Optimal Urban Transportation Policy: Evidence from Chicago

Milena Almagro, Juan Camilo Castillo, Nathaniel Hickok, Felipe Kup, and Tobias Salz

Motivation

Some Facts about Public Transit in the US

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→ Is current urban transit running **efficiently**?

Challenges in urban transportation policy

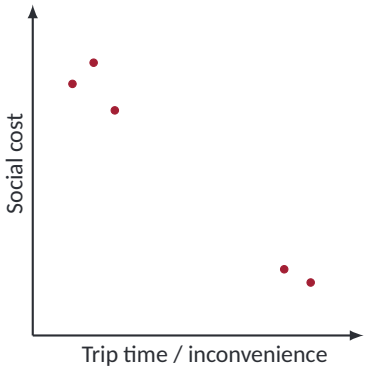
For a city government that operates and regulates urban transportation

People travel using different transportation modes

- Heterogeneous: car, bus, subway, taxi, ride-hailing

Challenges:

- Externalities: congestion, environmental, network
- Limited budget → market power distortion
- Distributive role of transportation



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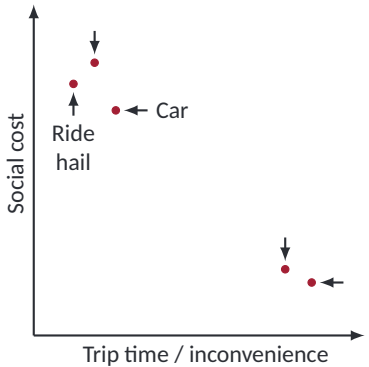
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Urban Transportation

City planner's problem:

- Maximize:

$$\text{Consumer Surplus} - \text{Costs} - \text{Externalities}$$

- Setting prices and capacities (frequencies) across modes
  - Results in a decentralized equilibrium
- Subject to budget constraint:

$$\text{Revenue} - \text{Costs} \leq \text{City Budget}$$

- Conditional on current infrastructure (short-run!)

Accounting for:

- Heterogeneity across consumers and locations
- Response of private providers: taxi/ride-hailing drivers, (not today) ride-hailing platforms

This Project

Research Questions:

1. What are the optimal **prices** and **capacities/frequencies** of an urban transit system?
2. What are the welfare gains and distributional effects relative to the current state?

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Strategy:

- Model of a city planner
  - Discrete choice **mode demand** (McFadden 1974, Berry et al. 1995)
  - Transportation **technology**: cost, trip times, and congestion/network externalities
- Estimation: construct novel dataset for all relevant modes for **Chicago**
- Counterfactuals to determine optimal policy and measure welfare effects

Counterfactual Results

Budget Constrained City Planner (Ramsey)

Preliminary!

Public transit shares increase by 8.4%:

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- On-demand transit: 1.9% → 3.3%
- Car market share: 70% → 65%.

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- Car market share: 70% → 65%.
- Taxi + ride hail: 7.7% → 4.1%.

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- Bus market share: 20% → 27%.
- On-demand transit: 1.9% → 3.3%
- Car market share: 70% → 65%.
- Taxi + ride hail: 7.7% → 4.1%.
- The cost of externalities is reduced by 1/3 or \$2M (CO_2, congestion) per day.

Literature Review

1. **Transportation:** McFadden (1974), Small (1982), Small (2005), Parry and Small (2009)

2. **Spatial Equilibrium Models:**
   - Theory: Arnott (1996), Lagos (2003)
   - Empirics: Frechètte et al. (2019), Buchholz (2021), Brancaccio et al. (2020), Arora et al. (2020), Castillo (2020), Buchholz et al. (2020), Cairncross et al. (2021), Rosaia (2021), Leccese (2021), Brancaccio el at. (2021), Kreindler (2022), Durrmeyer and Martínez (2022)

3. **Transportation in the long run:** Tsivanidis (2018), Allen and Arkolakis (2020), Barwick et al. (2021)

4. **Geo-location Data and Mobility:** Miyahuchi et al. (2020), Glaeser et al. (2020), Couture et al. (2021)

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$\Longrightarrow$ **A budget constrained city with heterogeneous agents setting optimal prices and capacities**

Roadmap

1. Data

2. Model and Estimation
   - 2.1 City Planer
   - 2.2 Demand
   - 2.3 Transportation Technology

3. Counterfactuals

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Data Sources

Chicago, June 2019-February 2020.

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Raw data sets:

1. Individual cell phone location records: 40% of all devices.
2. Universe of public transit trips through MIT-CTA partnership.
3. Universe of taxi and ride hailing (pooled + single rides) trips from the city of Chicago.
4. Block level census data.
5. 2019 Chicago transit survey for validation and calibration.

– Car trips are identified as:

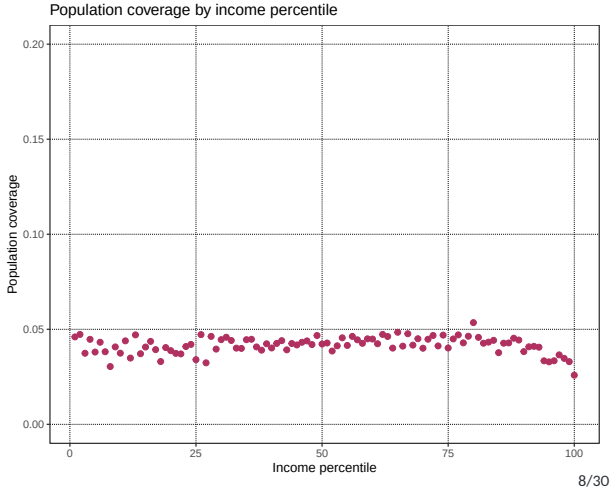
$$\text{Car Trips} = \text{Cell Phone Trips} - \text{Public Transit Trips} - \text{Ride-hailing Trips} - \text{Taxi Trips}$$

Goal: Hourly flows, prices, and travel times by mode across community areas + micro moments.

Cell Phone Data

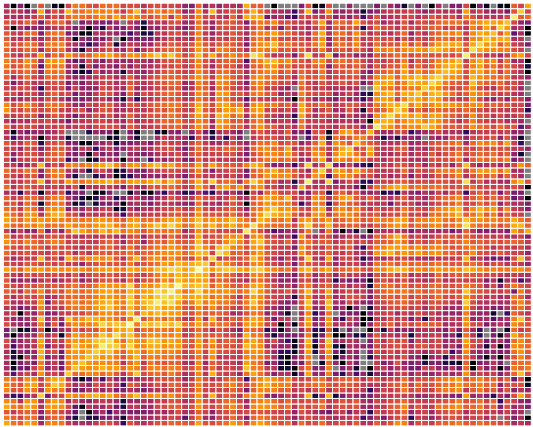
Representativeness Across Income Groups

1. Assign home census tract to cellphone id
2. Construct population coverage relative to census tract population in census
3. Order tracts by income percentiles

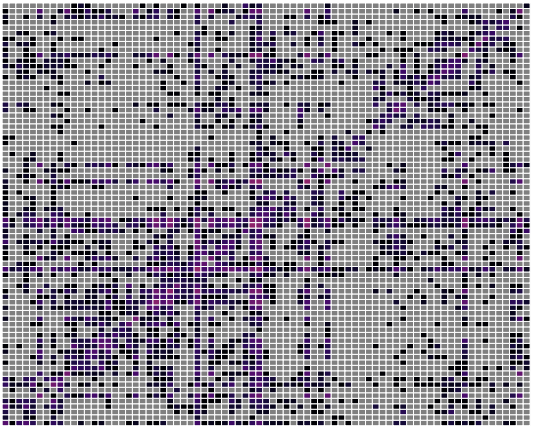


Combined vs. Survey Data: Flows Across Community Areas

Heatmap, combined data



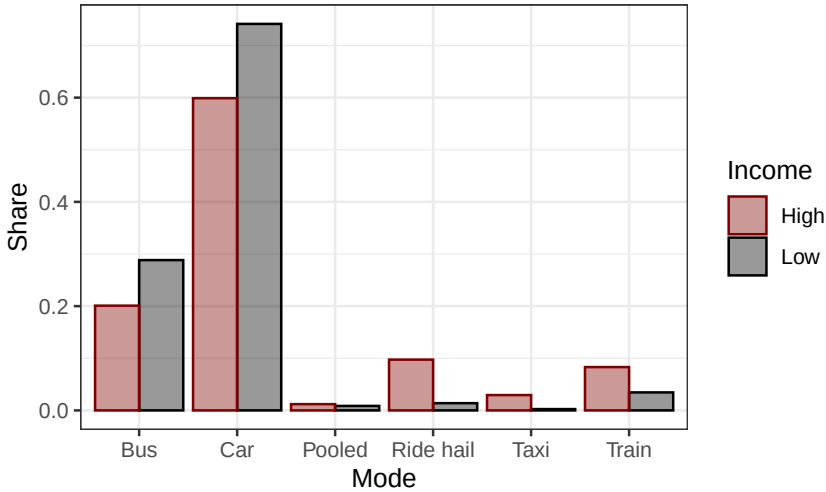
Heatmap, survey data



 # Trips

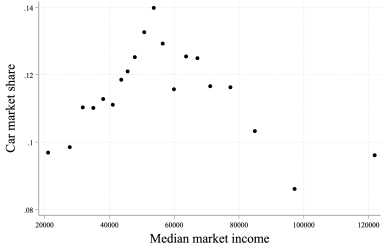
0 10 100 1,000 10,000 100,000 1,000,000

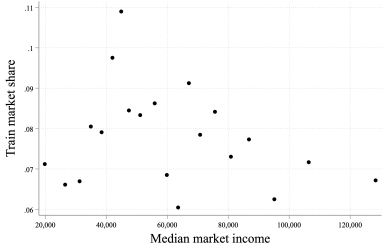
Mode Market Shares by Income

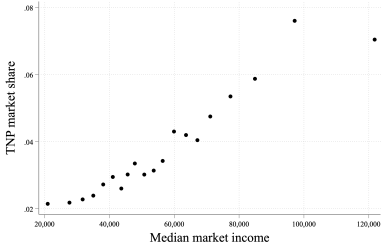


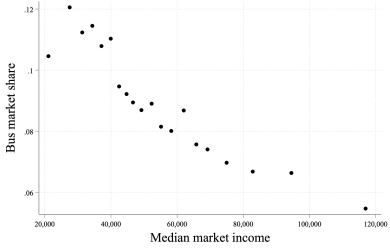
Heterogeneity across locations

Mode choice by income



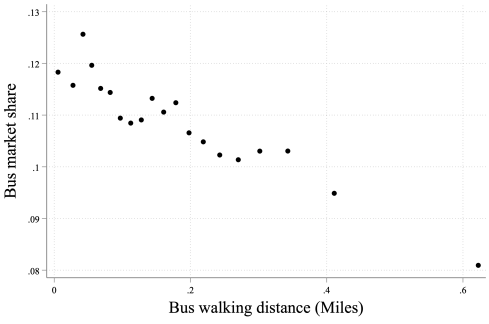


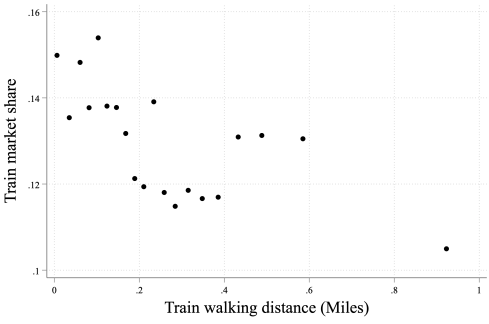




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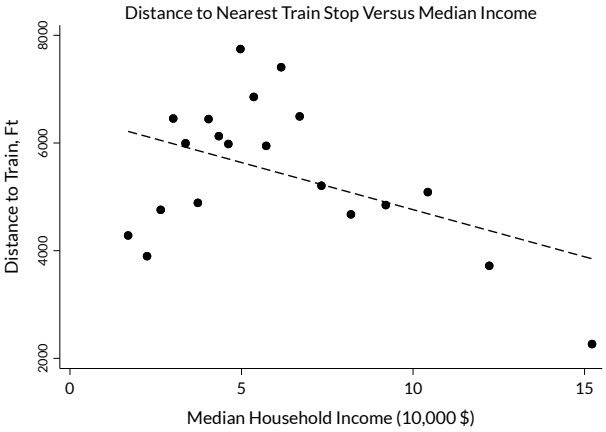
Mode choice correlates with accessibility





Heterogeneity across locations

Mode choice correlates with location's characteristics across space



	Car Ownership
Log Median HH Income	0.159***
	(0.006)
Log Distance to Train	0.051***
	(0.005)
Log Distance to Bus	0.101***
	(0.010)
Constant	-2.035***
	(0.086)
Observations	797
F	353.191

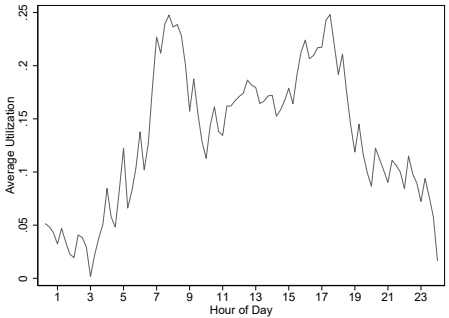
Summary Statistics

Utilization of Buses during Weekdays

The city runs 129 bus routes with 1,864 buses.

Utilization (across buses):

	mean	p10	p25	p50	p75	p90
7am to 9am	22%	8%	14%	22%	28%	36%
9am to 7am	14%	2%	6%	13%	20%	27%



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Model

Outline

There are 3 parts:

1. Commuters make mode choices: (prices and times) $\mapsto$ (# of people choosing each mode)
2. Transportation technology: (# of people choosing each mode) $\mapsto$ (times and social cost)
   - Accounting for taxi/ride-hailing drivers' searching behavior
3. City government: chooses prices and capacity of each mode, trades off welfare and budget (Ramsey)

Outside our model (for now):

- No market power from private providers (ride-hailing platforms, taxi fleets)

Next few slides: model with one O-D pair, one time period

- We estimate main model for different O-D pairs and times of the week

Model

Outline

Demand: $D_j(\mathbf{p}, \mathbf{t})$

- Prices p_j
- Total time t_j (wait + travel time)

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Transportation technology j is described by three functions of quantity and capacity $(\mathbf{q}, \boldsymbol{\kappa})$:

1. $\tau_j(q_j, \kappa_j)$: Wait + travel times (congestion, bus/train routing, taxi/ride-hail matching)
2. $C(\mathbf{q}, \boldsymbol{\kappa})$: Cost (fuel, depreciation, labor)
3. $E(\mathbf{q}, \boldsymbol{\kappa})$: Environmental externalities

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κ_j: Capacity of mode j, determines waiting times

- Taxis, ride-hailing, shared: Number of drivers working. More idle drivers → lower times.
- Buses, trains: Route frequency. More buses → lower times.

Model

City Government and Equilibrium

City government chooses prices and capacities $(\mathbf{p}, \boldsymbol{\kappa})$. Equilibrium $(\mathbf{q}, \mathbf{t})$ such that:

$$\underbrace{\mathbf{q} = \mathbf{D}(\mathbf{t}, \mathbf{p})}_{\text{demand}} \qquad \text{and} \qquad \underbrace{\mathbf{t} = \boldsymbol{\tau}(\mathbf{q}, \boldsymbol{\kappa})}_{\text{technology}}$$

- For any $(\mathbf{q}, \boldsymbol{\kappa})$, there is a unique $\mathbf{p}(\mathbf{q}, \boldsymbol{\kappa})$ that satisfies the equilibrium conditions.

Government's problem (Ramsey):

$$\max_{(\mathbf{q}, \boldsymbol{\kappa})} \underbrace{\overbrace{U(\mathbf{t}, \mathbf{p})}^{\text{Consumer Surplus}} - \mathbf{p}(\mathbf{q}, \boldsymbol{\kappa}) \cdot \mathbf{q} + \overbrace{\mathbf{p}(\mathbf{q}, \boldsymbol{\kappa}) \cdot \mathbf{q} - C(\mathbf{q}, \boldsymbol{\kappa})}^{\text{Gov. revenue \ Profits}} - E(\mathbf{q}, \boldsymbol{\kappa})}_{\text{Welfare}} \qquad \text{s.t.} \qquad \overbrace{\mathbf{p}(\mathbf{q}, \boldsymbol{\kappa}) \cdot \mathbf{q} - C(\mathbf{q}, \kappa) \geq B}^{\text{Budget constraint}}$$

Optimal Pricing

Lagrangian for government's problem:

$$\max_{\mathbf{q},\boldsymbol{\kappa}} U\big(\mathbf{q},\boldsymbol{\kappa}\big) - C(\mathbf{q},\boldsymbol{\kappa}) - E(\mathbf{q},\boldsymbol{\kappa}) + \lambda \cdot \left\{ \sum_j p_j(\mathbf{q},\boldsymbol{\kappa}) \cdot q_j - C(\mathbf{q},\boldsymbol{\kappa}) - B \right\}$$

First-order conditions

1. Quantity:

$$p_j = \frac{\partial C}{\partial q_j} - \frac{1}{1+\lambda} \cdot \frac{\partial U}{\partial t_j} \cdot \frac{\partial t_j}{\partial q_j} + \frac{1}{1+\lambda} \cdot \frac{\partial E}{\partial q_j} - \frac{\lambda}{1+\lambda} \cdot \sum_k q_k \cdot \frac{\partial p_k}{\partial q_j}$$

2. Capacity:

$$\frac{\partial C}{\partial \kappa_j} = \frac{1}{1+\lambda} \cdot \frac{\partial U}{\partial t_j} \cdot \frac{\partial t_j}{\partial \kappa_j} - \frac{1}{1+\lambda} \cdot \frac{\partial E}{\partial \kappa_j} + \frac{\lambda}{1+\lambda} \cdot \sum_k q_k \cdot \frac{\partial p_k}{\partial \kappa_j}$$

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$$p_j - \underbrace{\tilde{C}_j}_{\text{Mg. cost}} = \underbrace{\tilde{E}_j}_{\text{Mg. environ. externality}} - \sum_k \underbrace{\bar{u}_k^T}_{\text{Utility of time}} \cdot \underbrace{\tilde{T}_{kj}}_{\text{Network effects}} + \frac{\lambda}{1+\lambda} \cdot \left\{ - \tilde{E}_j - \underbrace{\sum_{k \in J} q_k \cdot \Omega_{kj}}_{\text{Market power distortion}} - \underbrace{\sum_k (\tilde{u}_k^T - \bar{u}_k^T) \cdot \tilde{T}_{kj}}_{\text{Spence distortion}} \right\}$$

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Notation:

- $\tilde{C}_j = \frac{\partial C_j}{\partial q_j} + \frac{\partial C}{\partial \kappa_j} \frac{\kappa_j}{q_j}$: Mg. cost of a trip, keeping capacity per trip $\frac{\kappa_j}{q_j}$ constant
- $\tilde{E}_j = \frac{\partial E}{\partial q_j} + \frac{\partial E_j}{\partial \kappa_j} \frac{\kappa_j}{q_j}$: Mg. externality of a trip, keeping capacity per trip $\frac{\kappa_j}{q_j}$ constant

$\Longrightarrow$ *"Standard"* ***Pigouvian tax/subsidy***

Optimal Pricing

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Notation:

- $\bar{u}_j^T = \frac{\partial CS}{\partial t_j}$: How does CS change if the time of mode j increases?
- $\tilde{T}_{kj} = \frac{\partial T_j}{\partial q_k} + \frac{\partial T_j}{\partial \kappa_k} \frac{\kappa_k}{q_k}$: How does mode-$j$ time change if mode-j trips and capacity increase? Two effects:
  1. Congestion: negative externality
  2. Returns to scale: positive externality (Arnott, 1996)

$\Longrightarrow$ *Tax modes that cause congestion, subsidize modes with large returns to scale*

Optimal Pricing

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Notation:

- Ω: Inverse Jacobian of demand (~ inverse price elasticities)
- $\tilde{u}_j^T$: If t_j increases by 1%, how much does utility of *marginal* commuters change?

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Notation:

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- $\tilde{u}_j^T$: If t_j increases by 1%, how much does utility of *marginal* commuters change on avg.?

Government cares about **budget**, so it behaves like a **monopolist** to some extent:

- Underweights externalities
- Market power markup: higher price for less elastic modes
- Caters to marginal rather than average consumer

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Demand

Market Definition:

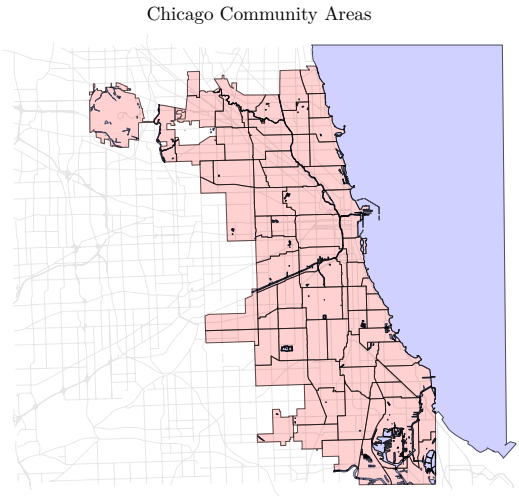
- m = community area a to a' during hour h
- Exogenous arrival rate λ_m of travelers

Choices:

$$j^\star = \underset{j \in \mathcal{J}_i \cup \{0\}}{\operatorname{argmax}} \, u^i_{mj}$$

Utility of agent i:

$$u^i_{mj} = \xi_{mj} - \alpha^i_T \cdot T_{ij} - \alpha^i_p \cdot p_{ij} + \epsilon^i_j,$$



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Transportation technology

Three parts:

1. Congestion
2. Public transit (bus/subway)
3. Private transit (taxis/ride hailing)

Congestion

Given vector $\mathbf{q}$ of all trips, what is the travel time from a to a' using mode j?

Approach: Model city as directed graph of community areas

- Edges e are adjacent community areas
- Agents in market m take a *route* r_m, a sequence of edges

During hour h, the congestion on edge e is

$$Q_{eh} = \sum_j \sum_{r \text{ s.t. } e \in r} \overbrace{b_j}^{\text{Congestion caused by mode } j} q_{rhj}$$

Travel times:

$$\text{By edge:} \quad \tau_{ehj} = \overbrace{A_{ej}}^{\text{“Fixed effect”}} \overbrace{Q_{eh}^{\alpha_j}}^{\text{Mode } j \text{ congestion elast.}} \qquad \text{By market:} \quad T_{mj}^{\text{travel}} = \sum_{e \in r_{mj}} \tau_{ehj}$$

Public transit (bus/subway)

Agents in market $m = (a, a', h)$ take a bus/train route R_m

Total time for agent i in market $m = (a, a', h)$, who takes route R:

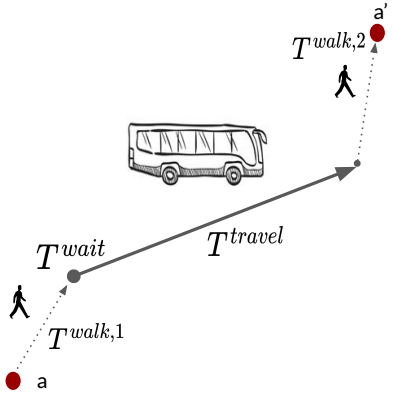
$$T_i = T_i^{\text{walk},1} + \underbrace{T_{Rh}^{\text{wait}}}_{\text{See below}} + \underbrace{T_{Rh}^{\text{travel}}}_{\text{Congestion}} + T_i^{\text{walk},2}$$

Let κ_{Rh} be the frequency of route R. Then the waiting time is

$$T_{Rh}^{\text{wait}} = \frac{1}{\kappa_{Rh}}$$

Cost and externality:

$$C_{Rh} = c_R \kappa_{Rh} \qquad E_{Rh} = e_R \kappa_{Rh}$$



Private transit (taxis and ride hailing)

Total time in private mode j in market m is $T_{mj}^{\text{wait}} + T_{mj}^{\text{travel}}$.

Waiting time depends on L_{ahj}, the number of available drivers at the origin a:

$$T_{mj}^{\text{wait}} = A_{aj} L_{ahj}^{-\phi_j}$$

The distribution of available drivers arises from a model of driver movements (Buchholz, 2021; Rosaia, 2020)

- There is a total number of drivers k_{hj}
- Travelers who chose mode j matched to drivers, who then become available at drop off location
- Available drivers tend to move towards high earnings neighborhoods

Roadmap

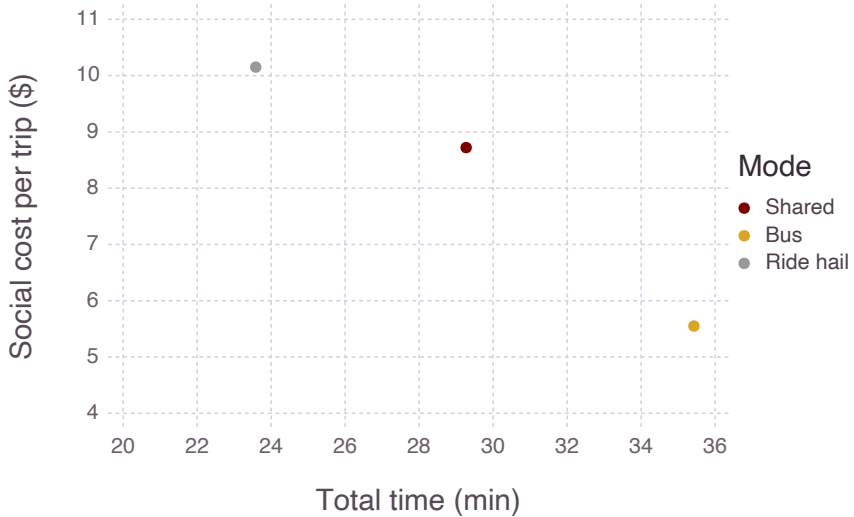
1. Data

2. Model and Estimation
   - 2.1 City Planer
   - 2.2 Demand
   - 2.3 Transportation Technology

3. Counterfactuals

Status Quo

Mode Comparison



Counterfactual
Additional Assumptions

Externalities:

- CO_2 cost: \$100 per ton; congestion externality: 10 cents per km.

City Budget:

- Pick budget constraint that corresponds to current transit spending.
- Capacity: city hires drivers at market wages.

Other (current) model restrictions:

- Bus technology.
  - Zero marginal cost, wait times inversely proportional to capital spending.
- Taxis and Ride Hail modeled as one technology.
- Random coefficient proportional to income.

Counterfactuals

Compare status quo to:

1. No shared / no ride hail
2. Ramsey (city planner with budget constraint)
3. Ramsey with more efficient sharing technology (50% detour reduction)

Counterfactual Results

	Status quo	No Shared / No Ride Hail	Ramsey	Improved Shared / Ramsey
Ride Hail Price ($)	24.5	∞	8.3	8.6
Bus Price ($)	2.5	2.5	0.2	0.7
On-demand Shared Price ($)	17.1	∞	0.8	3.1
Ride Hail T (mins)	20.0	∞	21.4	21.6
Bus T (mins)	36.5	36.5	32.7	32.8
On-demand Shared T (mins)	25.6	∞	24.7	22.6
Ride Hail %	7.7	0.0	4.1	3.2
Bus %	20.4	22.8	27.4	25.2
On-demand Shared %	1.9	0.0	3.3	7.7
Car %	70.1	77.2	65.2	63.9
Δ Welfare ($Million per day)	0.0	-14.4	22.32	25.1
Δ CS ($Million per day)	0.0	-8.1	20.1	22.5
Revenue / Profit ($Million per day)	-13.4	-19.6	-13.4	-13.4
Externalities ($Million per day)	7.6	7.7	5.4	5.5

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Graphs

Future Steps

Much Work Ahead!

- Add demand heterogeneity:
  - Income
  - Car ownership as choice set variation
  - Include heterogeneity in access
- Endogenize congestion (Couture, Duranton, and Turner (2018))
- Politically feasible counterfactuals
- Distributional effects

Conclusions

- Construct new dataset of all trips across all modes for a major urban area.
- Compute **optimal transit prices** and **capacities** with government budget constraints.
  $\Longrightarrow$ Application: can **on-demand** shared transit scale up?
- Preliminary results:
  - Public transit should be further subsidized
  - Potential of restricted on-demand sharing technology limited

Thank you!

Supply

Parametrizing Pooling Technology

Total trip time:

$$T = \underbrace{w(I)}_{\text{Waiting time}} + \underbrace{0.5 \cdot \tau}_{\text{Batch Length}} + \underbrace{T^0}_{\text{Direct time}} + \underbrace{P(q)}_{\text{Match prob.}} \cdot \underbrace{d(q)}_{\text{Expected detour}},$$

where I is the number of idle drivers, $w(I)$ and $d(q)$ are decreasing, $P(q)$ is increasing.

Supply

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Suppose that density of **trips with detour distance** x is proportional to

$$\overbrace{\alpha}^{\text{Efficiency}} \cdot \overbrace{q}^{\text{Requests}} \cdot \overbrace{\tau}^{\substack{\text{Batch} \\ \text{length}}} \cdot \frac{1}{\eta} \cdot x^{\overbrace{\eta-1}^{\text{Skewness}}},$$

then $x \sim$ **Weibull** (also shortest path btn. vertices on random graph; Bauckhage et al., 2013).

Supply
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then $x \sim$ **Weibull** (also shortest path btn. vertices on random graph; Bauckhage et al., 2013).

- Only match if detour $< \bar{x}$.
- $P(q)$ is the CDF of the shortest detour $1 - exp(-\alpha \cdot q \cdot \tau \cdot \bar{x}^{\eta})$.
- Expected detour $d(\bar{x}, \alpha, q, \tau)$: mean of detour, truncated at $\bar{x}$

Supply
Utilization

How much **driver time** does a trip take on average?

$$T^B = \underbrace{\left(1 - F\left(\bar{x}; \alpha, q, \tau\right)\right)}_{\text{Prob. of no match}} \cdot \underbrace{T^0}_{\substack{\text{Busy time} \\ \text{if unmatched}}} + \underbrace{F\left(\bar{x}; \alpha, q, \tau\right)}_{\text{Match prob.}} \cdot \underbrace{\frac{1}{2} \cdot \left(T^0 + d\left(\bar{x}, \alpha, q, \tau\right)\right)}_{\text{Busy time if matched}}$$

The number of idle drivers is:

$$I = L - q \cdot T^B.$$

Waiting time (distance to the closest driver):

- Avg. waiting time is $w(I) = \frac{\rho}{\sqrt{I}}$ (Arnott 1996).

Additional **assumptions:**

- Optimal match radius depends on density: $\bar{x}(q) = \delta \cdot q^{-\beta}$
- Batch length τ fixed at one minute.
- Set ρ so that avg. ride-hailing time is 4 min

Supply

From model to the data

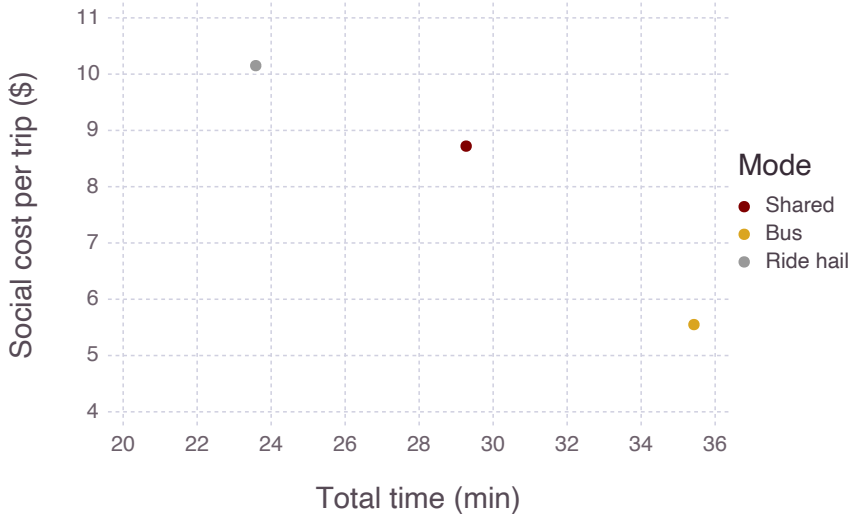
Given parameters $\alpha, \eta, \beta, \delta$, we can construct

- $P(q)$ of being pooled $1 - exp(-\alpha \cdot q \cdot \tau \cdot \bar{x}^{\eta})$.
- $E(q)$ Expected detour $d(\bar{x}, \alpha, q, \tau)$

$\Longrightarrow$ Both functions $P(q)$ and $E(q)$ can be directly constructed from the data!

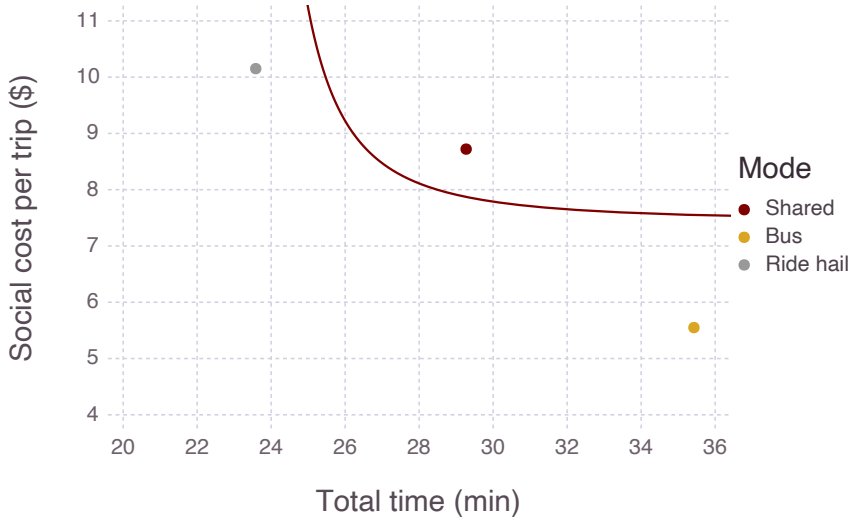
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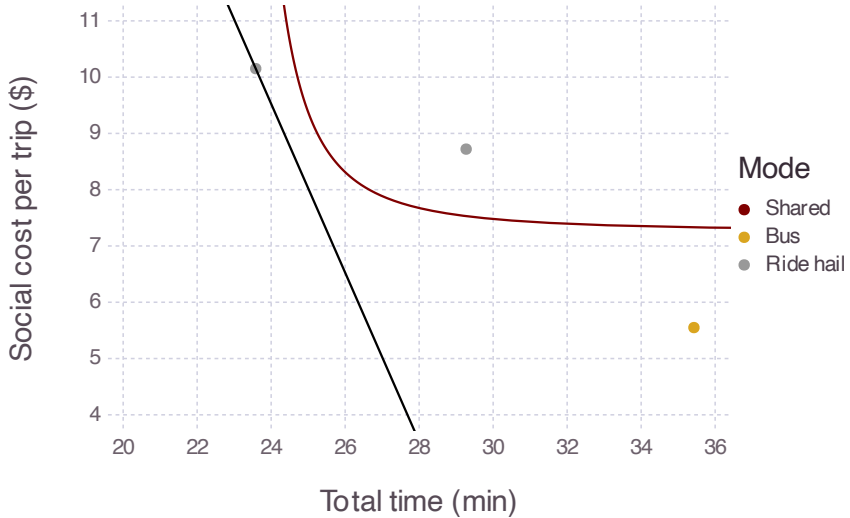
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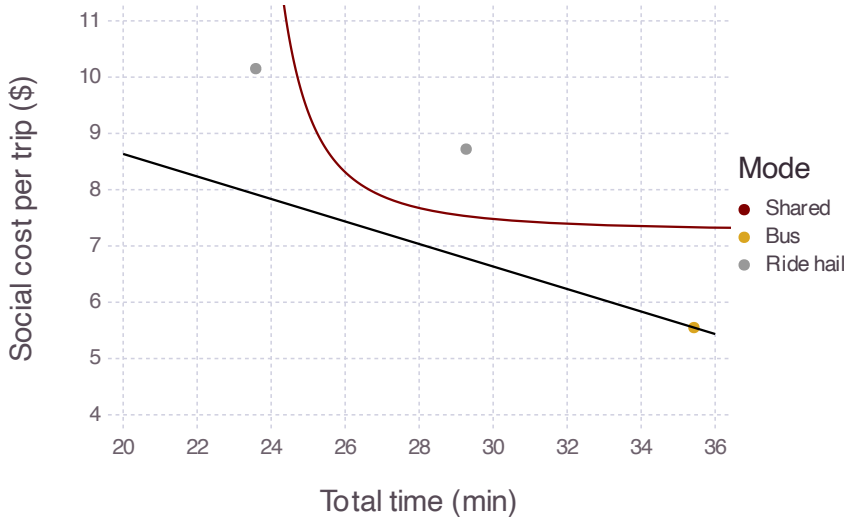
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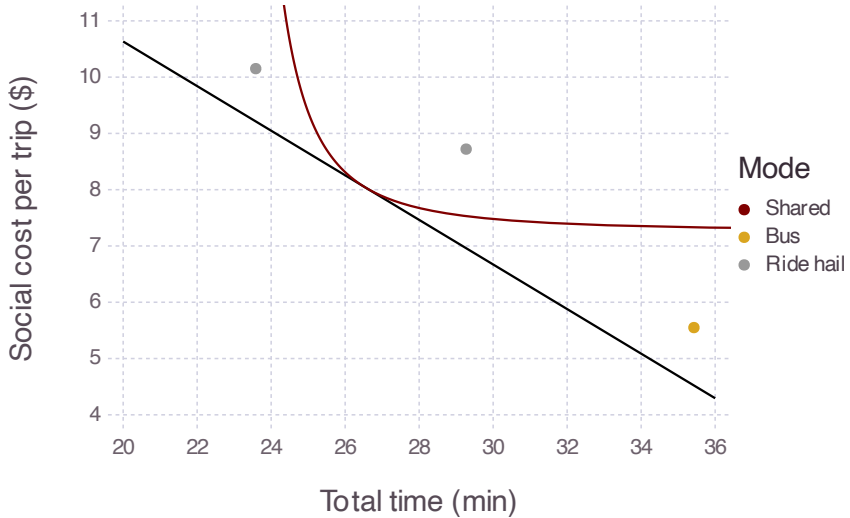
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