

BIKE SHARE TRIP GENERATION IN TWIN CITIES

MEASURING EQUITY OF ACCESS TO BIKE SHARE

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**HUMPHREY SCHOOL
OF PUBLIC AFFAIRS**

UNIVERSITY OF MINNESOTA

Driven to DiscoverSM

Background of Bike Share Programs

- Diversify transportation options
 - increase physical activity
 - bring environment benefits
 - reduce traffic congestion
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- Fairness
 - Understand demand

Bike Share Recent Growth

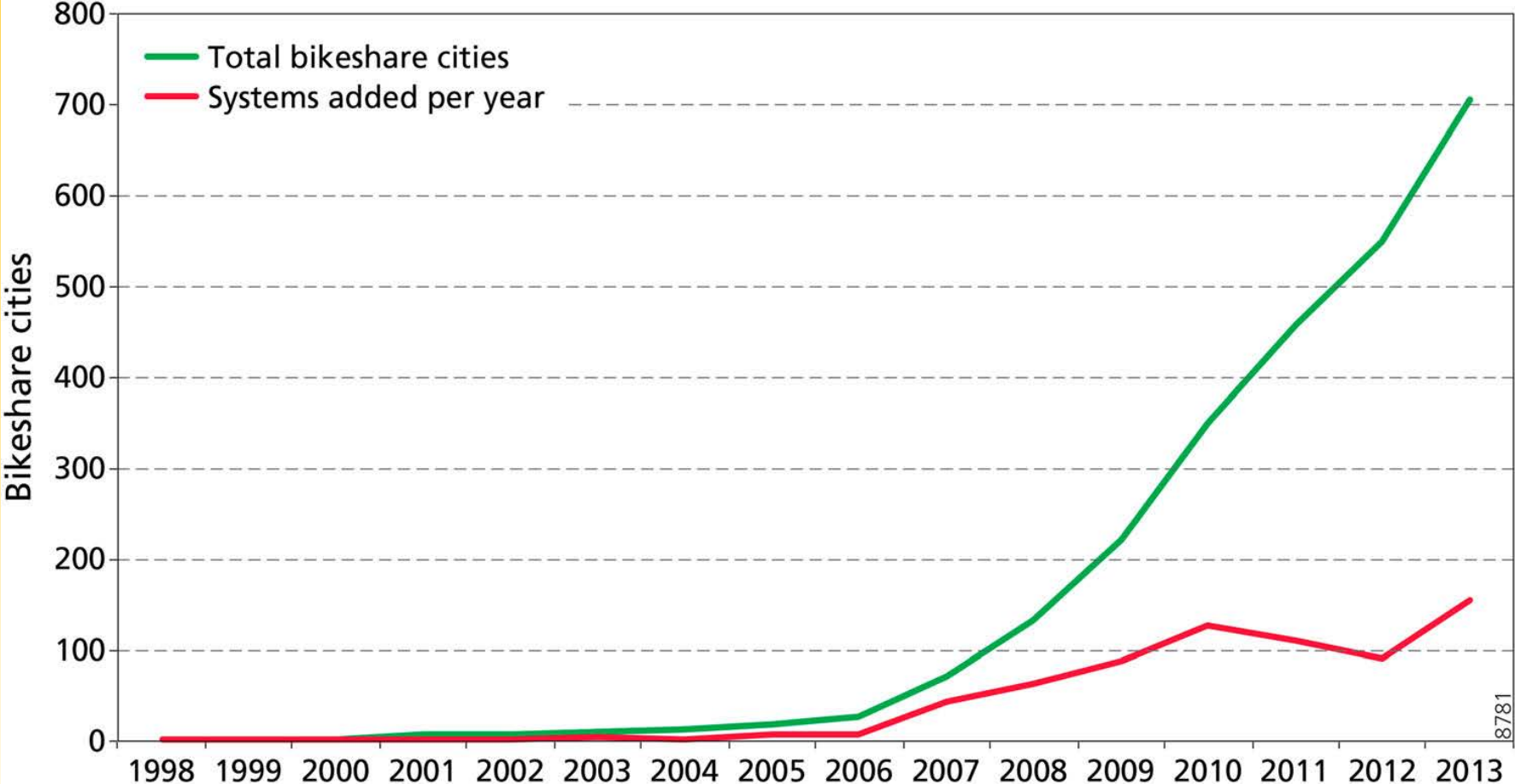


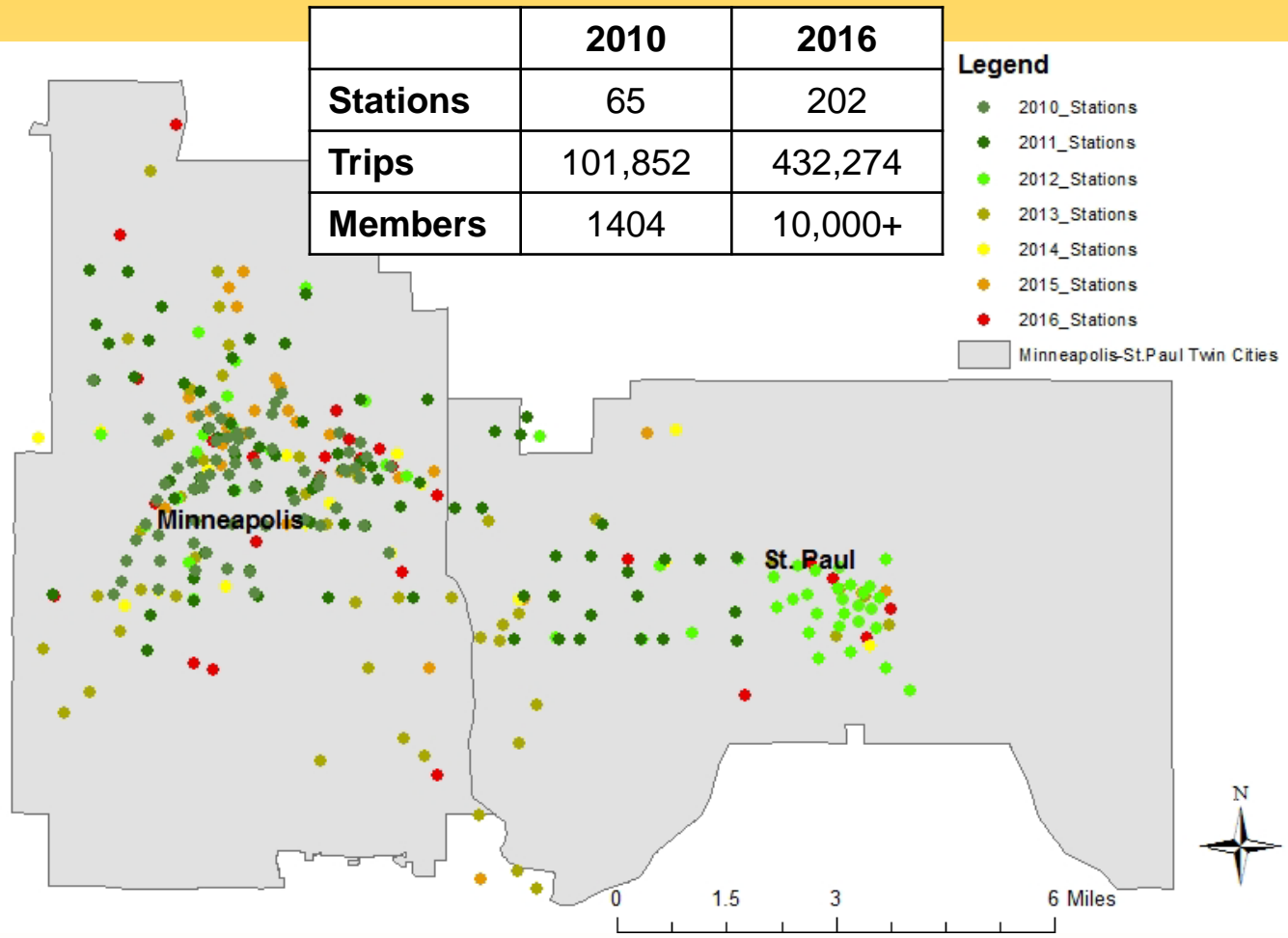
Figure 1: Global Bike Share Growth

Source: Meddin 2014

<http://bikes.oobrien.com/global.php#zoom=4&lon=-223.0972&lat=33.8346>

Nice Ride Bike Share System In Twin Cities

- Began in 2010, initially with 65 stations
- concentrated in downtown Minneapolis, commercial areas and the U
- Began to extend to North Minneapolis and St. Paul in 2011 and 2012



Some Descriptive Information About Nice Ride In Twin Cities

- Registration is highest in April 2015
- Males and females comparatively have similar proportion of memberships;
- Annual members are more likely to be young;
- Most of annual members live in the city of Minneapolis compared to the city of St. Paul

of registrations by Month



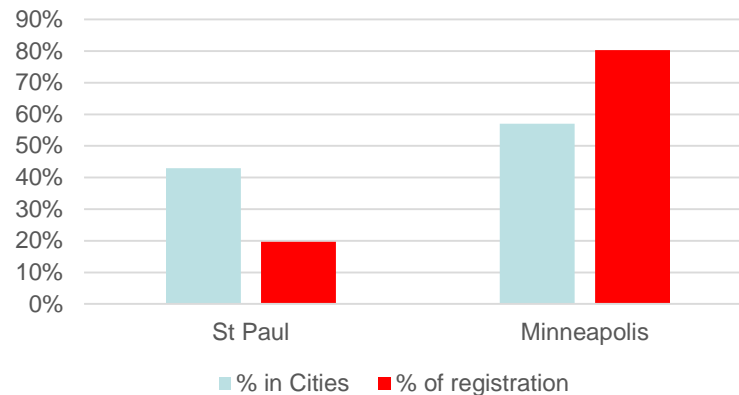
% Pop by Gender



% Pop by Age



% Pop by Locations



Correlates of Daily Bike Share Trip Generation

Previous studies	Our approaches
<p>Modeling Approaches:</p> <ul style="list-style-type: none"> Negative binomial; Linear regression model Few considered Spatial Autocorrelation: Spill-over effects Event and Time 	<p>Models:</p> <ul style="list-style-type: none"> Weekday vs Weekend Members vs. Casual Spatial models
<p>Variables:</p> <p>Transportation Infrastructure:</p> <ul style="list-style-type: none"> bicycle infrastructure (Buck and Buehler, 2012, Wang et al., 2015) Transit Infrastructure (Faghih-Imani et al., Noland et al., 2016) <p>Land Use Factors:</p> <ul style="list-style-type: none"> Population density & Job density business (Rixey, 2013), restaurants (Faghih Imani et al., 2017) or a university nearby (Faghih-Imani et al., 2014). <p>Weather</p> <ul style="list-style-type: none"> Seasonality pattern of bike trips (Gebhart & Noland, 2016) 	<p>Variables:</p> <ul style="list-style-type: none"> bike lanes length & Urban trail length Light rail stations & Transit Service Population density & Job density Job Accessibility; UMN Campus % of recreational land use % of residential land use % of office land use % of commercial land use average daily temperature, average daily precipitation, average daily wind speed average visibility

Data

Independent Variables:

Service Area: Quarter mile of bike stations

Bike Share Trips:

Year: 2016

Geographic-level: Bike Share Station Level

Time-level: Daily Bike Trips

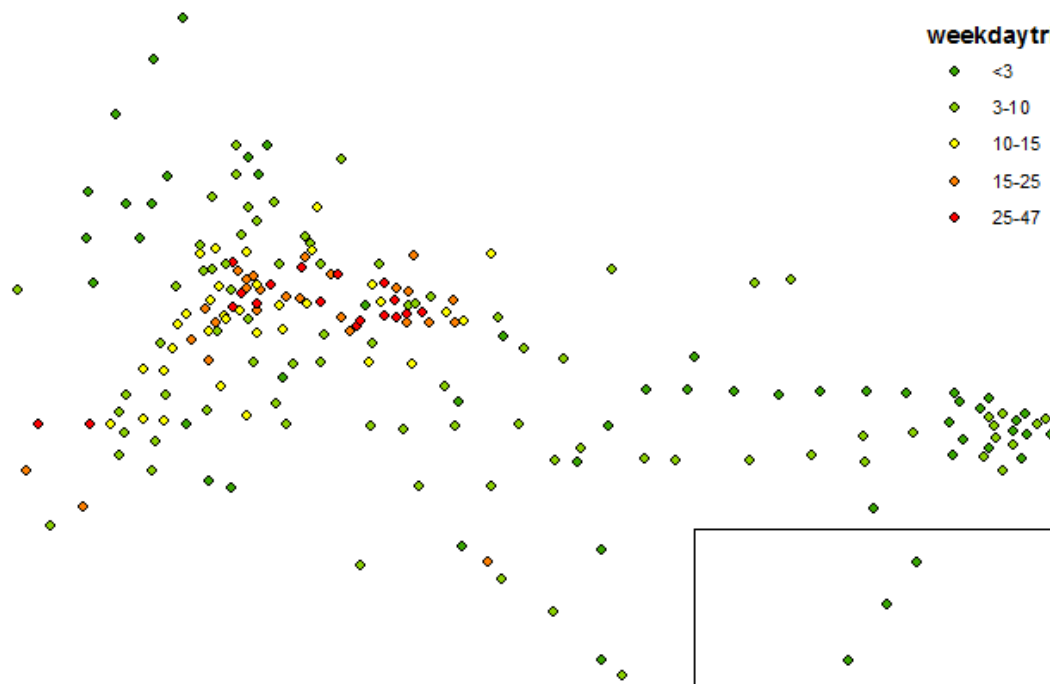
A Panel Data: Station Single Day Bike Trips, cross-sectional time series data

Variable	Mean daily trips for all stations	Std. Dev.	Min trips of single station single day	Max trips of single station single day
Weekday				
Total_trips	11	13	0	173
Member_trips	7	9	0	114
Casual_trips	3	6	0	131
Weekend				
Total_Trips	12	14	0	249
Member_trips	7	9	0	117
Casual_trips	5	9	0	221

Average Weekday daily trips per station

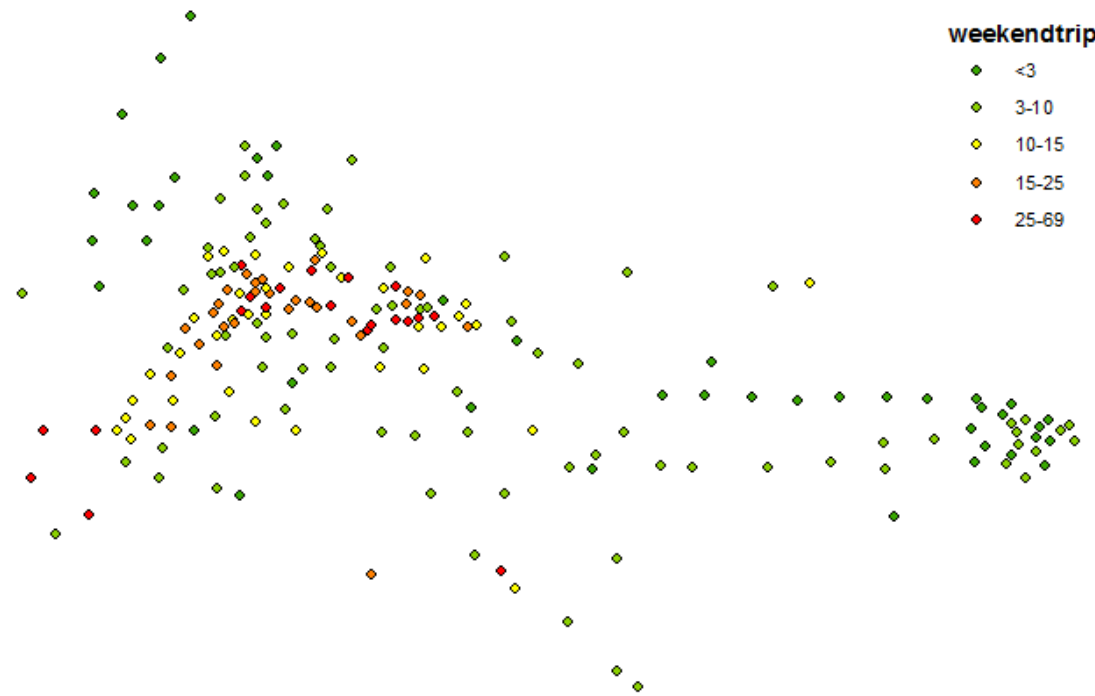
weekdaytrips

- <3
- 3-10
- 10-15
- 15-25
- 25-47



weekendtrips

- <3
- 3-10
- 10-15
- 15-25
- 25-69



Average Weekend daily
trips per station

Methods

- Random Effect Models

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + v_{it}$$

- **Spatial Random Effect Models:**

Spatial Lag: $y = \rho \mathbf{W}y + \mathbf{X}\beta + \varepsilon$

Spatial Error: $\varepsilon = \lambda \mathbf{W}\varepsilon + \mathbf{u}$

Y: Daily trip single station single day

X: correlates of bike share demand

W: Spatial Weights (Inverse Distance)

Estimation Results of Weekday Trips

	Random Effect Models			Spatial Random Effect Models		
	TotalTrips	MemberTrips	CasualTrips	TotalTrips	MemberTrips	CasualTrips
Transportation Infrastructure						
Bike Lane Lengths	+	+	+			
Trail Length	+		+	+		+
Existence of Light rail stations	+	+			+	
Transit Service Density						
Land use						
Population density						
Job density	+	+		+	+	
Job Accessibility	+	+	+	+	+	
% of recreational land use	+		+	+		+
% of residential land use						+
% of office land use						
% of commercial land use						
UMN	+	+		+	+	
Weather						
average daily temperature	+	+	+			+
average daily precipitation	-	-	-			
average daily wind speed	-	-	-			
average visibility	+	+	+			

Significant at P<0.005
 Significant at P<0.05
 Significant at P<0.1

Estimation Results of Weekend Trips

	Random Effect Models			Spatial Random Effect Models		
	TotalTrips	MemberTrips	CasualTrips	TotalTrips	MemberTrips	CasualTrips
Transportation Infrastructure						
Bike Lane Lengths	+	+				
Trail Length	+	+	+	+	+	+
Existence of Light rail stations						
Transit Service Density						
Land use						
Population density						
Job density		+			+	
Job Accessibility	+	+		+	+	
% of recreational land use	+	+	+	+	+	+
% of residential land use						
% of office land use						
% of commercial land use						
UMN	+	+		+	+	
Weather						
average daily temperature	+	+	+			+
average daily precipitation	-	-				
average daily wind speed	-	-	-			
average visibility	+	+	+			

Significant at P<0.005
 Significant at P<0.05
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Discussion and Conclusion

Findings:

- A new understanding of the correlated factors and the seasonal and weekly variation that can occur, as well as the differences between types of users.
 - Member weekday trips: Job density, Complementary effects of bike share to metro system
 - Casual user weekday trips: Trail lengths, % Recreation use, % residential use,
 - Member weekend trips: trail lengths, Job density, % recreation use, trail length
 - Casual user weekend trips: trail lengths, % recreation
- The importance of considering the spatial autocorrelation when modeling bike share trips.
 - The results are similar but minor differences in the coefficients and statistical significances
 - spatial autoregressive coefficients are all significant in all models

Implications:

- For Bike Share Planning
 - Importance of Urban Trails (recreation)
 - Job-rich area (commute)
 - Importance of linking transit to bike share(commute)
 - % residential use

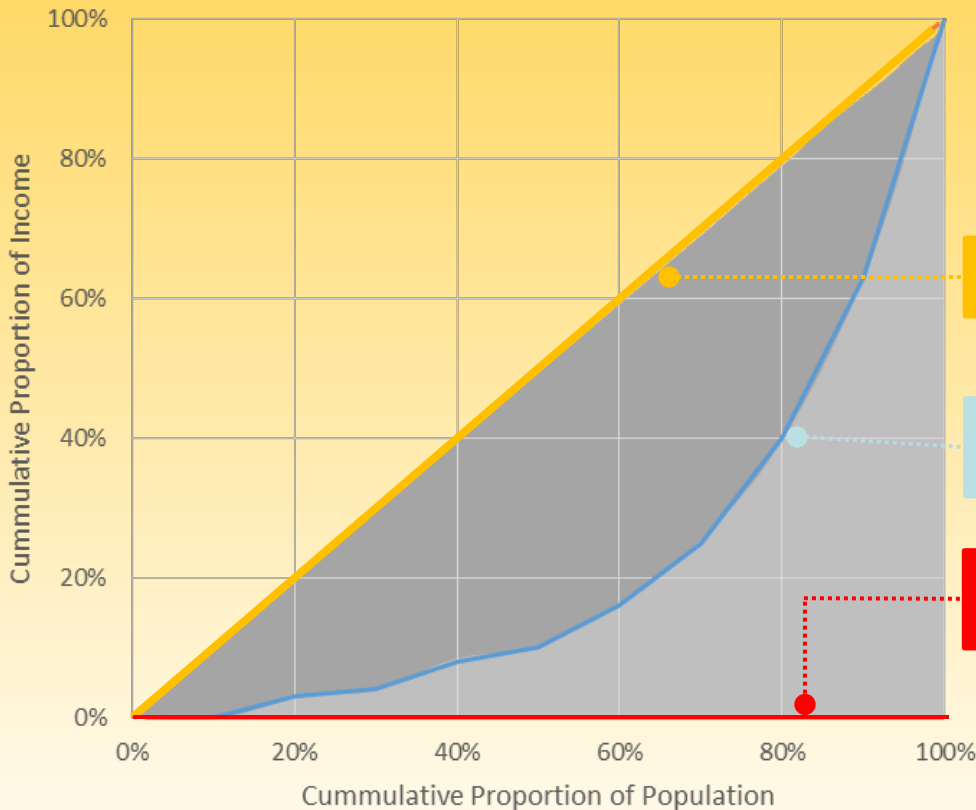
MEASURING EQUITY OF ACCESS TO BIKE SHARE

Research Questions

1. How does equity of access to bike share vary in the Twin Cities?
How much do measures of equity of access to bike share vary among subpopulations and job types?
2. How much do bike share membership and frequency of riding vary among subpopulations?
3. What are the effects of neighborhood sociodemographic characteristics on frequency of riding?

GINI Coefficient: Index of Inequity

Lorenz Curve



GINI
COEFFICIENT=
The Dark Shaded Area
The Entire Shaded Area

Perfect equity: GINI=0

inequity: $0 < \text{GINI} < 1$

Perfect inequality: GINI=1

The smaller GINI is, the more equal the distribution is

Methods

Statistics Analyses (Year 2015)

- *Socio-Economic Characteristics Comparison*

	In Service Areas	Outside Service Areas	Total
Bike Share Stations	190	--	190
Population (% of total)	206,000 (29.6%)	488,975 (70.4%)	694975
Jobs (% of total)	354,529 (70.8%)	146,405 (29.2%)	500,934
Area (% of total) (Square miles)	22.8 (20%)	90.8 (80%)	113.6
# of Census Blocks	2, 673 (25.2%)	7,918 (74.8%)	10,591
Mean Population per blocks	77	62	62
Mean Job per blocks	133	18	47

- *Bike Trip Frequency Modeling*

Research Questions

1. **How does equity of access to bike share vary in the Twin Cities?**

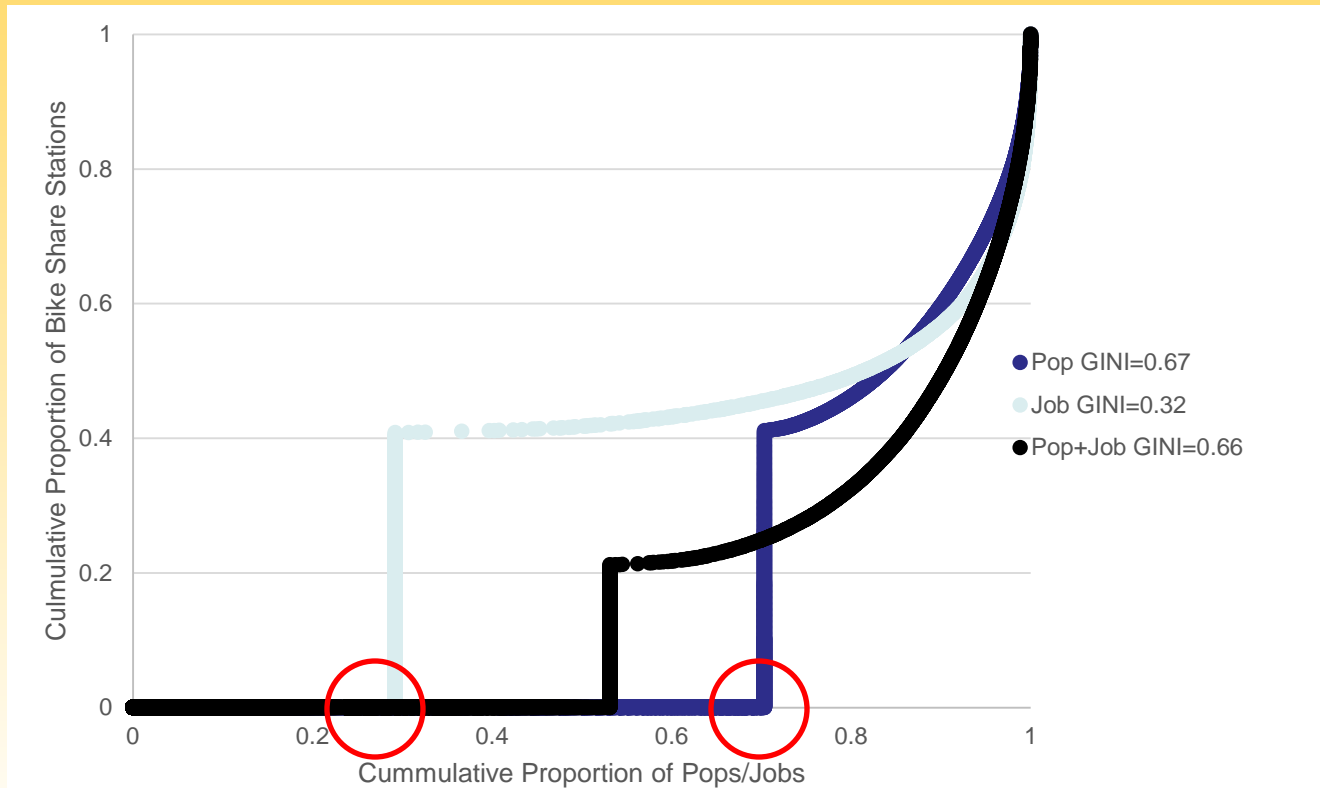
How much do measures of equity of access to bike share vary among subpopulations and job types?

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3. What are the effects of neighborhood sociodemographic characteristics on frequency of riding?

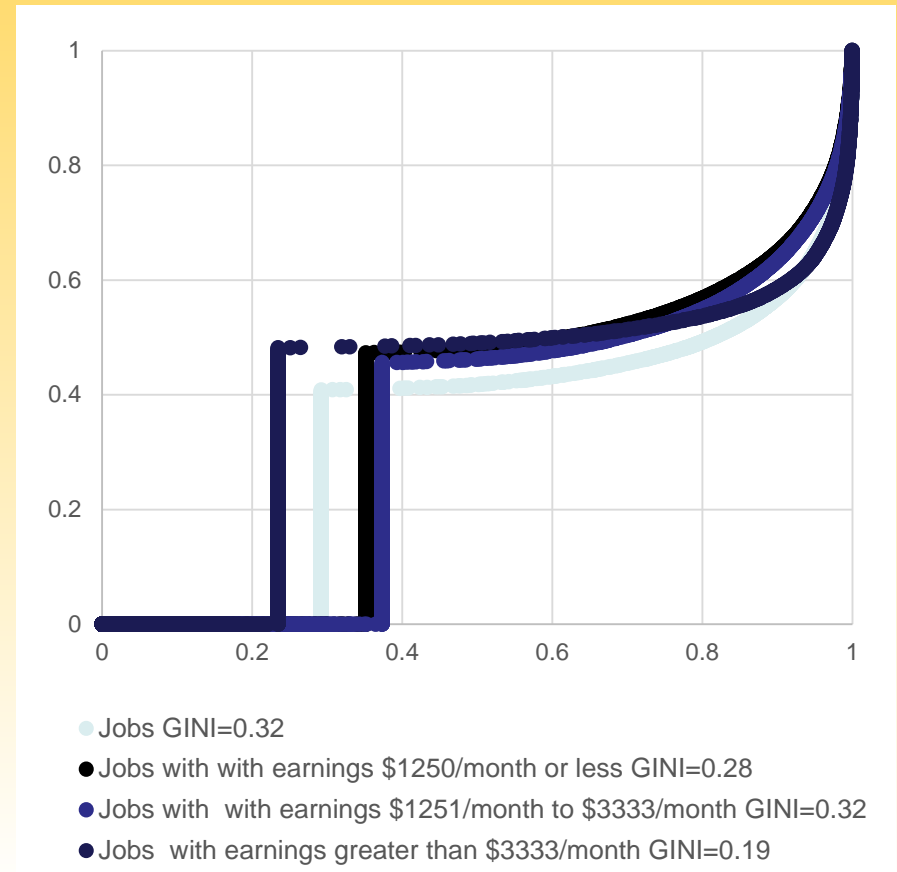
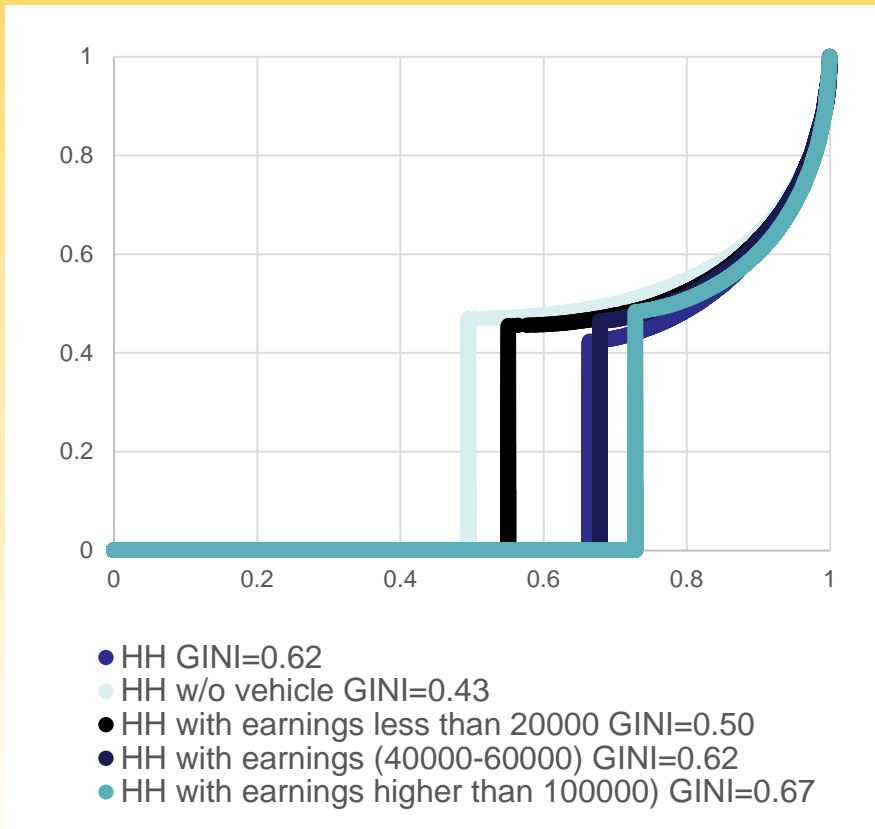
Q1. How does equity of access to bike share vary in the Twin Cities?

Not everyone has the equal accessibility to bike stations and bike stations is more unequally distributed in term of general population compared with jobs.



Q1. How does equity of access to bike share vary in the Twin Cities?

- households without vehicle available and lower income households, bike stations are more equally distributed.
- bike stations concentrated in the downtown areas of two cities serve mainly the high-paid jobs



Q1. How does equity of access to bike share vary in the Twin Cities?

GINI coefficients for subgroups of Pops (lower=greater equity):

- the White < African Americans;
- female < male.
- People with high school degree or below < General pop;
- households without vehicle available < HHs
- HH with low monthly earnings < HHs
- families under poverty < families.

GINI coefficients for subgroups of Jobs (lower=greater equity):

- High-paid jobs < low-paid jobs
- jobs for female worker < jobs for male workers.
- jobs for non-white workers and African Americans workers < that of jobs for white workers.

Research Questions

1. How does equity of access to bike share vary in the Twin Cities?

How much do measures of equity of access to bike share vary among subpopulations and job types?

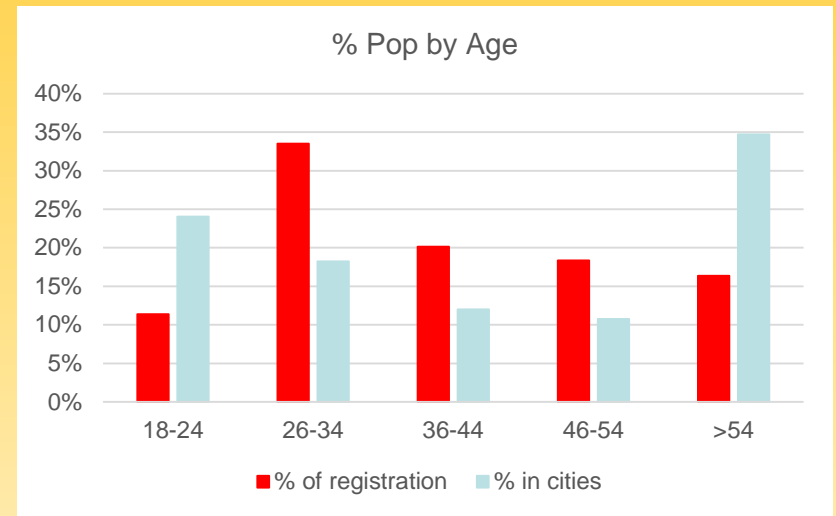
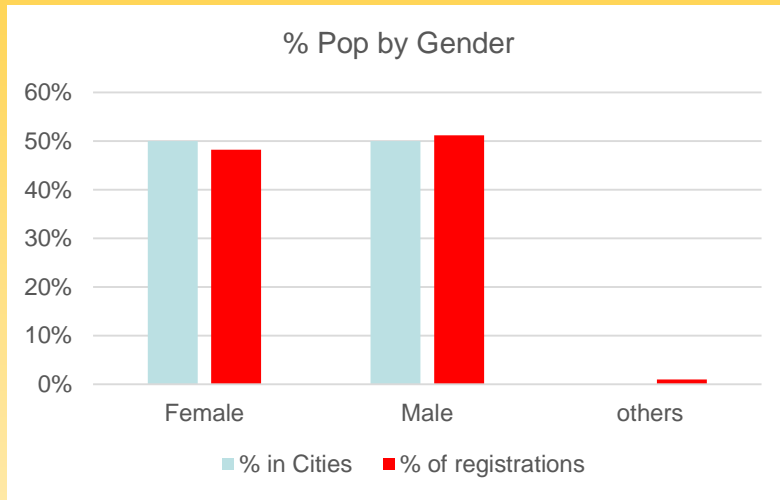
2. **How much do bike share membership and frequency of riding vary among subpopulations?**

3. **What are the effects of neighborhood sociodemographic characteristics on frequency of riding?**

Estimation Results of Weekly Usage Model of Annual Members

Variables	Model	
	Coef.	P-Value
Neighborhood Characteristics		
% white	0.008	0.977
% African Americans	0.009	0.881
% pop with high school degree or below	-1.109	0.033
% pop with bachelor or above	0.349	0.215
% HH w/o vehicle	0.609	0.115
% families under poverty	0.835	0.005
% HH with earnings less than 20000	-0.108	0.797
% HH with earnings between 20000 and 40000	0.606	0.175
% HH with earnings between 40000 and 60000	-0.252	0.625
% HH with earnings between 60000 and 100000	-0.987	0.028
% HH with earnings more than 100,000	-0.609	0.121
Socio-demographic of annual members		
Age	-0.015	0.000
Male	0.865	0.000
Student	1.165	0.000
Bike Facility Variables		
Within Service Areas of Bike Stations	0.3567	0.0000
Distance to the nearest bike lane	-0.0003	0.0310
Distance to the nearest urban trail	-0.0003	0.0180
Transportation Infrastructure		
Transit Density	-0.021	0.335
Light Rail	-0.002	0.775
Land Use Variables		
Pop density	0.138	0.808
Job density	0.004	0.539
Job Accessibility	-0.024	0.687
% retail and commercial	-0.049	0.089
% recreation	0.002	0.776
% office	0.002	0.754
% residential	-0.244	0.924
Weather		
Average temperature	-0.543	0.908
Average precipitation	-0.474	0.902
constant	3.452	0.001
Adjust R2	0.114	

Q2. How much do bike share membership and frequency of riding vary among subpopulations?



Variables	Coef.	P-Value
Age	-0.019	0.000
Male	0.881	0.000

The results may indicate that despite of providing similar bike share accessibility, bike facility and others, females are still making fewer bike trips after joining bike share programs.

Q3: What are the effects of neighborhood sociodemographic characteristics on frequency of riding?

Variables	Coef.	P-Value
% white	0.008	0.977
% African Americans	0.009	0.881
% pop with high school degree or below	-1.109	0.033
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SUMMARY & IMPLICATIONS

FINDINGS

- bike stations are more unequally distributed comparing with jobs over population.
- neighborhoods with higher percentage of low-income households have comparatively good access to bike stations outside of service areas
- annual members living in disadvantaged areas are more likely to have a great demand of bike share programs.

IMPLICATIONS

- The tool, GINI coefficient developed in the paper can provide a simple yet easy-to-apply measure of macro-level bike share equity access a geographic region
- planners and managers should take the factor into consideration that members in low-income neighborhoods might have a great demand of using bike share