

Role of Bicycle Sharing System Infrastructure on Usage: Evidence from Montreal



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Overview

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- Conclusion

Introduction

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□ Bicycle-Sharing Systems (BSS)

- a service in which bicycles are made available for shared use to individuals on a short term basis
- more than 500,000 public bicycles around the world and more than 500 cities have installed or planning to install a bicycle-sharing system



Wuhan, China
90,000 bicycles
1318 stations



Paris, France
20,600 bicycles
1451 stations



New York, US
6,000 bicycles
332 stations

Introduction

- Benefits
 - ▣ Flexible mobility
 - ▣ Physical activity benefits
 - ▣ Support for multimodal transport connections
 - ▣ Does not have the costs and responsibilities associated with owning a bicycle for short trips
 - ▣ No need to secure bicycles
 - ▣ The decision to make a trip by bicycle can be made in a short time frame

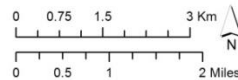
Introduction

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- ❑ **BIXI** (**B**icycle and **taXI**) installed in 2009
- ❑ Began with 3000 bicycles and 300 stations
- ❑ In 2012, 410 stations, more than 4000 bicycles
- ❑ More than 3.4 million trips in the 2010 season



- ★ Downtown Area
- Bixi Stations
- Major Streets
- Water Bodies



Data Sources:
DMTI street center line files
Bixi online system

Coordinate System: NAD 1983 MTM 8



Earlier Studies

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- Relatively very few studies on BSS

- Feasibility analysis
 - proposing different BSS for different cities
 - for example see Gregerson et al., (2010)

- User behavior studies
 - survey data rather than actual bicycle flows
 - BIXI studies:
 - Bachand-Marleau et al. (2011, 2012), Fuller et al., (2011).

Earlier Studies

- Few quantitative studies on bicycle-sharing systems employing actual bicycle usage data
 - Nair et al. (2013) - Velib' bicycle-sharing system in Paris, France.
 - Buck and Buehler (2012), Daddio (2012) - Capital Bicycle-sharing system in Washington.
 - Krykewycz et al. (2010) estimated demand for a proposed BSS for Philadelphia using observed bicycle flow rates in European cities.
 - Rixey (2013) - three different cities in the US.
 - Wang et al. (2012) – twin cities, Minnesota , US.

Earlier Studies

- Problems:
 - Aggregated bike flows (Monthly or yearly)
 - Neglect variations in the short terms
 - Cannot provide the operators the bicycle demand profiles including excess and shortage information
- Hampshire et al. (2013) – Barcelona and Seville – Hourly rates, at SCD level
- Gebhert and Noland (2013) - Capital Bicycle-sharing system in Washington – Hourly rates and Station level, but only exploring weather impact on flows and usage
- Faghieh-Imani et al. 2014 recently used hourly data and concluded that bicycle infrastructure (number of stations and capacity) have a substantial influence on BSS usage

Motivation

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- Growing installation of BSS
 - What are the contributing factors on usage?
 - Bicycle infrastructure
 - Land use and urban form attributes
 - Temporal characteristics

- However, these studies ignore the potential impact of the decision to install BSS infrastructure
 - The current infrastructure (No. of stations and capacity) are not randomly assigned

Motivation

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- Impact of the decision to install BSS infrastructure (number of stations and capacity) on usage
 - the BSS infrastructure installed is based on expected bicycle usage patterns
 - the BSS usage models consider the bicycle flows as the dependent variable and BSS infrastructure as an independent variable
 - the measured dependent variable is closely tied to one of the independent variables BSS infrastructure
 - a classic violation of the most basic assumption in econometric modeling
 - the dependent variable is not correlated with the exogenous variables

Objective

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- Capturing the potential impact of the decision to install BSS infrastructure:
 - consider the bicycle infrastructure installation itself as a dependent variable - simultaneously along with usage patterns
 - consider the impact of common unobserved variables influencing infrastructure installation and usage patterns
 - → a joint modelling process
- Gives rise to the classic endogeneity problem
- In this study, we examine self-selection in the context of BSSs

Data

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- From the BIXI website
 - Bicycles/docks availability at each station for every minute
 - Station capacity and location
 - Records from April to August 2012

- The minute by minute arrival or departure rates

- Aggregate to 5min level for consideration of rebalancing operation
 - A heuristic mechanism to capture removal/refill operations

Data

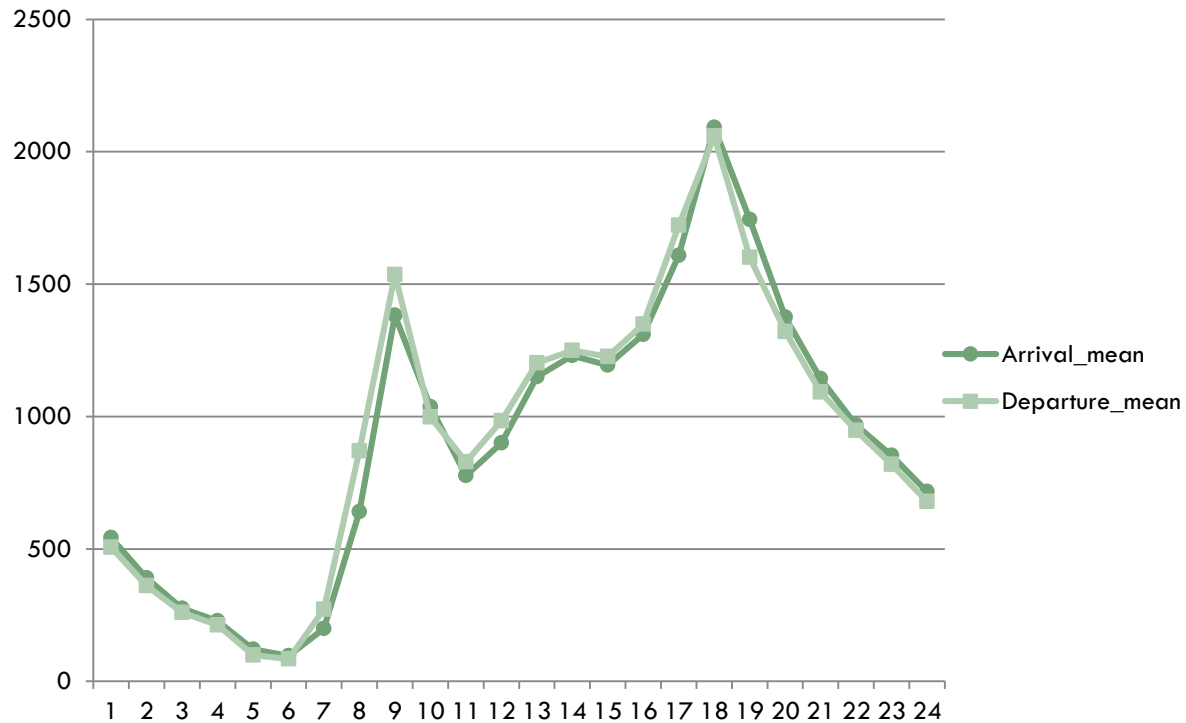
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- Consideration of rebalancing operation
 - a rebalancing operation has occurred if the 5-minute arrival/departure rate is greater than the 99th percentile arrival/departure for that station
 - when such a trigger is identified, the actual bicycle flow for this 5-minute period is obtained by averaging the bicycle flow rates of the two earlier 5-minute periods and the remainder of the flow is allocated to the rebalancing operation
 - Example: for station1 these are arrivals for every 5minutes
 - Arrivals: ..., 2, 0, 3, 5, 2, 20, 4, 2, ...
 - 99 percentile rate is 12, rebalancing is identified → true arrivals: $(3+5)/2=4$, the refill flows: $20-4=16$ bikes
- Obtain “true” arrival or departure rates
- Aggregate to an hourly level rates

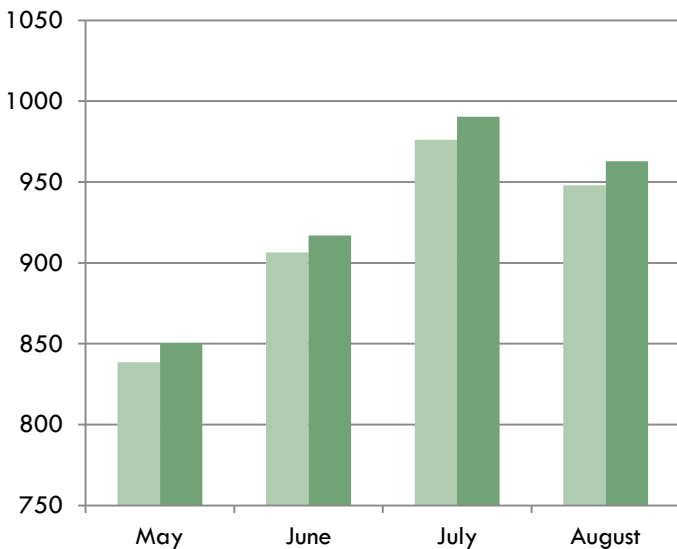
Data

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- hourly arrival and departure rates for every station
- May, June, July and August 2012



■ Arrival_mean
■ Departure_mean



Data

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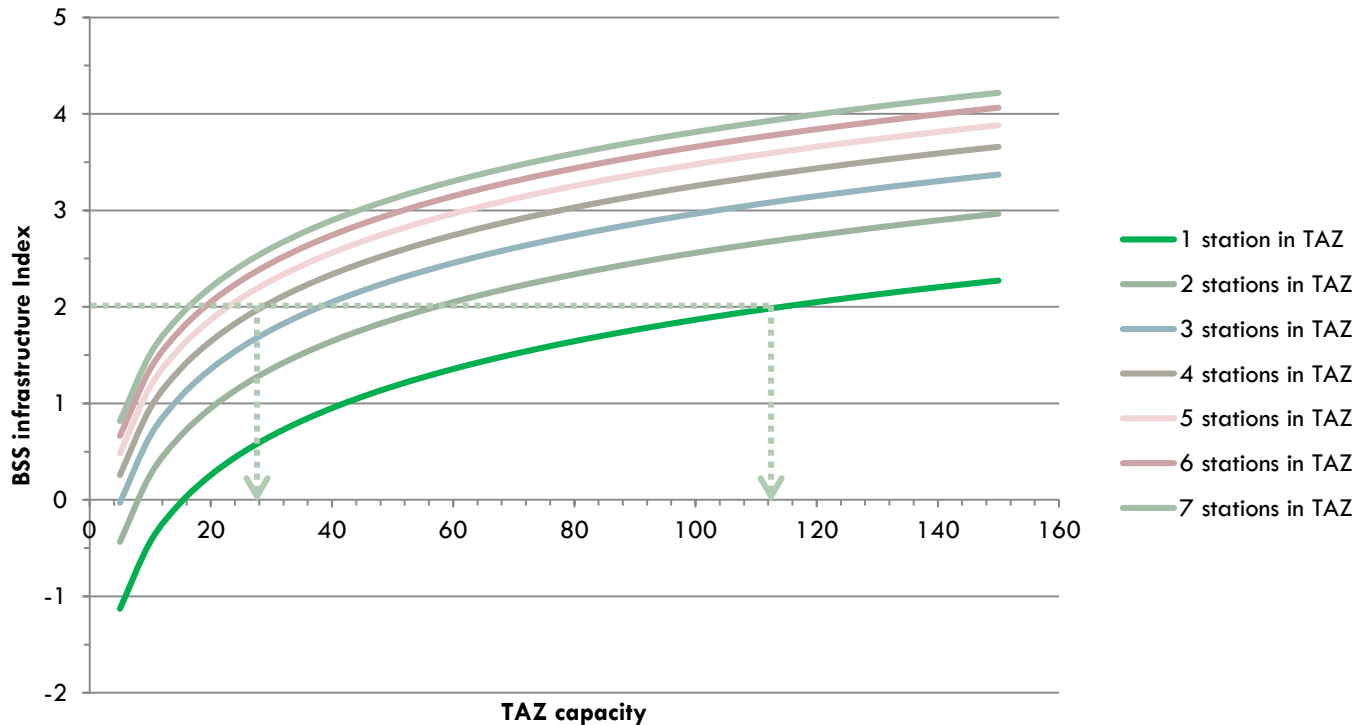
- TAZ level flows: adding arrival and departure flows of all the stations in one TAZ
- 5 time periods: AM (6-10), Midday (10-16), PM(16-20), Evening (20-24), and Night (24-6)
- Randomly select seven consecutive days for every TAZ
- The final sample: 8225 records (5 time periods * 7 days * 235 TAZs) of arrivals and departures at TAZ level

- What should represent BSS infrastructure? Number of Stations or Capacity of Stations?

Data

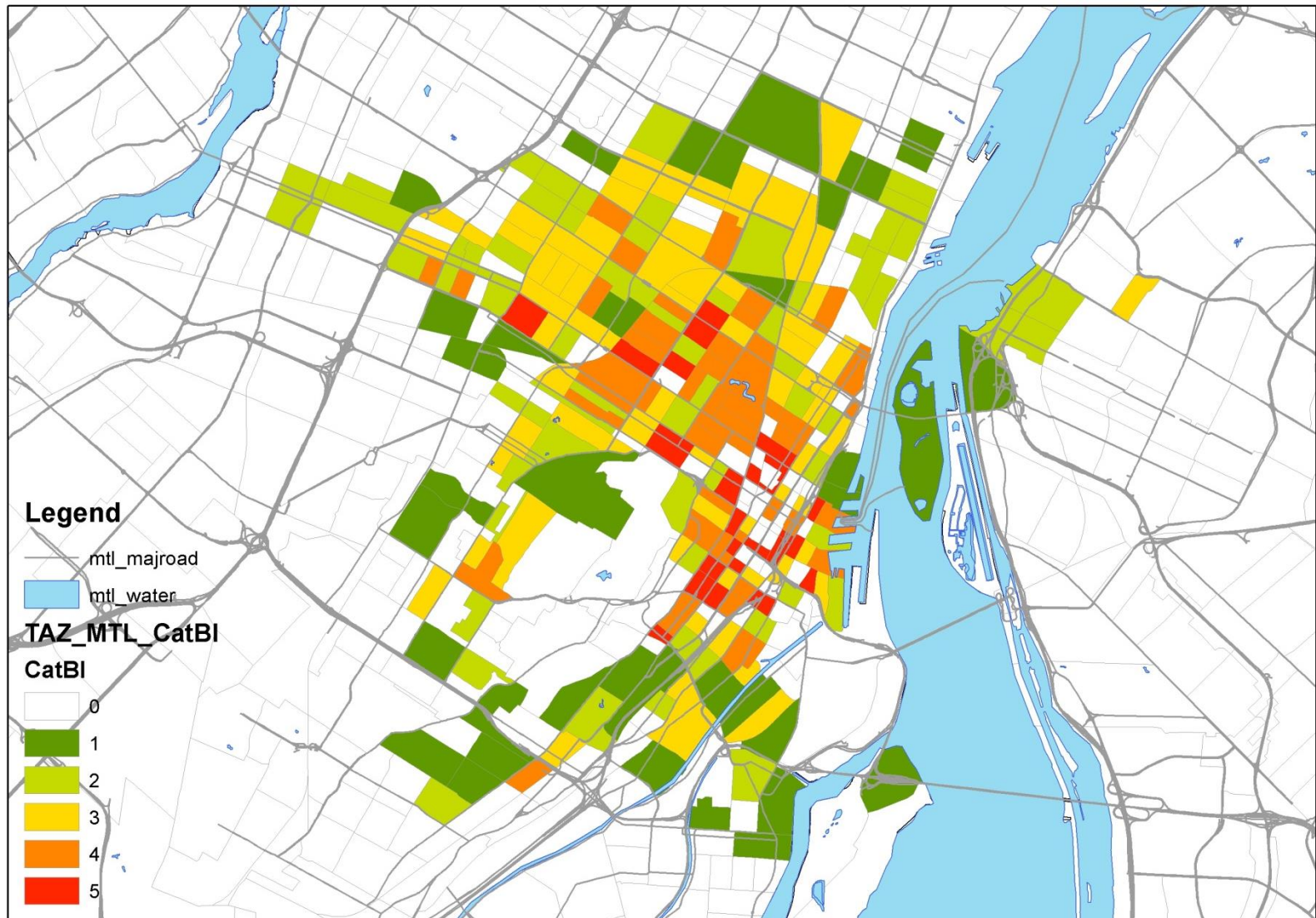
□ BSS infrastructure (BSSI) variable

$$BSSI = \ln\left(\frac{\text{Number of Stations in TAZ}}{\text{Average Number of Stations in TAZ}} \times \frac{\text{TAZ Capacity}}{\text{Average TAZ Capacity}} \times \frac{1}{\text{TAZ area}}\right)$$



BSS infrastructure (BSSI) variable

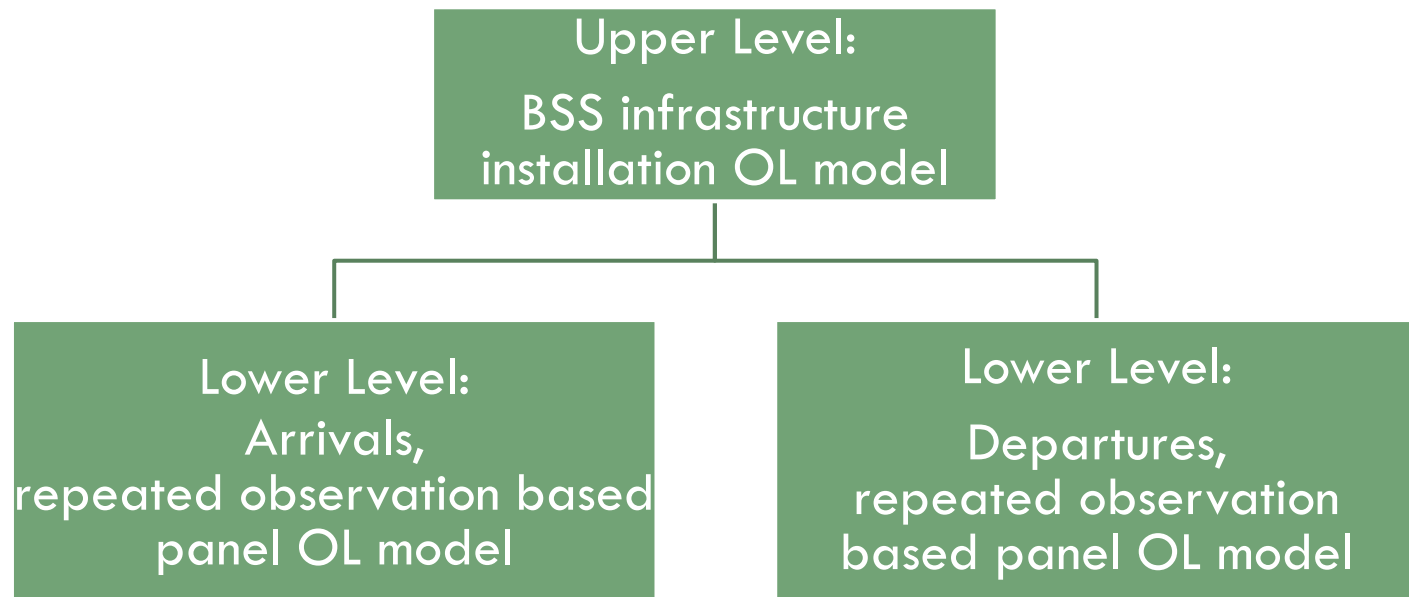
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Methodology

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- Econometric framework: a 3 dimensional panel ordered formulation



- BSS infrastructure installation: a one-time decision process
- Arrivals and Departures: repeated observations

Methodology

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- (1) BSS installation $u^*_q = (\beta' + \gamma'_q)x_q + \eta_q x_q + \varepsilon_q$, $u_q = j$ if $\psi_{j-1} < u_{qt} < \psi_j$
- (2) Arrivals $y^*_{qt} = (\alpha' + \delta'_q)f_{qt} \pm \eta_q x_q \pm v_q f_{qt} + \xi_{qt}$, $y_{qt} = k$ if $\omega_{k-1} < y^*_{qt} < \omega_k$
- (3) Departures $z^*_{qt} = (\tau' + \lambda'_q)f_{qt} \pm \eta_q x_q \pm v_q f_{qt} + \zeta_{qt}$, $z_{qt} = l$ if $\omega_{l-1} < z^*_{qt} < \omega_l$

Where:

- q is an index to represent TAZ
- t is an index to represent Time
- x and f represent independent elements in models
- β , α , τ represent corresponding vector of mean effects of the elements
- γ , δ , λ represent vector of unobserved factors moderating the influence of attributes in corresponding vector
- η captures unobserved factors that simultaneously impact BSS installation and arrivals/departures
- v captures unobserved factors that simultaneously impact arrivals and departures for a TAZ
- ε , ξ , ζ are idiosyncratic random error terms assumed to be identically and independently standard gumbel distributed across TAZs

Dependent Variable

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- First-level Model, BSS infrastructure model
 - BSS infrastructure (BSSI) variable
 - 5 Categories

- Second-level Model, BSS flows models
 - TAZ bicycle arrival and departure rates
 - 4 Categories
 - Zero, Low rates (1-5), Medium (6-10), High (+10)

Independent Variables

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- Weather:
 - hourly temperature, relative humidity, and hourly weather condition (rainy or not)

- Time:
 - time of day: morning (6AM-10AM), mid-day (10AM-3PM), PM (3PM-7PM) evening (7PM- 12AM)
 - day of the week: weekend or weekday
 - Friday and Saturday night: to account for young individual users

Independent Variables

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- Land-use and built environment:
 - The length (or length/area) of bicycle facilities (including bicycle lanes, bicycle paths etc.), the length of streets and major roads in TAZ
 - Average distance of TAZ to CBD
 - Number of metro and bus stations and length of railroads and bus lines in TAZ
 - Points of interest:
 - Restaurants
 - Commercial enterprises
 - Universities
 - TAZ population and job density

Sample Characteristics

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<u>Continuous Variables</u>	Min	Max	Mean
Number of BIXI stations in TAZ	1	6	1.74
Capacity of BIXI stations in TAZ	11	141	34.07
Station Capacity	7	65	19.53

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Results

Models estimated

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- We estimate two models
 - Model 1: 3 independent OL models
 - Model 2: 3POL model for BSSI, arrivals and departures

- Goodness of fit measures:
 - Mean Log likelihood
 - Model 1 -14725.2
 - Model 2 -11549.3

- Clearly the model that recognizes BSS infrastructure installation process performs better.

Results – Joint Model

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- BSS Installation Model:
 - Bicycle Facility Density ↑
 - Metro stations in TAZ ↑
 - Downtown ↑
 - Number of Restaurants in TAZ ↑
 - TAZ Job Density ↑
 - TAZ Pop Density ↑

 - Highway Density ↓
 - Rails length ↓
 - Distance to CBD ↓

Results – Joint Model

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- Both Arrival and Departure:
 - Weather:
 - Temperature ↑
 - Relative Humidity ↓
 - Rainy Weather ↓
 - Time:
 - PM ↑
 - Night ↓
 - Weekend ↓

Results – Joint Model

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- Both Arrival and Departure:
 - Land-use and built environment:
 - Bicycle Facility Density ↑
 - Metro Station ↑
 - Number of Restaurants in TAZ ↑
 - BSS infrastructure ↑
 - Highway Density ↓
 - Distance to CBD ↓

Results – Joint Model

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□ Arrival and Departure Specific Variables:

Parameter	Arrival Rate		Departure Rate	
	Estimate	t-statistic	Estimate	t-statistic
University in TAZ * AM	0.6977	3.022	-0.7636	-3.277
University in TAZ * PM	-0.4355	-2.016	0.6948	2.784
TAZ Job Density * AM	0.9486	14.035	-0.3332	-4.882
TAZ Pop Density * AM	-9.5456	-9.003	9.628	7.93
TAZ Pop Density * PM	-	-	-6.5949	-4.527

Policy Exercise

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Marginal Effects for TAZ Arrival and Departure Rates

3OL Model	Arrival Rate			
Scenario	Zero	Low	Medium	High
Number of Station +5, Capacity constant	-7.184	1.048	6.969	7.125
Capacity +25, Number of Stations constant	-7.144	1.362	6.729	5.993
Number of Station +3, Capacity +15	-11.640	2.557	10.167	9.498
Pop Density +25%	0.974	-0.162	-0.819	-1.071
Job Density +25%	0.012	0.055	-0.101	-0.126
Bicycle Facility Density +25%	-3.014	-0.156	2.367	6.443
3POL Model				
Scenario	Zero	Low	Medium	High
Number of Station +5, Capacity constant	-6.054	0.457	5.749	6.923
Capacity +25, Number of Stations constant	-5.882	0.694	5.752	4.715
Number of Station +3, Capacity +15	-9.788	1.727	7.581	8.590
Pop Density +25%	1.253	-0.233	-0.890	-1.200
Job Density +25%	-0.039	-0.108	-0.140	1.170
Bicycle Facility Density +25%	-4.753	-0.331	3.572	11.252

Policy Exercise - Findings

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- Ignoring the installation decision results in over prediction of BSS infrastructure impact on usage
- Increase in the number of stations without increasing capacity in the TAZ has greater impact than increasing capacity by as much as an average station
 - ▣ reallocate very large stations as smaller stations with lower capacity in multiple locations to increase BIXI system usage
- Increasing bicycle facilities density (bike lane, etc.) has a significant positive impact on BSS usage

Conclusion

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- Growing installation of BSS across the world
 - need more studies
- Determining accurately the contribution of various factors to BSS usage at TAZ level:
 - meteorological data
 - temporal characteristics
 - bicycle infrastructure
 - land use and urban form attributes

Conclusion

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- Ignoring the installation decision lead to over prediction of BSS infrastructure impact on usage and reduce precision of estimation
 - use of more advanced econometric models
 - Adding a BIXI station has a predominantly stronger impact on bicycle flows compared to increasing station capacity
 - adding additional stations
 - reallocating existing capacity from large stations to multiple small size stations
 - or adding new bicycle slots
- is more beneficial in terms of BSS usage compared to adding capacity to existing stations

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Thank You!

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Questions?

