UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

Investigating Unintended Consequences of Automated Traffic Law Enforcement in Commuting

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ATLE’s efficacy is unproven

- **Reduce severity of crashes but not total number**
- **Lack of human judgement**
- **Disputes on their legality**

Sources: Center for Disease Control (2022) *cdc.gov*

Does ATLE have positives?

- **Indiscriminately issues fines**

However…

… their placement is not devoid of bias.

OAKBROOK TERRACE MAYOR RESIGNS AMID RED-LIGHT CAMERA PROBE

by JANUARY 23, 2020

Federal investigators have been digging into the political corruption surrounding red-light cameras, including a pair of the multi-million dollar traffic devices in Oakbrook Terrace.

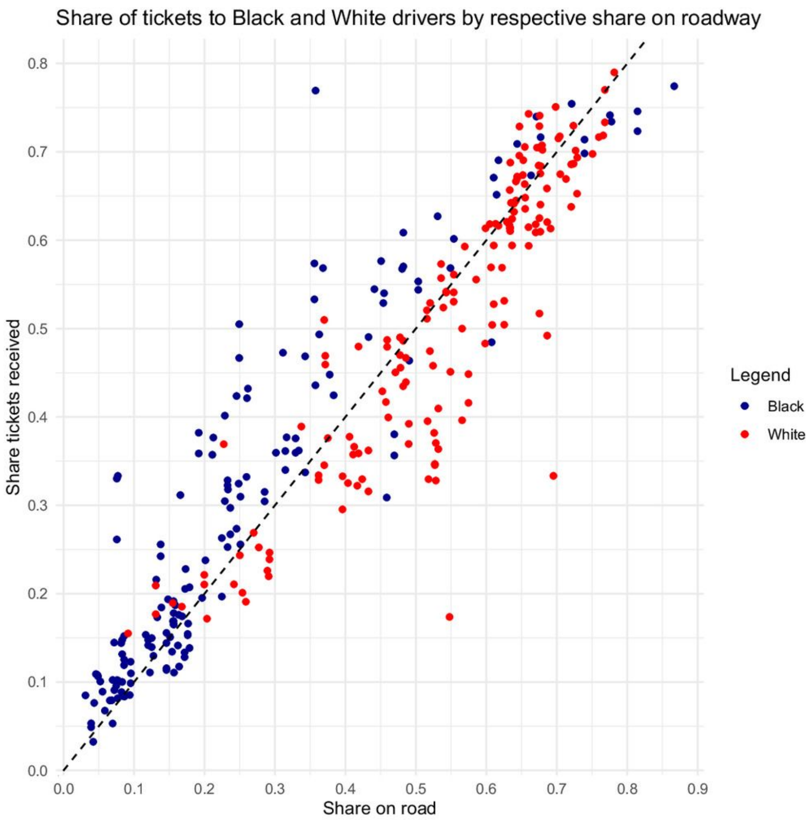
Sources: Illinois Policy (2020) *IllinoisPolicy.org*

Unequal outcomes in enforcement are observed

Black drivers get ticketed at a rate 10 (!!) times higher than white drivers.

Xu et al. (2024) proved that drivers from different demographic groups commit offenses at similar rates.

So clearly, something is at play. We theorize that the placement of the cameras is unfair.



Sources: Xu et al. (2024) *PNAS*

How do we quantify the burden of red light cameras?

Different metrics are available to measure potential disparities in impact due to camera placement

Time to avoid cameras

Find shortest path between two points, with and without avoiding the cameras, and measure difference in travel time.

Number of cameras encountered

Find shortest path and count number of cameras we come across.

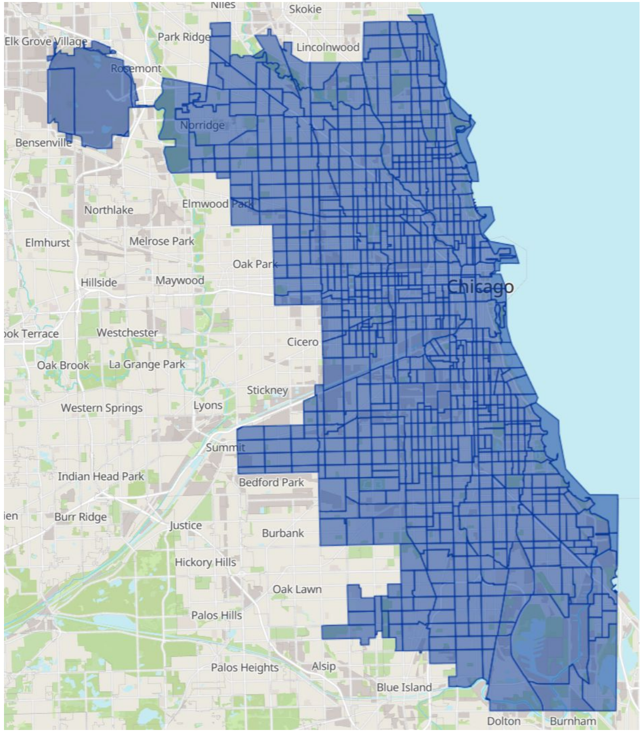
- **Apply Operations Research methods to objectively measure ATLE's impact**
- **Determine potential impact disparities using statistical tools**

Using public data to model commuting patterns

We used the Chicago Metropolitan Agency for Planning (CMAP) **MyDailyTravel** dataset, which contains >10,000 data points.

It was filtered and aggregated on the Census Tract level.

sampno	locno	loctype	state	latitude	longitude
20000083	10000	1	IL	42.141870	-87.953126
20000083	10002	2	IL	42.145289	-87.863023
20000136	10000	1	IL	41.891022	-87.612931
20000136	10002	2	IL	41.928424	-87.684906
20000136	20002	2	IL	41.895035	-87.619717

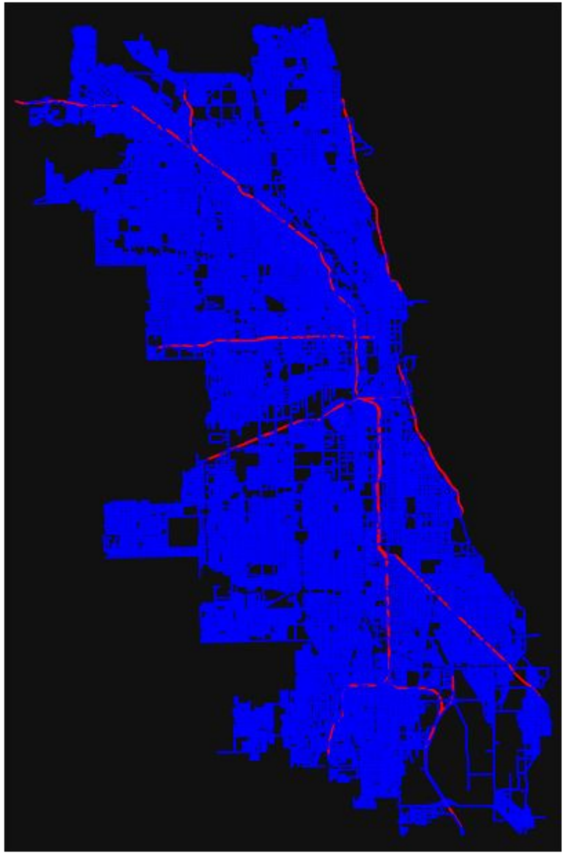


Representing Chicago’s street network

We used OpenStreetMap NetworkX (OSMNX), a Python library.

Contains:

- All roads and intersections
- Types of roads
- Time needed to travel



Model objectives

- **Minimize travel time between two points**
- **Enforce valid path — no cycles or broken route**
- **Can choose to avoid certain edges**

Can be modeled as a Mixed-Integer Linear Program (MILP), choose which edges to travel that fulfill the above requirements. Thus, let $\boldsymbol{f} \in \mathbb{R}^{|E|}$ where

$$\boldsymbol{f}_j = \begin{cases} 1 & \text{if we travel along road } j \\ 0 & \text{otherwise} \end{cases}$$

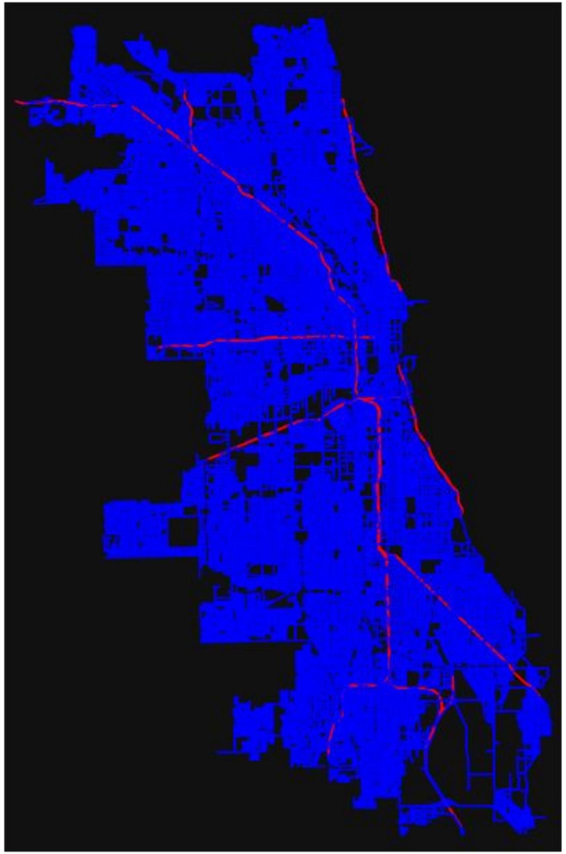
Defining constraints to enforce desired behavior

Define A as the directed incidence matrix for Chicago's street network, thus

$$A_{ij} = \begin{cases} -1 & \text{if edge } E_j \text{ leaves node } V_i \\ 1 & \text{if edge } E_j \text{ enters node } V_i \\ 0 & \text{otherwise} \end{cases}$$

Let $\boldsymbol{e}_i \in \mathbb{R}^n$ be a vector of 0's with 1 at the i-th entry, and s and t be the starting and final nodes.

$$A\boldsymbol{f} = \boldsymbol{e}_s - \boldsymbol{e}_t$$



Final model can also be relaxed to speed up computation

Defining $\boldsymbol{w}$ as the vector representing the cost of traveling along each edge, we get

$$\min \quad \boldsymbol{w} \cdot \boldsymbol{f}$$

subject to

$$A\boldsymbol{f} = \boldsymbol{e}_s - \boldsymbol{e}_t$$

$$\boldsymbol{f}_j \geq 0$$

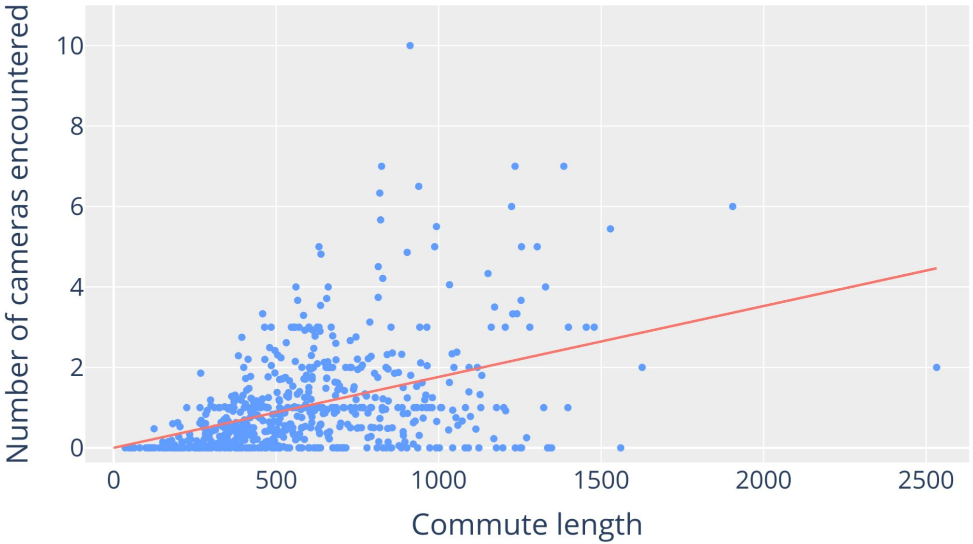
MILP is relaxed into LP to provide 4x reduction in computing time.

Model can be tweaked to avoid certain nodes/edges

Deleting nodes/edges from network guarantees they remain unvisited and maintains total unimodularity.

Cameras encountered are proportional to commute time

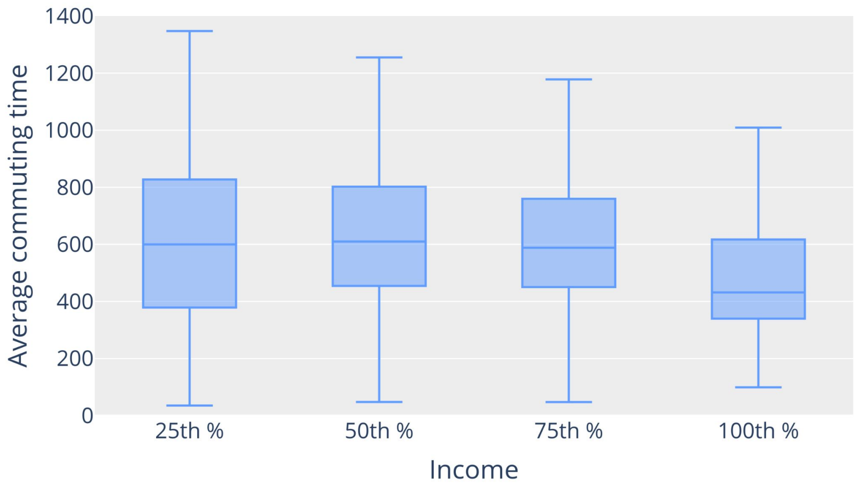
$$\# \text{ cameras} = 0.001763 \cdot \text{Commute time} \qquad (p < 0.001)$$



Tracts with longer commutes are more impacted by ATLE.

Negative quadratic relation is observed between time and income

$$\text{Commute time} = 654.2 - 6.029 \cdot 10^{-9} \cdot \text{Income}^2 \qquad (p < 0.001)$$



Lower income tracts tend to have longer commutes.

Validating observations; differences in # of cameras by income

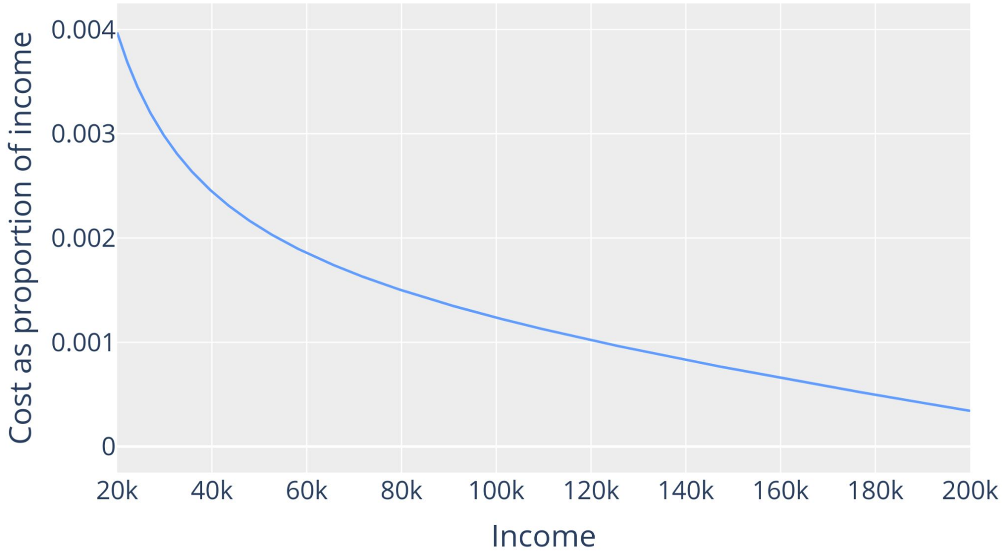
$$\#\ \text{cameras} = 0.56 + 1.3 \cdot 10^{-5} \cdot \text{Inc.} - 6.1 \cdot 10^{-11} \cdot \text{Inc.}^2 \quad (p < .01)$$

Lower income tracts have more frequent encounters with ATLE.

Lower income levels see far greater impact from ATLE

$$\text{Cost as proportion of income} = \frac{\#\text{Cameras per commute}}{\text{Household income}} \cdot \text{Ticket cost}$$

Graphing it for all income levels, we get:



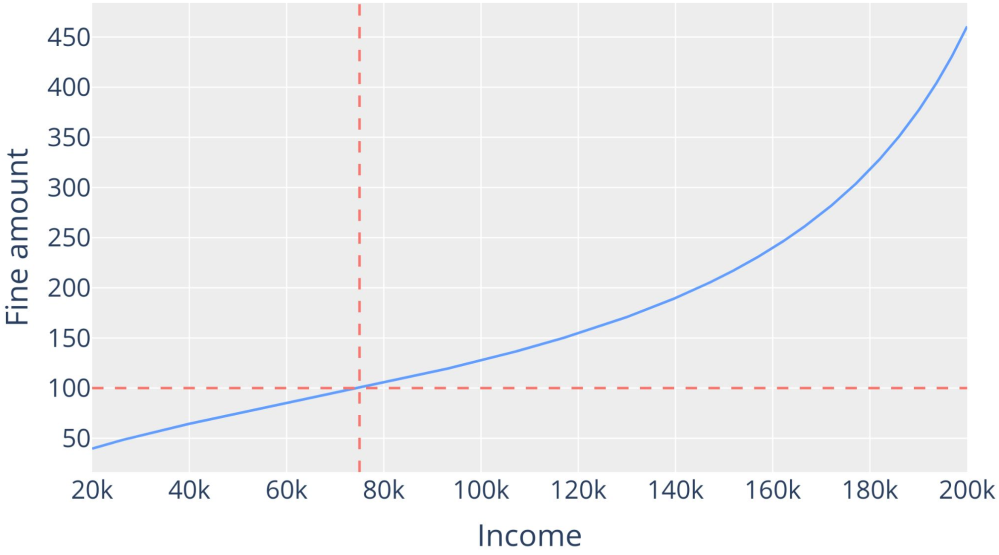
Proportionally, a household with $30k annual income is impacted

8.7 times

more by ATLE than one making $200k.

Fines should be commensurate with income levels

Currently, fines are a flat $100. Normalizing around the average Chicago household ($75k), those earning $200k yearly should be paying



$460

While those earning $30k should pay

$53

Impactful results lead to many future directions

- **Use our framework to determine fairer camera placement**
- **Expand to other infrastructure types (e.g. speed cameras)**
- **Measure behavioral responses to ATLE — avoidance, etc.**

We still have room for future improvements

- No rerouting & Non-deterministic times
- Doesn’t take into account commuters from outside city
- Core assumption that all income groups commit infractions at similar rates

Current system is inherently regressive

- ATLE places disproportionate burden on low income communities
- Using OR methods, calculated a 9x discrepancy in impact between $30k vs. $200k annual income
- Income-scaled/pay-by-day fines should be considered
- Our method offers a framework to audit camera placement

Thank you!
Questions?

Acknowledgment:
INFORMS 2024 DEI Ambassadors Program