we can use the results from that active outreach to build a model that generalizes to a larger number of employers
  - Same challenge of less biased label of issues than complaints (in the NYC case, to 311; in this case, to the US Department of Labor), and includes results from things like observing housing conditions, but still requires disclosure from individuals who fear retaliation
- **Points of difference:**
  - **Unit of analysis:** buildings (aggregated up from tenants/residential units) versus employers
  - **Available predictors:** due to process where employers need to submit info to DOL to get authorization to hire guestworkers, more employer-level features in this project than landlord-level features in the other project
  - **Sample size:** in that, target universe was 6000-7000 buildings in the 20 relevant zip codes; here, around 20,000-30,000 employers

Results: ML didn't work particularly well!

https://rb.gy/jjdw6p

Discussion

Questions:

1. Do these projects spark any ideas for data-driven policy decisions in the contexts you work in?
2. These projects are both with a combination of U.S. local goverments and the U.S. federal government; what do you see as strengths that various government organizations in Ukraine can bring to this work?
3. Do you think there are important distinctions when it comes to the ethics of data-driven policymaking (e.g., using data to identify need/enforce rights versus using data to target punishment)?

Broader questions and areas for future research

- **Sample selection biases:** SML requires that we model some label Pr(Issue found) but oftentimes, whether that label is observed (Yes/No) or missing is conditional, on some endogenous process Pr(Issue found|visit by outreach worker); Pr(Issue found|inspection)
  - Easy if inspections or visits are actively randomized; when they're not, some very context-specific solutions (e.g., Lakarraju et al. deal with similar issues in recidivism prediction where Pr(Defendant re-offends when on bail|Granted bail) by exploiting random between-judge variation in Pr(Granted bail))
  - Otherwise reliance on ability to model selection into the sample based on observables
- **Agency responsibilities and balance between reactive and proactive enforcement:** in practice, agencies are often evaluated on their responsiveness to complaints (e.g., time-to-response on a 311 call); how to allocate resources for more proactive enforcement/random audits
- **Transparency versus strategic behavior by targets of oversight**

Thanks!

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