Market coverage and network competition: Evidence from shared electric scooters

Nicolás Martínez - Toulouse School of Economics

Spatial competition and capacity constraints

- The spatial allocation of supply is a strategic variable for competing firms:
  - Incentives to **agglomerate** or **spatially differentiate**
- Imposed capacity constraints commonly used to deal with externalities
  - Particularly common in transportation markets (ex: taxi medallions, airport slots)
  - Supply level: direct impact on service quality (waiting times, congestion, etc...)

I quantify the welfare effects of spatial competition and capacity regulations

- Use unique data from a new industry: **shared electric scooters** ▸ Headlines

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I quantify the welfare effects of spatial competition and capacity regulations

- Use unique data from a new industry: **shared electric scooters** Headlines
  - 400+ cities across the North America and Europe
  - 2022: 72.2 million trips in North America
  - Firms' decisions: number of scooters per location

This paper

- Build dynamic model of firms' allocation decisions
  - Imposed capacity constraints
  - Economies of density implied by the spatial distribution of actions
  - Demand generates a dynamic externality across locations
- Apply it to a unique dataset for Kansas City
  - Built combining collected data, public records, and proprietary data
  - Partially identify firms' costs parameters using moment inequalities
- Quantify welfare effects and provide feasible policy recommendations
  - Trade-off between welfare maximization and distributional concerns
  - Imposed capacity constraints are regressive across space

Preview of results

Market structure: trade-off between welfare maximization and distributional concerns

Over a two month period:

- Monopolist improves welfare by 222 thousand dollars
  - Distributional concerns: only serves high demand locations
  - Spatial competition leads to better coverage, particularly in low income areas
- Imposed capacity constraints cost 284 thousand dollars in total welfare
  - Spatial distribution highlights regressive nature of constraints
  - Cost informative of trade-off faced by town-halls

Contribution

Regulations for transportation markets

- Two-sided markets (Buchholz 2021, Brancaccio et al. 2022, Castillo 2022, Rosaia 2023)
- Inefficient competition (Berry and Waldfogel 1997, Crawford et al. 2019, Betancourt et al. 2022)
- I analyze the distributional effects of transportation policies in a new industry (Hall 2021, Akbar 2022, Durrmeyer and Martinez 2022)

Contribution

Regulations for transportation markets

- Two-sided markets (Buchholz 2021, Brancaccio et al. 2022, Castillo 2022, Rosaia 2023)
  - **This paper:** vehicle rentals require centralized actions
  - Importance of capacity constraints and economies of density
- Inefficient competition (Berry and Waldfogel 1997, Crawford et al. 2019, Betancourt et al. 2022)
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- Inefficient competition (Berry and Waldfogel 1997, Crawford et al. 2019, Betancourt et al. 2022)
    - **This paper:** study both intensive (# vehicles) and extensive (# locations) margins
- I analyze the distributional effects of transportation policies in a new industry (Hall 2021, Akbar 2022, Durrmeyer and Martinez 2022)

Contribution

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- Inefficient competition (Berry and Waldfogel 1997, Crawford et al. 2019, Betancourt et al. 2022)
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Methodology

- Combinatorial problems in dynamic games (Aguirregabiria and Ho 2012, Zheng 2016)
- Moment inequalities and dynamics (Holmes 2011, Morales et al. 2019, Houde et al. 2022)
    - **This paper:** Exploit finite-horizon nature of the game

Outline

1. Context and data

2. Motivating evidence

3. Model

    Environment

    Demand model

    Supply model

4. Policy analysis

Context

Shared electric scooters:

- Consumers can start and finish the trip **anywhere**, no stations needed ▸ Service illustration
- Without intervention, supply distribution **degenerates** over time
- **Across the day**, firms optimize their network by sending trucks to move scooters

Context

Shared electric scooters:

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Kansas City - Missouri (March 1st 2021 - May 9th 2022):

- 2 firms (Bird and Spin):
  - Brand and month specific capacity constraints **imposed** by the town-hall
  - **Same price**: 1 \$ to start + 39 cents per minute, average duration: 17min (= 7.63 \$)

Data - supply decisions and trips

- **Collect real-time data** of idle scooters' locations, for all brands, **every two minutes**:
  - Location of every scooter not in use (7 meter accuracy)
  - Cannot track the movements of a single scooter across time
- Kansas City townhall **public records** containing all scooter trips:
  - Exact start and end time, as well as origin and destination (7 meter accuracy)
  - Cannot track consumers over time
- Matching datasets allows to **recover coverage decisions** of both firms

Data - demand controls

I observe starting location of trips but not of individuals:

- Simulate location specific mapping of walking time to reach a scooter ▸ Spatial heterogeneity

Additional controls:

- Hourly rainfall and temperature
- Number of visits to business from cellphone records
- Census tract income data (2021), location of bus stops

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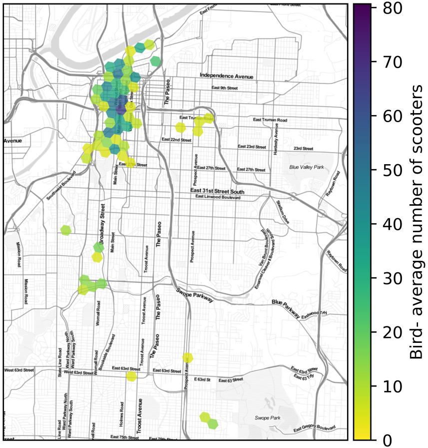
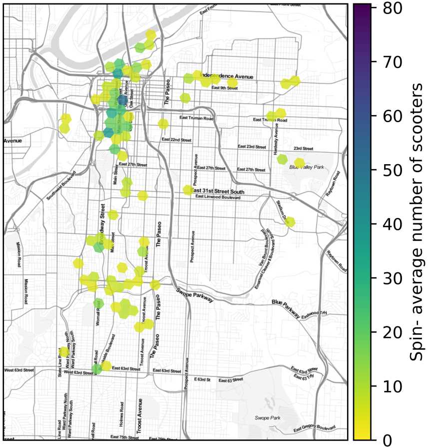
Main coverage areas - 6:00 am to 12:00 pm - April 2021

Only areas with on average $\geq$ 4 scooters, hexagon ($\simeq$ 10 hectares)



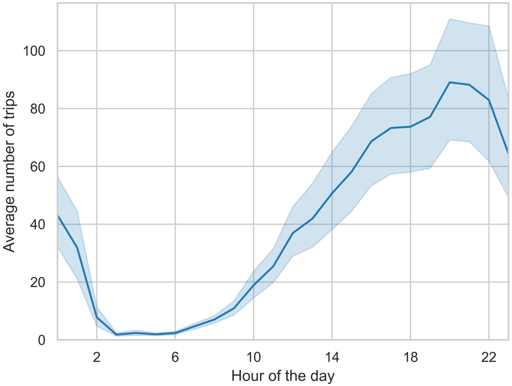
Bird $\simeq$ 1000 scooters



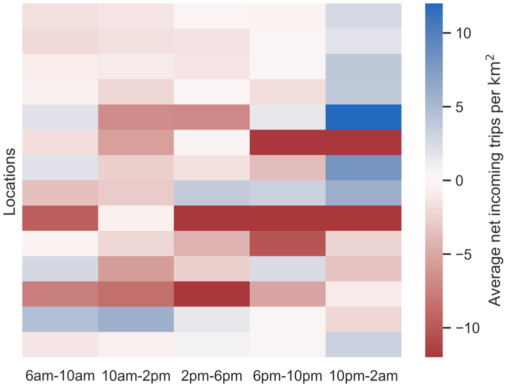
Spin $\simeq$ 600 scooters

▸ k-means grid

Intraday Demand patterns



Demand



Downtown mean net incoming trips / km^2

Note: The shaded area is the 95% confidence interval for the mean. Net incoming trips = arrivals - departures.

Descriptive regressions on firms' behavior

- Probit regressions of firm's decision y_{ilt} = # scooters to add in a location
- Fixed effects: brand, location, period of the day, day of the week, and month
- Demand controls: # visits to business, temperature, and rainfall

Variable	(1)	(2)	(3)
# scooters competitor	-0.011**	-0.011**	-0.011**
	(0.001)	(0.001)	(0.001)
Net incoming trips		-0.043**	-0.043**
		(0.004)	(0.004)
Δ visits to business			0.02**
			(0.006)
Pseudo R2	0.169	0.171	0.171
Observations	40151	40151	40151

Note: Standard errors clustered by location-period. Δ is the variation between next period and current period. Significance level: **1%, *5%, †10%.

▸ Descriptives firms' actions

Summary of motivating evidence

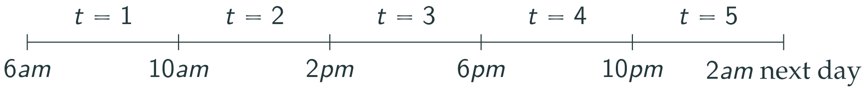
- Spatial market segmentation outside the city center
  - Strategic incentive to spatially differentiate
  - Possible cost advantage of serving certain locations
  - Possible role for economies of density when offering a compact network
- Demand dynamics
  - Total demand, origins, and destinations vary across the day
  - Dynamic externalities across locations (net incoming trips)
- Firms decisions correlated with dynamic incentives and competitor's presence

A **structural model** allows to recover cost structure and capture role of dynamics

Outline

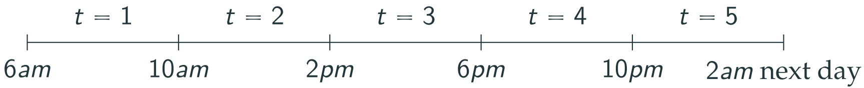
Environment

- Represent city as grid of locations, i.e. a location $l \in \mathcal{L} = \{1, ..., L\}$ ▸ k-means grid
- Each day: **finite horizon game** in discrete time



- Firm i action: g_{ilt} = supply in location l at time t, subject to a citywide constraint
- State space at time t: $X_t = \{S_{it}, S_{jt}, Z_t, \boldsymbol{\eta_{it}}, \boldsymbol{\eta_{jt}}\}$
    - Endogenous: S_{it} = vector with # scooters from brand i in each location
    - Exogenous: Z_t = weather, # visits to business in each location
    - η_{it} = unobserved cost shock (to econometrician) but known by all firms

Model timing



Within period timing:

1. All firms observe the state X_t
2. Firms take decisions G_{it}, G_{jt} **simultaneously**, realized instantly
3. Demand realizations and firms' decisions generate states' transitions:

$$S_{it+1} = G_{it} + \underbrace{A_{it}(G_{it}, G_{jt}, Z_t)}_{\text{Arriving trips}} - \underbrace{D_{it}(G_{it}, G_{jt}, Z_t)}_{\text{Departing trips}}$$

4. Firms receive revenue from trips and pay cost from actions

Demand

Demand for firm i in location l is the sum of the demands for each destination h:

$$\lambda_{ilt} = \sum_{h \in \mathcal{H}_l} \lambda_{ilht}$$

Model origin-destination flows as a constant elasticity demand:

$$\lambda_{ilht} = exp\left(\beta_{il1} ln(p_{lh}) + \beta_{i2} ln(w_l(g_{ilt})) + \beta_{i3} ln(w_l(g_{jlt})) + \mathbf{b}_{lht}\gamma + \boldsymbol{\alpha}_{ilht} + \varepsilon_{ilht}\right)$$

- $w_l(g_{ilt})$ = walking time to reach a scooter ▸ Spatial heterogeneity
- $\mathbf{b}_{lht}$ = temperature, rainfall, and # visits to business at origin and destination
- $\boldsymbol{\alpha}_{ilht}$ = brand, origin, destination, period, day of the week, and month fixed effects
- ε_{ilht} = unobserved conditions

Control function correction for endogeneity

Estimate using Poisson Pseudo maximum likelihood:

$$\lambda_{ilht} = exp\left(\beta_{il1} ln(p_{lh}) + \beta_{i2} ln(w_l(g_{ilt})) + \beta_{i3} ln(w_l(g_{jlt})) + \boldsymbol{b_{lht}}\gamma + \boldsymbol{\alpha_{ilht}} + \varepsilon_{ilht}\right)$$

Instruments inside the control function (Wooldridge 2014):

- Same period supply level one week before
- Lagged sports and concerts indicators interacted with number of bars

First-stage regressions using polynomial of instruments to recover residuals $\hat{\nu}_{ilt}$

$$\lambda_{ilht} = exp\left(\beta_{il1} ln(p_{lh}) + \beta_{i2} ln(w_l(g_{ilt})) + \beta_{i3} ln(w_l(g_{jlt})) + \boldsymbol{b_{lht}}\gamma + \boldsymbol{\alpha_{ilht}} + \boldsymbol{\rho_1 \hat{\nu}_{ilt}} + \boldsymbol{\rho_2 \hat{\nu}_{jlt}}\right)$$

Demand estimates

Variable	(1) Bird	(1) Spin	(2) Bird	(2) Spin
log price	-3.72**	-3.7**	-3.71**	-3.72**
	(0.068)	(0.087)	(0.068)	(0.087)
log price × Bottom 25% access to public transport	0.81 **		0.81 **	
	(0.08)		(0.08)	
log price × Top 25% access to public transport	-0.14 *		-0.14 *	
	(0.069)		(0.069)	
log price × Bottom 25% income	0.49 **		0.49 **	
	(0.07)		(0.07)	
log price × Top 25% income	-0.33 **		-0.33 **	
	(0.07)		(0.07)	
Walking time to own vehicle (in min)	-1.08**	-1.18**	-1.01**	-1.09**
	(0.033)	(0.043)	(0.063)	(0.068)
Walking time to competitor vehicle (in min)	0.05*	0.34**	0.36**	0.6**
	(0.022)	(0.037)	(0.055)	(0.057)
Control function correction	No		Yes	
FE controls	Yes		Yes	
Pseudo R2	0.43		0.43	
Observations	1 453 469		1 453 469	

*Walking time in minutes. Additional controls: temperature, rainfall, and # visits to business at origin and destination. Fixed effects: origin location, destination location, period of the day, day of the week, month. Significance level: **1%, *5%, †10%.*

▸ Spatial heterogeneity in supply elasticities ▸ Fit demand predictions

Supply model - overview

At each period, firms maximize their inter-temporal problem:

$$V_{it}(X_t) = \max_{G_{it}} \left\{ \Pi_{it}(G_{it}; G_{jt}, X_t) + \beta \mathbb{E}\left[V_{it+1}(X_{t+1}) | G_{it}, G_{jt}, X_t \right] \right\}$$

$$\text{s.t.} \sum_{l \in \mathcal{L}} g_{ilt} = Capacity_{it}$$

The period profit, $\Pi_i(G_{it}; G_{jt}, X_t)$, corresponds to the sum of the location specific profits:

$$\Pi_i(G_{it}; G_{jt}, X_t) = \sum_{l \in \mathcal{L}} \pi_{ilt}(G_{it}; g_{jlt}, x_{lt})$$

Finally, the location profit, $\pi_{ilt}(G_{it}; g_{jlt}, x_{ilt})$, is given by:

$$\pi_{ilt}(G_{it}; g_{jlt}, x_{ilt}) = \sum_{h \in \mathcal{H}_l} p_{lh} \cdot \lambda_{ilht}\left(p_{lh}, g_{ilt}, g_{jlt}, \mathbf{b_{lht}}\right) - c_{il}(G_{it}; X_t, \boldsymbol{\theta_i})$$

Supply model - cost of supply changes

Cost depends on location specific factors and on the actions in other locations:

$$c_{il}(G_{it}; X_t, \theta_{\mathbf{i}}) = |g_{ilt} - s_{ilt}| \cdot \left(\underbrace{\theta_{i1} \cdot \kappa_{il}}_{\text{Proximity to warehouse}} + \underbrace{\theta_{i2} \cdot \sum_{m \neq l} \frac{\mathbb{1}_{\{g_{imt} \neq s_{imt}\}}}{\delta_{l,m}}}_{\text{Economies of density}} + \underbrace{\theta_{i3} \cdot \mathbb{1}_{\{g_{ilt} < s_{ilt}\}} \cdot d_{ilt}}_{\text{Hours since last trip}} + \eta_{ilt} \right)$$

κ_{il} = distance between location l and firm i's warehouse

$\delta_{l,m}$ = distance between locations l and m

d_{ilt} = time (in hours) since last trip in l using i

η_{ilt} = unobserved cost shock in location l, for firm i, at period t

From best-responses to moment inequalities

- Focus on the **last period T** to deal with the high dimension of the action space
- Compare observed decisions with **pairs** of deviations:

$$\tilde{g}_{ilT} = g^*_{ilT} - k \text{ and } \tilde{g}_{il'T} = g^*_{il'T} + k$$

- If the observed actions are an **equilibrium** of the game, G^*_{iT} is a **best-response**:

$$\Pi_{iT}(G^*_{ilT}; G^*_{jT}, X_T) - \Pi_{iT}(G^*_{ilT} \setminus \{g^*_{ilT}, g^*_{il'T}\} \cup \{\tilde{g}_{ilT}, \tilde{g}_{il'T}\}; G^*_{jT}, X_T) \geq 0$$

- Taking the expectation across all deviations w.r.t. observed actions gives moment inequalities that identify a set of feasible values for θ_i

Details inequalities

Selection bias in moment inequalities

Observed actions depend on unobservables η_{ilt}, creating a **selection bias** ▸ Additional details

Instruments: select deviations where η_{ilt} is less important for the firm's decision

For supply increases:

- Locations in the higher 40% of the rival's warehouse distance distribution
  - Independent of unobservables, less likely to have competition (higher rival costs)

For supply decreases:

- Bottom 40% of the rival's warehouse distance distribution
  - Rival's cost advantage, similar intuition as above

▸ Cost advantage from warehouses' locations ▸ Confidence region - Chernozhukov et al. (2019)

Cost estimates

Variable	Bird		Spin	
Distance to warehouse θ_{i1} (\$/km)	[0.27, 0.65]		[0.03, 0.47]	
Density θ_{i2} (\$)	[-0.5, -0.02]		[-0.27, -0.01]	
Hours since last trip θ_{i3} (\$/hr)	[-0.52, -0.1]		[-0.17, -0.02]	
Mean of draws from the confidence region	Increase	Decrease	Increase	Decrease
Cost per scooter (\$)	1.83	1.26	2.08	1.62
Density savings per scooter (%)	-25.85	-22.61	-7.74	-6.84

Mean cost and savings computed using 100000 draws from the identified set and using the observed actions of both firms.

- Schellong et al. (2019) estimate the "operations and charging" costs per scooter to be 1.7$
- Heineke et al. (2020) estimate the "relocation" costs per scooter to be between 1.3$ and 2.5$

▸ Mean cost distribution across observed actions ▸ Mean cost distribution across parameters' draws

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Overview

Scenarios:

- Compare competitive equilibrium with monopolist and social planner
- Compare with outcomes after lifting the imposed capacity constraint
- Monopolist with minimum supply quota and subsidies for low income areas

Setup:

- Use mean of draws from confidence region for cost function
- Approximate each period's value function separately (Arcidiacono et al. 2013)
- LASSO to select relevant state variables for approximation ▸ Details value function approximation

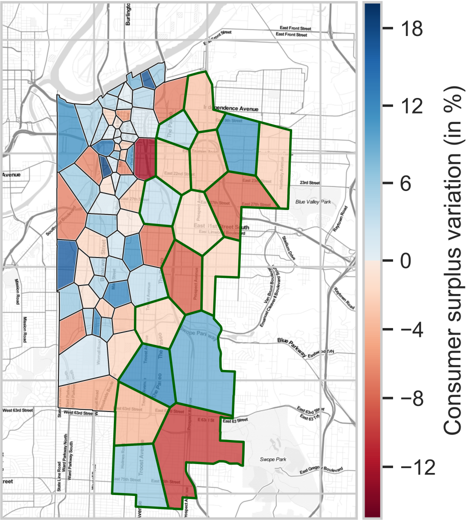
Policy analysis - aggregate outcomes

	Δ Welfare	Δ CS	Δ profit	Δ demand
Total variation w.r.t. observed equilibrium				
Monopolist	222.3	81.8	140.5	25 673
Social planner	222.4	91.3	131.1	28 066
Additional improvement if no capacity constraints				
Monopolist	284.0	79.7	204.3	24 707
Social planner	293.2	84.3	208.9	26 432

In thousands $ for welfare, CS, and profits; in number of trips for demand.

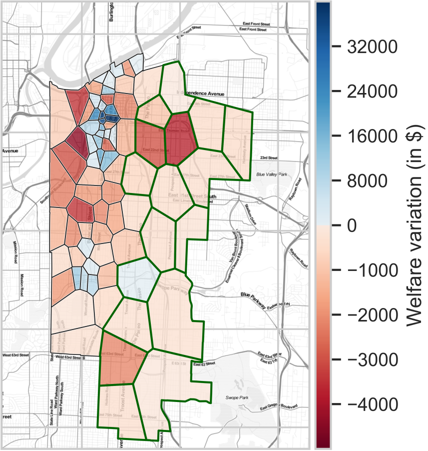
- The capacity constraints have an implied cost of 284 thousand dollars
    - **Important**: Does not include externalitites such as sidewalk clutter or accidents

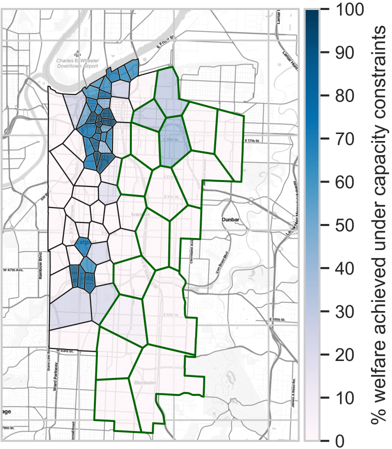
Consumer surplus differences between monopolist and social planner



Note: Area with green border corresponds to low income areas (LifeX) as defined by Kansas City's town-hall.

Welfare variation under the monopolist





Change w.r.t. initial state

Role of capacity distortions

Note: Area with green border corresponds to low income areas (LifeX) as defined by Kansas City's town-hall.

▸ Temporal distribution of supply changes

Policies for distributional concerns

Policies targeting low income areas (LifeX):

- Minimum % from each brand's capacity has to be deployed in LifeX (10%)
- Subsidize price paid by consumers for trips starting in LifeX (10 and 20%)

	Min. supply quota	**Subsidy to consumers**	
	10%	**10%**	**20%**
Δ welfare	-76 269.1	8 806.6	15 151.0
Δ profit	-78 488.2	7 018.4	13 762.5
Δ CS LifeX locations	7 534.8	2 288.5	6 540.0
Δ demand LifeX locations	981.6	331.3	937.8
Cost policy	0	1585.4	4580.8

Welfare and consumer surplus variations in dollars. Demand variation in number of trips. Welfare accounts for the policy's cost.

Conclusion

- Build and estimate model that captures role of capacity constraints, economies of density, and dynamic-spatial externalities
- Trade-offs when regulating market structure:
  - Monopolist improves welfare in high demand areas at the cost of the rest of the city
  - Competition leads to better coverage across the city
- Imposed capacity constraints generate regressive welfare distortions across space
- Results apply to all types of vehicle rentals such as electric bikes and car sharing

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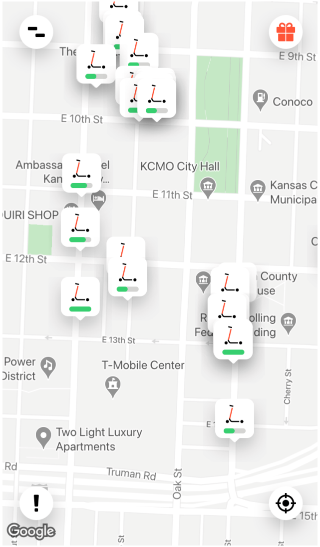
Service illustration



Back

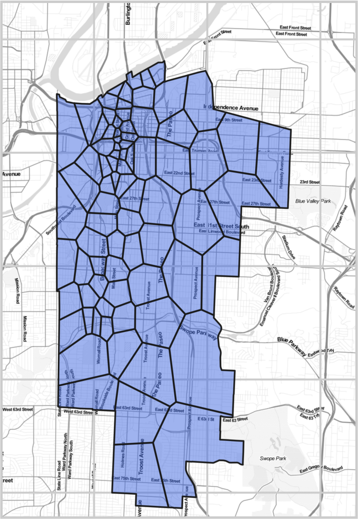
Firms' actions across periods of the day

	Increase		Decrease	
Period	% Covered	# vehicles	% Covered	# vehicles
2am to 6am	6.7	2.7	14.8	-2.0
6am to 10am	9.8	2.9	17.1	-1.9
10am to 2pm	13.6	4.0	19.4	-2.7
2pm to 6pm	14.5	4.4	18.1	-3.5
6pm to 10pm	12.9	5.0	19.6	-4.4
10pm to 2am	11.1	4.1	16.3	-4.1

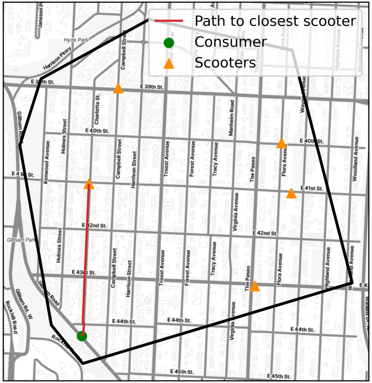
Note: Average % of city locations where a positive (negative) action leads to a positive (negative) increase in the supply after accounting for net incoming trips. Average # vehicles per action computed using only locations where an action took place.

▸ Back

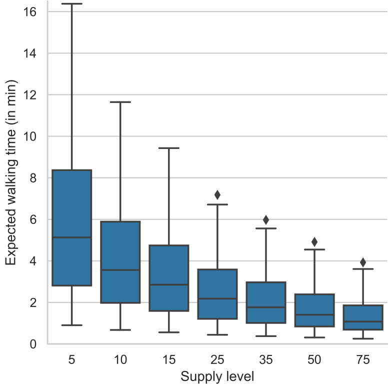
K-means voronoid cells (80 locations)



Simulating the walking time to the closest scooter



(a) Example walking time simulation

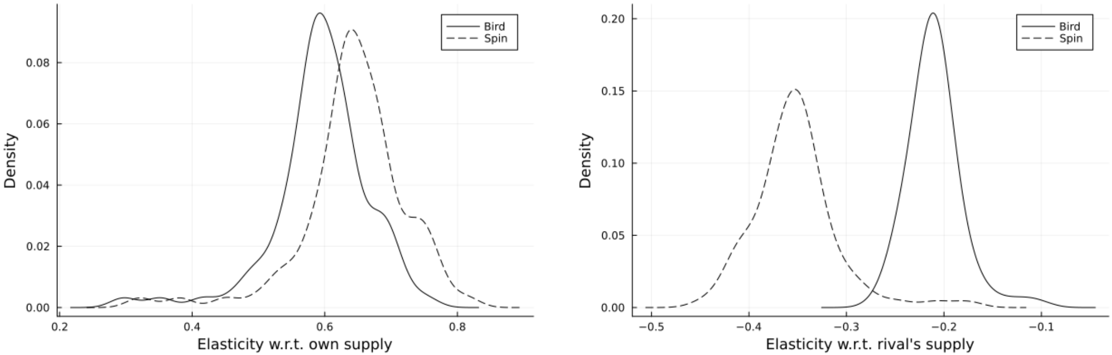


(b) Dispersion estimated walking times

1. Compute walking times for a large set of simulated distributions
2. Estimate mapping using OLS: $ln(w_l) = \beta_{0l} + \beta_{1l} ln(g_l + 1) + \eta_l$

▸ Back 1 ▸ Back 2

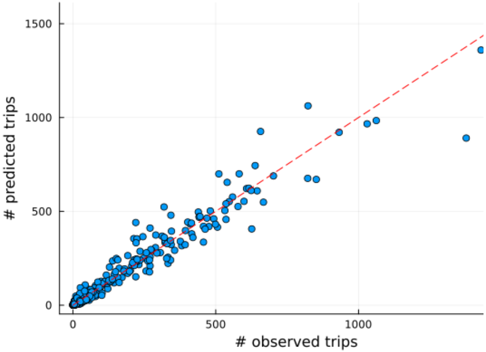
Spatial distribution of demand elastiticities w.r.t. supply



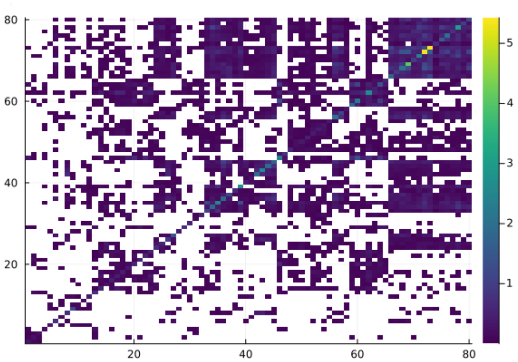
Note: The figures show the kernel density estimated distribution of elasticities across all locations in the city.

Back

Fit demand predictions



(a) Total predicted vs actual number of trips per location and period



(b) Root MSE per origin destination

Back

Inequalities

Upper bound:

$$\sum_{h \in \mathcal{H}_l} p_{lh} \cdot \Delta\lambda_{ilhT}\left(g^*_{ilT}, g^*_{ilT} - k\right) - \sum_{h \in \mathcal{H}_{l'}} p_{l'h} \cdot \Delta\lambda_{il'hT}\left(g^*_{il'T} + k, g^*_{il'T}\right) \geq$$

$$\Delta c_{ilT}\left(g^*_{ilT}, g^*_{ilT} - k; \boldsymbol{\theta_i}\right) - \Delta c_{il'T}\left(g^*_{il'T} + k, g^*_{il'T}; \boldsymbol{\theta_i}\right) + k(\eta_{lT} - \eta_{l'T})$$

Lower bound:

$$\Delta c_{il'T}\left(g^*_{il'T} - k, g^*_{il'T}; \boldsymbol{\theta_i}\right) - \Delta c_{ilT}\left(g^*_{ilT}, g^*_{ilT} + k; \boldsymbol{\theta_i}\right) \geq$$

$$\sum_{h \in \mathcal{H}_{l'}} p_{l'h} \cdot \Delta\lambda_{il'hT}\left(g^*_{il'T} - k, g^*_{il'T}\right) - \sum_{h \in \mathcal{H}_l} p_{lh} \cdot \Delta\lambda_{ilhT}\left(g^*_{ilT}, g^*_{ilT} - k\right) + k(\eta_{l'T} - \eta_{lT})$$

Where $\Delta\lambda_{ilht}\left(a, b\right) = \lambda_{ilht}(a, g_{jlt}) - \lambda_{ilht}(b, g_{jlt})$ and $\Delta c_{ilt}\left(a, b; \boldsymbol{\theta_i}\right) = c_{ilt}(a; \boldsymbol{\theta_i}) - c_{ilt}(b; \boldsymbol{\theta_i})$

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Selection bias in moment inequalities - details

Assume unobserved term can be decomposed: $\eta_{ilT} = \eta_{lT} + \eta_{iT}$

Defining $\Delta\Pi_{ill'T}(\boldsymbol{\theta_i})$ as the observed part of the moment inequalities:

$$\mathbb{E}\left[\mathbb{1}_{\{g^*_{ilT} - s_{ilT} - k > 0\}} \cdot \mathbb{1}_{\left\{g^*_{il'T} - s_{il'T} - k > 0\right\}} \cdot \left(\Delta\Pi_{ill'T}(\boldsymbol{\theta_i}) - k(\eta_{l'T} - \eta_{lT})\right)\right] \geq 0$$

Identification requires: $\mathbb{E}\left[\mathbb{1}_{\{g^*_{ilT} - s_{ilT} - k > 0\}} \cdot \mathbb{1}_{\left\{g^*_{il'T} - s_{il'T} - k > 0\right\}} \cdot k(\eta_{l'T} - \eta_{lT})\right] = 0$

Add a selector, $\Psi_{ll'w}$ such that observations chosen verify $\mathbb{E}\left[\eta_{l'T} - \eta_{lT} | \Psi_{ll'Tw}\right] = 0$

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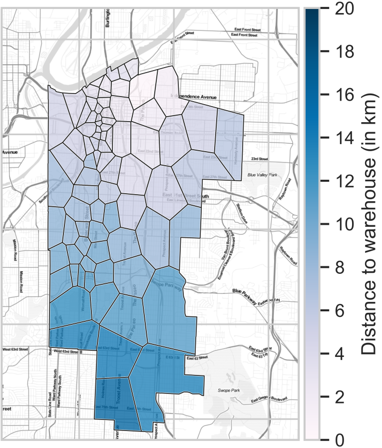
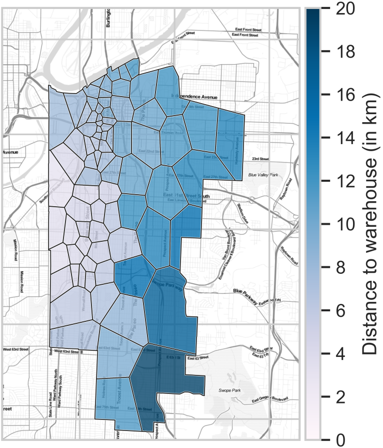
Distance to warehouse



Bird



Spin

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Confidence region

- Following Chernozhukov et al. (2019) for each candidate of parameters $\boldsymbol{\theta_i} = (\theta_{i1}, \theta_{i2}, \theta_{i3})$ the test statistic is defined as:

$$T_i(\boldsymbol{\theta_i}) = \max_{p \in \mathcal{P}} \left\{ \frac{\sqrt{N_p}\bar{m}_p(X_{lt}, \theta_i)}{\hat{\sigma}_p} \right\}$$

- Least favorable critical value for the test is given by:

$$\hat{c}_i^{lf}(1-\alpha, \boldsymbol{\theta_i}) = \frac{\Phi^{-1}(1-\alpha/3)}{\sqrt{(1-\Phi^{-1}(1-\alpha/3)^2)/N_p}}$$

- The confidence region corresponds to parameter candidates such that:

$$CR_i = \left\{ \boldsymbol{\theta_i} : T_i(\boldsymbol{\theta_i}) \leq \hat{c}^{lf}(1-\alpha, \theta) \right\}$$

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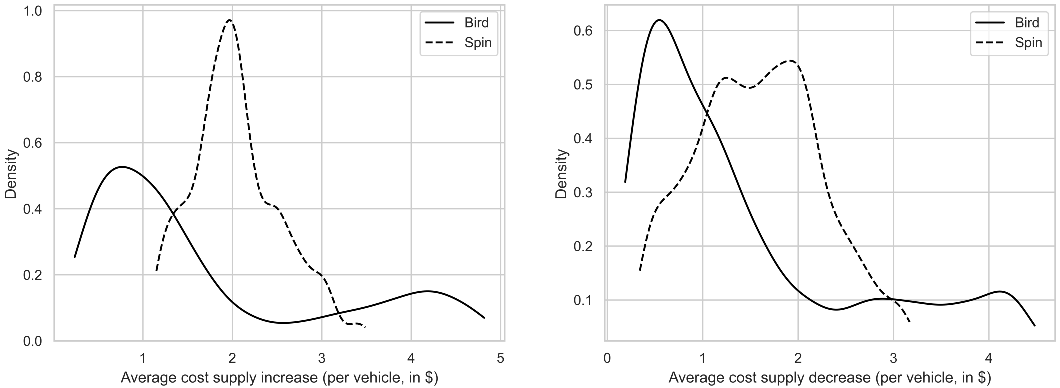
Distribution cost per vehicle across observed actions



Note: Cost per vehicle computed using the mean of draws from the confidence region.

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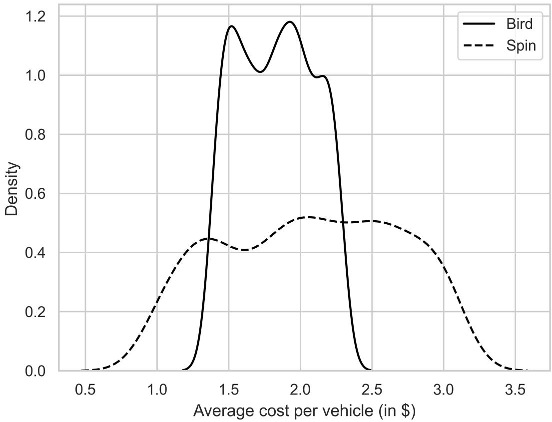
Distribution of mean cost of observed actions across parameters' draws



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Counterfactuals computation

- Need to approximate the high dimensional value function for each time horizon (Arcidiacono et al 2013)
- Go backwards: solve the model for many perturbations of observed states
- Approximate by: $V_t(X_t) = b_t(X_t)'\rho_t + \xi_t$

$$V_t(X_t) = \rho_t \cdot b_t(X_t) = \max_{G_{it}, G_{jt}} \left\{ F_t(G_{it}, G_{jt}; X_t) + \beta \mathbb{E}\left[b_{t+1}(X_{t+1})'\rho_{t+1} | G_{it}, G_{jt}, X_t \right] \right\}$$

$$\text{s.t.} \sum_{l \in \mathcal{L}} g_{ilt} = Capacity_{it} \text{ and } \sum_{l \in \mathcal{L}} g_{jlt} = Capacity_{jt}$$

- Very large state space: Select basis $b_t(X_t)$ using LASSO and OLS estimates of ρ_t (Kalouptsidi 2018)

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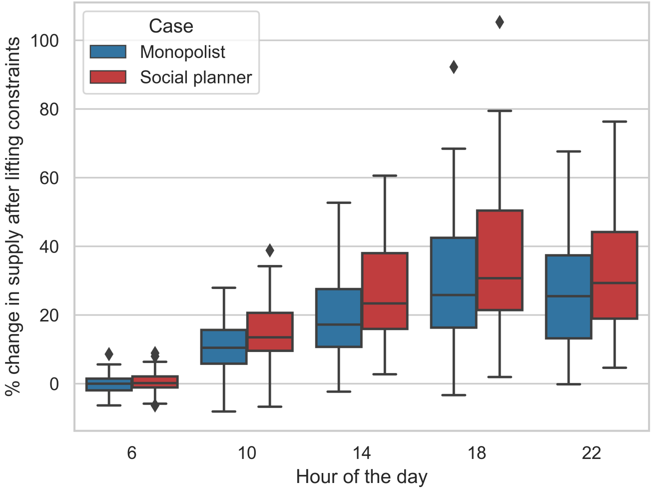
Temporal distribution of supply changes without capacity constraints



Note: Box plot of the distribution, across all periods and days, of supply changes when capacity constraints are lifted.

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