Administrative Records Mask Racially Biased Policing

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\[1\text{We thank Michael Pomirchy for research assistance.}\]
How do we measure racial bias in policing?

Eric Garner, 2014
Racial bias in policing

- Causal question.
Racial bias in policing

➤ Causal question. Focus on traditional omitted variable bias.
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- Overlooked:
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- Overlooked:
  Sample selection bias due to post-treatment conditioning
Intuition for the problem

- Goal: estimate effect of civilian race on police use of force

Suppose perfect as-if experimental conditions: a set of police encounters (i.e. sightings) identical but for race of civilians.

Suppose racial bias leads police to stop white civilians if engaged in serious crime (e.g. bank robbery), stop black civilians regardless of behavior.

Now throw away all data on civilians police observe but do not stop (e.g. the NYPD "Stop, Question and Frisk" (SQF) database).

We've just ruined our experiment!

Comparing white bank robbers to black civilians committing no crime.

If we then found no disparity in rates of force against black/white civilians, that should be alarming!

Current literature reads this result as "no evidence of racial bias in the use of force"
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6. New research designs to avoid this pitfall
Defining the Statistical Problem
A causal mediation framework

- Unit of analysis: police-civilian encounters:
  - "Encounter" = sighting of individual by police officer
  - Counterfactual: substitution of individual of differing race into police-civilian encounter, holding circumstance and civilian behavior fixed
  - Treatment (civilian is racial minority) \( D \in \{0, 1\} \)
  - Outcome (use of force) \( Y_i \in \{0, 1\} \)
  - Mediator (being stopped by police) \( M_i \in \{0, 1\} \)
  - Racial bias in police stops \( (D_i \rightarrow M_i) \) (e.g. Gelman, Fagan & Kiss 2007; Glaser 2014; Lerman & Weaver 2014; Goel, Rao & Shroff 2016)
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Existing theory of race and police-civilian encounters

D → Y
(race) (force)
Existing theory of race and police-civilian encounters

V

D (race) → Y (force)
Existing theory of race and police-civilian encounters

Diagram:

V

D -> V <- Y
(race)  (force)
A more complete theory

D (race) → M (stop) → Y (force)

V
A more complete theory

D (race) → W → M (stop) → U → Y (force)
Potential outcomes with mediation

Normally we consider $Y(d) \in \{ Y(1), Y(0) \}$; potential force given race (treatment)
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- $Y(1, 1) =$ potential use of force if minority civilian stopped
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Formalizing the Missing Data Problem
Solution: principal stratification

If $D \rightarrow M$, four types of police-civilian encounters:

<table>
<thead>
<tr>
<th>$M_i(0) = 1$</th>
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</tr>
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<tbody>
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<td>$M_i(1) = 1$</td>
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What do we get to see in police data?
Types of police-civilian encounters

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For white civilians . . .
Encounters (sightings) belong to one of four principal strata

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Within each, civilian is treated (black) or not (white)

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Four potential outcomes we may need to estimate

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Causal Quantities of Interest
Which causal effect?

- Prior work does not name specific causal estimands

Average Treatment Effect (ATE) in the population

Effect among those who interact with police (ATE$_M=1$)

Effect among minorities who interact with police (ATT$_M=1$)
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- Without naming an estimand, we can’t consider identifying assumptions or evaluate validity of an analysis
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## Causal estimands

\[ TE = E[Y_i(1, M_i(1))] - E[Y_i(0, M_i(0))] \]

<table>
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<tr>
<th>( i )</th>
<th>Stratum</th>
<th>( D_i )</th>
<th>( M_i )</th>
<th>( M_i(0) )</th>
<th>( M_i(1) )</th>
<th>( Y_i(1, 1) )</th>
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</tr>
<tr>
<td>2</td>
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</tr>
<tr>
<td>3</td>
<td>Racial Stop</td>
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<td>1</td>
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<td>1</td>
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<tr>
<td>4</td>
<td>Never-Stop</td>
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<td>0</td>
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</tr>
</tbody>
</table>
Average Treatment Effect

\[ ATE = \mathbb{E}[Y_i(1, M_i(1)) - Y_i(0, M_i(0))] \]

<table>
<thead>
<tr>
<th>(i)</th>
<th>Stratum</th>
<th>(D_i)</th>
<th>(M_i)</th>
<th>(M_i(0))</th>
<th>(M_i(1))</th>
<th>(Y_i(1, 1))</th>
<th>(Y_i(1, 0))</th>
<th>(Y_i(0, 1))</th>
<th>(Y_i(0, 0))</th>
<th>ATE</th>
<th>(ATE_{M=1})</th>
<th>(ATT_{M=1})</th>
<th>(CDE_{M=1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Always-Stop</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Always-Stop</td>
<td>0</td>
<td>1</td>
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<td>4</td>
<td>Never-Stop</td>
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</tr>
</tbody>
</table>
Average Treatment Effect Among the Stopped

\[ \text{ATE}_{M=1} = \mathbb{E}[Y_i(1, M_i(1)) - Y_i(0, M_i(0)) | M_i = 1] \]

<table>
<thead>
<tr>
<th>(i)</th>
<th>Stratum</th>
<th>(D_i)</th>
<th>(M_i)</th>
<th>(M_i(0))</th>
<th>(M_i(1))</th>
<th>(Y_i(1, 1))</th>
<th>(Y_i(1, 0))</th>
<th>(Y_i(0, 1))</th>
<th>(Y_i(0, 0))</th>
<th>(\text{ATE})</th>
<th>(\text{ATE}_{M=1})</th>
<th>(\text{ATT}_{M=1})</th>
<th>(\text{CDE}_{M=1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Always-Stop</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
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<td>Always-Stop</td>
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</tbody>
</table>
Average Treatment Effect Among the Treated and Stopped

\[ ATT_{M=1} = \mathbb{E}[Y_i(1, M_i(1)) - Y_i(0, M_i(0))|D_i = 1, M_i = 1] \]

<table>
<thead>
<tr>
<th>( i )</th>
<th>Stratum</th>
<th>( D_i )</th>
<th>( M_i )</th>
<th>( M_i(0) )</th>
<th>( M_i(1) )</th>
<th>( Y_i(1, 1) )</th>
<th>( Y_i(1, 0) )</th>
<th>( Y_i(0, 1) )</th>
<th>( Y_i(0, 0) )</th>
<th>( ATE )</th>
<th>( ATE_{M=1} )</th>
<th>( ATT_{M=1} )</th>
<th>( CDE_{M=1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Always-Stop</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
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<td>1</td>
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</tr>
</tbody>
</table>
Can anything causal be estimated with these data?

- To estimate causal quantities, need additional assumptions
Can anything causal be estimated with these data?

- To estimate causal quantities, need additional assumptions
- Goal: minimal, non-parametric, plausible
Assumptions
Assumption 1: Mandatory reporting

\[ Y_i(d, 0) = 0 \]

- If encounter not in the data, no force was applied
Assumption 1: Mandatory reporting

\[ Y_i(d, 0) = 0 \]

- If encounter not in the data, no force was applied
- Highly plausible for lethal/severe force
Assumption 1: Mandatory reporting

\[ Y_i(d, 0) = 0 \]

- If encounter not in the data, no force was applied
- Highly plausible for lethal/severe force
- Increasingly plausible for sub-lethal force given civilian oversight boards, cell phone cameras
Assumption 1: Mandatory reporting

<table>
<thead>
<tr>
<th>always-stop</th>
<th>anti-black racial-stop</th>
<th>anti-white racial-stop</th>
<th>never-stop</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_i(1) = M_i(0) = 1$</td>
<td>$M_i(1) = 1, M_i(0) = 0$</td>
<td>$M_i(1) = 0, M_i(0) = 1$</td>
<td>$M_i(1) = 0, M_i(0) = 0$</td>
</tr>
<tr>
<td>$D_i = 0$</td>
<td>$D_i = 0$</td>
<td>$D_i = 0$</td>
<td>$D_i = 0$</td>
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<tr>
<td>$D_i = 1$</td>
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</tr>
<tr>
<td>$Y_i(1, 1)$</td>
<td>$Y_i(1, 1)$</td>
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<td>$Y_i(1, 1)$</td>
</tr>
<tr>
<td>$Y_i(1, 0)$</td>
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<td>$Y_i(0, 0)$</td>
</tr>
</tbody>
</table>
Assumption 1: Mandatory reporting

### Always-stop

\[
\begin{align*}
M_i(1) &= M_i(0) = 1 \\
D_i &= 0 \quad D_i = 1 \\
Y_i(1,1) &= Y_i(1,1) \\
Y_i(0,1) &= Y_i(0,1)
\end{align*}
\]

### Anti-black racial-stop

\[
\begin{align*}
M_i(1) &= 1, M_i(0) = 0 \\
D_i &= 0 \quad D_i = 1 \\
Y_i(1,1) &= Y_i(1,1) \\
Y_i(0,1) &= Y_i(0,1)
\end{align*}
\]

### Anti-white racial-stop

\[
\begin{align*}
M_i(1) &= 0, M_i(0) = 1 \\
D_i &= 0 \quad D_i = 1 \\
Y_i(1,1) &= Y_i(1,1) \\
Y_i(0,1) &= Y_i(0,1)
\end{align*}
\]

### Never-stop

\[
\begin{align*}
M_i(1) &= 0, M_i(0) = 0 \\
D_i &= 0 \quad D_i = 1 \\
Y_i(1,1) &= Y_i(1,1) \\
Y_i(0,1) &= Y_i(0,1)
\end{align*}
\]
Assumption 2: Mediator monotonicity

\[ M_i(1) \geq M_i(0) \]

- No anti-white bias in stopping
**Assumption 2: Mediator monotonicity**

<table>
<thead>
<tr>
<th>Condition</th>
<th>$M_i(1)$</th>
<th>$M_i(0)$</th>
<th>$D_i$</th>
<th>$Y_i(1,1)$</th>
<th>$Y_i(0,1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Always-stop</td>
<td>$1$</td>
<td>$1$</td>
<td>$0$</td>
<td>$0$</td>
<td>$0$</td>
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<tr>
<td>Anti-black racial-stop</td>
<td>$1$</td>
<td>$0$</td>
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<td>$0$</td>
<td>$1$</td>
<td>$0$</td>
<td>$0$</td>
<td>$0$</td>
</tr>
<tr>
<td>Never-stop</td>
<td>$0$</td>
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Assumption 2: Mediator monotonicity

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</tr>
<tr>
<td>$D_i = 0$</td>
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</tr>
<tr>
<td>$Y_i(1, 1)$</td>
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<tr>
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<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Assumption 3: Relative non-severity of racial stops

\[
E[Y_i(d, m) | D_i = d', M_i(1) = 1, M_i(0) = 1] \geq E[Y_i(d, m) | D_i = d', M_i(1) = 1, M_i(0) = 0]
\]

- Level of force applied in always-stop encounters (serious crimes) \( \geq \) level applied in racial stop encounters on average
Assumption 3: Relative non-severity of racial stops

<table>
<thead>
<tr>
<th>always-stop</th>
<th>anti-black racial-stop</th>
<th>never-stop</th>
</tr>
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<tbody>
<tr>
<td>$M_i(1) = M_i(0) = 1$</td>
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</tr>
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<tr>
<td>0</td>
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</tbody>
</table>
Assumption 3: Relative non-severity of racial stops

always-stop
\[ M_i(1) = M_i(0) = 1 \]
\[ D_i = 0 \quad D_i = 1 \]
\[ Y_i(1, 1) \quad Y_i(1, 1) \]
\[ 0 \quad 0 \]
\[ Y_i(0, 1) \quad Y_i(0, 1) \]
\[ 0 \quad 0 \]

anti-black racial-stop
\[ M_i(1) = 1, M_i(0) = 0 \]
\[ D_i = 0 \quad D_i = 1 \]
\[ Y_i(1, 1) \quad Y_i(1, 1) \]
\[ 0 \quad 0 \]
\[ Y_i(0, 1) \quad Y_i(0, 1) \]
\[ 0 \quad 0 \]

never-stop
\[ M_i(1) = 0, M_i(0) = 0 \]
\[ D_i = 0 \quad D_i = 1 \]
\[ Y_i(1, 1) \quad Y_i(1, 1) \]
\[ 0 \quad 0 \]
\[ Y_i(0, 1) \quad Y_i(0, 1) \]
\[ 0 \quad 0 \]
Assumption 4: Treatment ignorability

\[ M_i(d) \perp \perp D_i \]
\[ Y_i(d, M(d)) \perp \perp D_i | M_i(0) = m', M_i(1) = m'' \]

- No omitted variables with respect to mediator or outcome
Assumption 4: Treatment ignorability

\[ M_i(d) \perp\!\!\!\!\!\!\perp D_i \]
\[ Y_i(d, M(d)) \perp\!\!\!\!\!\!\perp D_i | M_i(0) = m', M_i(1) = m'' \]

- No omitted variables with respect to mediator or outcome
- More plausible in recent years (data on lat/lon, time, officer and suspect features, etc.)
Assumption 4: Treatment Ignorability

always-stop

\[ M_i(1) = M_i(0) = 1 \]
\[
\begin{array}{cc}
D_i = 0 & D_i = 1 \\
Y_i(1,1) & Y_i(1,1) \\
0 & 0 \\
Y_i(0,1) & Y_i(0,1) \\
0 & 0 \\
\end{array}
\geq
\begin{array}{cc}
D_i = 0 & D_i = 1 \\
Y_i(1,1) & Y_i(1,1) \\
0 & 0 \\
Y_i(0,1) & Y_i(0,1) \\
0 & 0 \\
\end{array}
\]

anti-black racial-stop

\[ M_i(1) = 1, M_i(0) = 0 \]

never-stop

\[ M_i(1) = 0, M_i(0) = 0 \]
\[
\begin{array}{cc}
D_i = 0 & D_i = 1 \\
Y_i(1,1) & Y_i(1,1) \\
0 & 0 \\
Y_i(0,1) & Y_i(0,1) \\
0 & 0 \\
\end{array}
\]
Assumption 4: Treatment Ignorability

always-stop
$M_i(1) = M_i(0) = 1$

anti-black racial-stop
$M_i(1) = 1, M_i(0) = 0$

never-stop
$M_i(1) = 0, M_i(0) = 0$

$Y_i(1, 1)$
$0$
$Y_i(0, 1)$
$0$
$Y_i(1, 1)$
$0$
$Y_i(0, 1)$
$0$
Given assumptions 1-4, can we recover a causal quantity?

Consider the naïve estimator:

\[ \hat{\Delta} = \hat{E}[Y_i|D_i = 1, M_i = 1] - \hat{E}[Y_i|D_i = 0, M_i = 1] \]
Given assumptions 1-4, can we recover a causal quantity?

- Consider the naïve estimator:

\[
\hat{\Delta} = \hat{\mathbb{E}}[Y_i|D_i = 1, M_i = 1] - \hat{\mathbb{E}}[Y_i|D_i = 0, M_i = 1]
\]

- Target the \(ATE_{M=1}\) and \(ATT_{M=1}\)
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

$$
\mathbb{E}[\hat{\Delta}] - ATE_{M=1} = (\mathbb{E}[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0] \\
\times \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1) \\
- (\mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0] \\
\times \Pr(M_i(0) = 0|D_i = 1, M_i = 1))$$
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

$$\mathbb{E}[\hat{\Delta}] - ATE_{M=1}$$

$$= \left( \mathbb{E}[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1] - \mathbb{E}[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0] \right) \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1)$$

$$- \left( \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1] - \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0] \right) \Pr(M_i(0) = 0|D_i = 1, M_i = 1)$$
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

$$
\mathbb{E}[\hat{\Delta}] - ATE_{M=1} \\
= (\mathbb{E}[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0] \\
\times \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1) \\
- (\mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0] \\
\times \Pr(M_i(0) = 0|D_i = 1, M_i = 1)$$
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

\[
\mathbb{E}[\hat{\Delta}] - ATE_{M=1} = (\mathbb{E}[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0] \\
\text{Pr}(M_i(0) = 0|D_i = 1, M_i = 1)\text{Pr}(D_i = 1|M_i = 1) \\
- (\mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1] \\
- \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0] \\
\text{Pr}(M_i(0) = 0|D_i = 1, M_i = 1))
\]

Biased even without omitted variables.
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

$$
\mathbb{E}[\hat{\Delta}] - ATE_{M=1}
= (\mathbb{E}[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1]
- \mathbb{E}[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0]
\cdot \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1)
- (\mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1]
- \mathbb{E}[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0]
\cdot \Pr(M_i(0) = 0|D_i = 1, M_i = 1)
$$

Biased even without omitted variables. Bias is always nonpositive.
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

$$E[\hat{\Delta}] - ATE_{M=1}$$

$$= \left( E[Y_i(1, 1) - Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1] 
- E[Y_i(1, 1) - Y_i(0, 0)|M_i(1) = 1, M_i(0) = 0] \right) \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1)$$

$$- \left( E[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 1] 
- E[Y_i(1, 1)|M_i(1) = 1, M_i(0) = 0] \right) \Pr(M_i(0) = 0|D_i = 1, M_i = 1)$$

Bias remains unless there are no racial stops.
Bias in the naïve estimator for $ATE_{M=1}$

Under Assumptions 1-4:

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\quad \Pr(M_i(0) = 0|D_i = 1, M_i = 1)\Pr(D_i = 1|M_i = 1)
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\quad \Pr(M_i(0) = 0|D_i = 1, M_i = 1))
$$

Biased even if goal is to estimate effect among the stopped.
Bias in the naïve estimator for $\text{ATT}_{M=1}$

What about $\text{ATT}_{M=1}$, the total effect among stopped black civilians?
Bias in the naïve estimator for $\text{ATT}_{M=1}$

What about $\text{ATT}_{M=1}$, the total effect among stopped black civilians?

$$
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What about $ATT_{M=1}$, the total effect among stopped black civilians?

$$\mathbb{E}[\hat{\Delta}] - ATT_{M=1} = -\mathbb{E}[Y_i(0, 1)|M_i(1) = 1, M_i(0) = 1]\Pr(M_i(0) = 0|M_i(1) = 1)$$

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Again, bias remains unless there are no racial stops, or no use of force against whites
Bias in the naïve estimator for $ATT_{M=1}$

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Again, bias remains unless there are no racial stops, or no use of force against whites (empirically falsified).
What have we learned?

Under assumptions 1-4, which are implicit in prior work, the naïve estimator:

- is biased for the ATE
- is biased for the ATT
- unless we assume no racial stops
- even with a perfect set of pre-treatment control variables

Can we estimate racial bias with police administrative data?
What have we learned?

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Can we estimate racial bias with police administrative data?
Using precise form of bias, we can construct nonparametric sharp bounds on true effects.
Bounding the true $ATE_{M=1}$
Bounding the true $ATE_{M=1}$

1. $\rho = Pr(M|D_i=1, M_i(0)=0)$: share of minority stops due to race (unknown)
2. $\theta = E[Y(1,1)|D_i=1, M_i(1)=1, M_i(0)=0]$, violence rate among racially stopped minorities

If we knew the joint distribution $Pr(Y(1,1), M_i(0)=0|D_i=1, M_i(1)=1, M_i(0)=0) = Pr(A, B)$, we could then back out $\theta = P(A|B)$, the conditional probability

$\theta = P(A|B) = \frac{Pr(A, B)}{Pr(B)} = \frac{Pr(A, B)}{Pr(B)}$
Bounding the true $ATE_{M=1}$

- Bias can be re-written in terms of all things that can be directly estimated from data except two:

  1. $\rho = \Pr(M_i(0) = 0|D_i = 1, M_i = 1)$: share of minority stops due to race
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$$\theta = P(A|B) = \frac{\Pr(A,B)}{\Pr(B)} = \frac{\Pr(A,B)}{\rho}$$
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- $\theta = P(A|B) = \frac{\Pr(A,B)}{\Pr(B)} = \frac{\Pr(A,B)}{\rho}$

- We don’t, but we can place Fréchet bounds on $\Pr(A, B)$
Maurice Fréchet
Fréchet Inequalities

Given two marginal distributions $\Pr(A)$ and $\Pr(B)$, the joint distribution $\Pr(A, B)$ is bounded by:

$$\max\{0, Pr(A) + Pr(B) - 1\} \leq P(A, B) \leq \min\{Pr(A), Pr(B)\}$$
Fréchet Inequalities

Given two marginal distributions \( Pr(A) \) and \( Pr(B) \), the joint distribution \( (A, B) \) is bounded by:

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Deriving sharp bounds for true $ATE_{M=1}$

If we can bound $\Pr(A, B)$ we can also bound $\theta = \frac{\Pr(A, B)}{\rho}$ and plug the bounds back into the bias term.
Deriving sharp bounds for true $ATE_{M=1}$

- If we can bound $\Pr(A, B)$ we can also bound $\theta = \frac{\Pr(A,B)}{\rho}$ and plug the bounds back into the bias term.

- If $ATE_{M=1} = \mathbb{E}[\hat{\Delta}] + bias$, then subbing in Fréchet bounds for $\theta$ into the bias term $\Rightarrow$

$$\mathbb{E}[\hat{\Delta}] + bias_{LB} \leq ATE_{M=1} \leq \mathbb{E}[\hat{\Delta}] + bias_{UB}$$
Sharp nonparametric bounds

Given $\rho$, bounds for the true $ATE_{M=1}$ are given by:

$$\mathbb{E}[\hat{\Delta}] + \rho \mathbb{E}[Y_i|D_i = 0, M_i = 1] \left(1 - \Pr(D_i = 0|M_i = 1)\right) \leq ATE_{M=1} \leq \mathbb{E}[\hat{\Delta}] + \rho \frac{\mathbb{E}[Y_i|D_i = 1, M_i = 1]}{1 - \rho} \left(\mathbb{E}[Y_i|D_i = 1, M_i = 1] - K\right) \Pr(D_i = 0|M_i = 1) + \rho \mathbb{E}[Y_i|D_i = 0, M_i = 1] \left(1 - \Pr(D_i = 0|M_i = 1)\right).$$

where

$$K = \max \left\{0, 1 + \frac{1}{\rho} \mathbb{E}[Y_i|D_i = 1, M_i = 1] - \frac{1}{\rho}\right\}.$$
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where

$$K = \max \left\{ 0, 1 + \frac{1}{\rho} E[Y_i|D_i = 1, M_i = 1] - \frac{1}{\rho} \right\}.$$

The $ATT_{M=1}$ must similarly satisfy:

$$ATT_{M=1} = E[\hat{\Delta}] + \rho E[Y_i|D_i = 0, M_i = 1]$$
Does this matter in practice?
Does this matter in practice?

Replication and Extension: Fryer (2019)
Fryer (2019)

- Police-civilian interactions (e.g. Stop and Frisk, arrest records, summaries of shootings)
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- Logistic regressions of force measures on race dummies, controls for circumstance, suspect features, officer features

Conclusions:
- Some racial bias in sub-lethal force
- No bias in lethal force
- Problem: No data on those police observe but do not stop
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encounter recounted by police. A second type of bias is that officers may be more likely to charge black suspects with crimes such as resisting arrest or attempted assault on a public safety officer rather than misdemeanors, relative to whites, for identical behavior. This type of bias is an important limitation of Fryer (forthcoming) because it implies that the counterfactuals coded from arrest data may themselves contain bias. It is unclear how to estimate the extent of such bias or how to address it statistically.
Replication of Fryer (2019)

- Replicate two analyses of sub-lethal force using NYPD’s “Stop, Question and Frisk” (SQF) data (2003-2013), $N \approx 5$ million
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  - Force thresholds (e.g. at least handcuffs) with seven categories: laying hands; push to wall; handcuffs; draw weapon; push to ground; point weapon; baton/pepper spray
Bounds on race effects, black vs. white
Bounds on race effects, black vs. white
Bounds on race effects, black vs. white

Civilians subject to any racially discriminatory use of force (thousands)

Proportion of racially discriminatory stops

naïve TE × \#{stopped} TES × \#{stopped}
Bounds on race effects, black vs. white

Proportion of racially discriminatory stops

Civilians subject to any racially discriminatory use of force (thousands)

naive $T \times E \times S \times \#\{\text{stopped}\}$

naive $T \times E \times S \times \#\{\text{stopped minorities}\}$

naive $T \times E \times S \times \#\{\text{stopped}\}$
What is $\rho$?

What is the share of minority stops that would not have happened if civilians had been white?
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Bounds on race effects, black vs. white

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$\text{naïve \ TE} \times \ #\{\text{stopped}\}$

$\text{TEST} \times \ #\{\text{stopped minorities}\}$
Bounds on race effects, black vs. white

Civilians subject to any racially discriminatory use of force (thousands)

naive TE = \frac{\text{#{stopped}}}{\text{#{stopped minorities}}}

Proportion of racially discriminatory stops

Civilian stops

Proportion of racially discriminatory stops

0.00 0.25 0.50 0.75 1.00
<table>
<thead>
<tr>
<th>Minimum force</th>
<th>TEₜ for encounters with black civilians (vs. white)</th>
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<tbody>
<tr>
<td></td>
<td>No covariates</td>
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<td></td>
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<tr>
<td>Use of hands</td>
<td>(112.66, 124.59)</td>
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## Bounds for force thresholds, black vs. white

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<tr>
<td></td>
<td>(84.6, 151.84)</td>
</tr>
<tr>
<td>Push to wall</td>
<td>(24.15, 27.75)</td>
</tr>
<tr>
<td></td>
<td>(15.5, 37.35)</td>
</tr>
<tr>
<td>Use of handcuffs</td>
<td>(14.6, 16.92)</td>
</tr>
<tr>
<td></td>
<td>(9.45, 22.61)</td>
</tr>
<tr>
<td>Draw weapon</td>
<td>(4.52, 5.14)</td>
</tr>
<tr>
<td></td>
<td>(3.13, 6.67)</td>
</tr>
<tr>
<td>Push to ground</td>
<td>(4.04, 4.58)</td>
</tr>
<tr>
<td></td>
<td>(2.79, 5.97)</td>
</tr>
<tr>
<td>Point weapon</td>
<td>(1.49, 1.7)</td>
</tr>
<tr>
<td></td>
<td>(0.96, 2.29)</td>
</tr>
<tr>
<td>Baton or pepper spray</td>
<td>(0.17, 0.19)</td>
</tr>
<tr>
<td></td>
<td>(0.1, 0.26)</td>
</tr>
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</tbody>
</table>
How can we do better?

- Only partially identified.
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- Only partially identified. Can’t get the population $ATE$. 
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- Only way to do better: improved research design
Option 1:

- Identify situations with race-blind contact with police (e.g. rules for DUI stops; traffic stops and night; traffic accidents?)
Option 2: Gather data on the non-stopped

- Need data on those police observe but do not stop
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- Answer: traffic cameras.
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  Passive data collection on non-stop encounters.
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- Link cars to DMV records, ticket/arrest data
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- But, plausible to measure most (all?) observable covariates available to officer when making stop
- No need to condition on being stopped during analysis
- Post-treatment conditioning avoided by design
Police data mask racially biased policing

- Lots of new/big data on policing → raft of studies estimating racial bias
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- At present, inadequate theory: insufficient attention to role of race throughout entire process risks severely understating racial violence
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- At present, inadequate theory: insufficient attention to role of race *throughout entire process* risks severely understating racial violence

- Risk confusing/misleading the public and policymakers
Thanks!

Please send feedback to:

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