Beyond Forecasting: Transport Modeling for Science and Policy

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Technische Universität München

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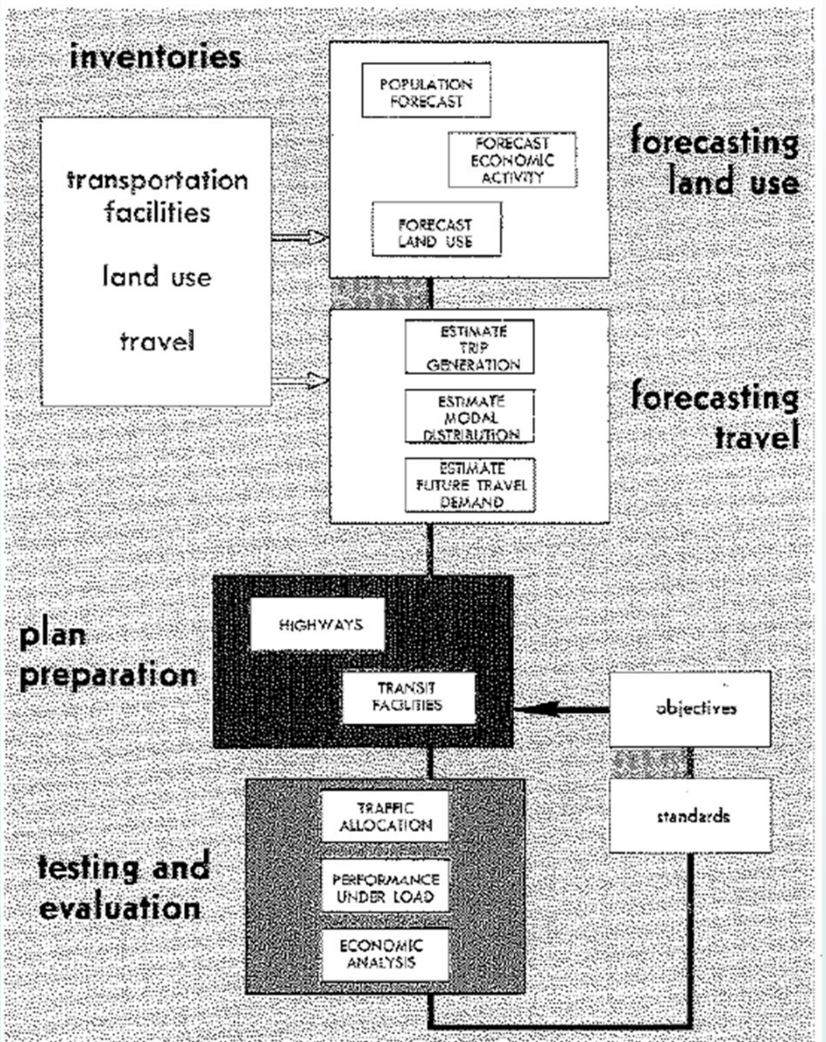

FIGURE 1—THE PLANNING PROCESS

This volume concentrates on the preparation, testing and evaluating of a transportation plan.

For many decades, planners have used transport models to forecast the long-term effects of proposed projects and evaluate alternatives. However, many important decisions are made outside the bounds of this traditional “rational planning model”.

Using a series of examples, this talk explores the role of transport models in understanding recent trends and informing policy. It goes on to consider the implications for model design.

“Chicago Area Transportation Study.” Final Report: In Three Parts, April 1962.

Five Examples

1. Models as our laboratory

   Why is traffic congestion getting worse?

2. Models across many cities

   Why has transit ridership declined?

3. Modeling the big picture

   How much did induced demand contribute to VMT growth?

4. Models for project ranking

   How to evaluate 1,200 projects efficiently?

5. Models to set targets

   Which trips have the most “mode shift potential”?

Models as our laboratory

Contents lists available at ScienceDirect

Case Studies on Transport Policy

journal homepage: www.elsevier.com/locate/cstp

Why is traffic congestion getting worse? A decomposition of the contributors to growing congestion in San Francisco-Determining the Role of TNCs

Sneha Roy [a,*,1], Drew Cooper [b], Alex Mucci [a], Bhargava Sana [b], Mei Chen [a], Joe Castiglione [b], Gregory D. Erhardt [a]

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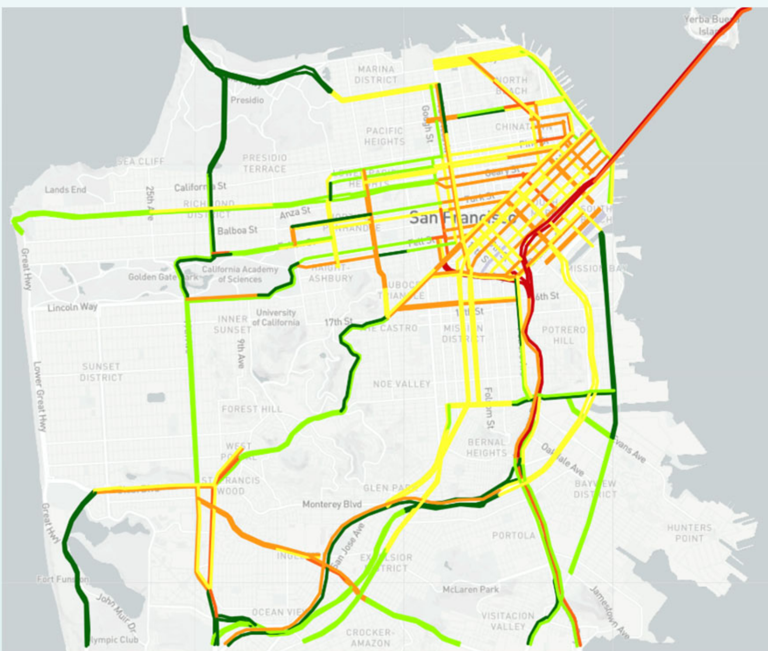
[b] *San Francisco County Transportation Authority, 1455 Market St, San Francisco, CA 94103, United States*

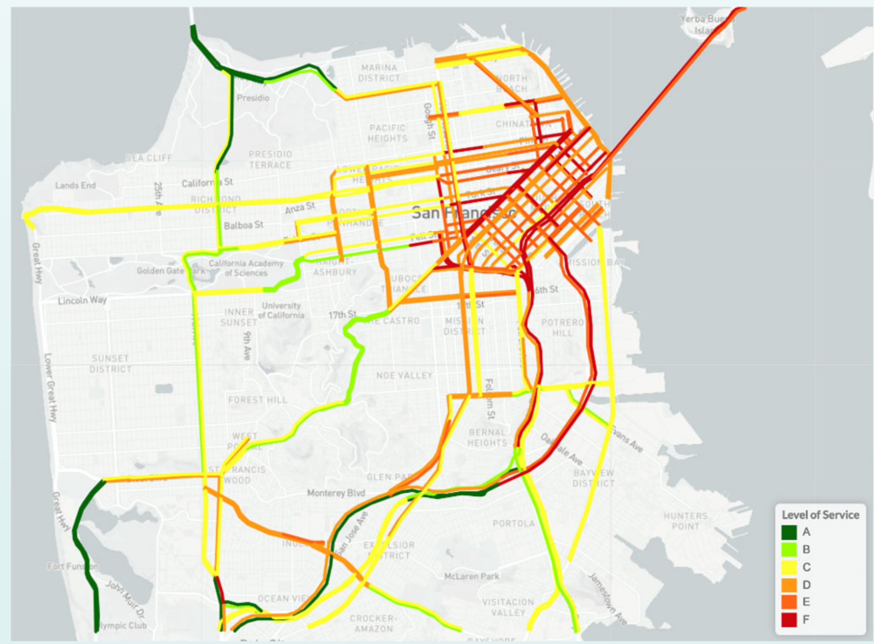
Why is traffic congestion getting worse?

Motivation: Between 2012 and 2016, traffic congestion in San Francisco worsened dramatically. Why?

2009 PM Level-of-Service



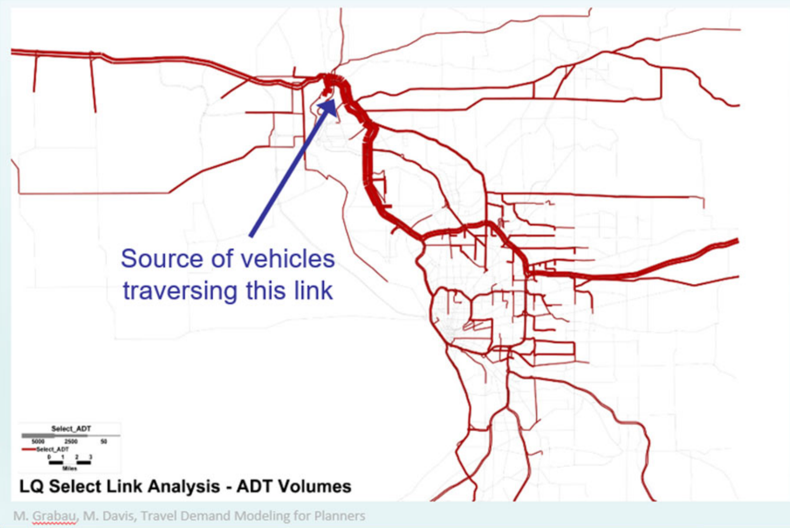
2017 PM Level-of-Service



- Average speed: 25.6 to 22.2 mph
- Vehicle hours of delay (VHD): +63%

Challenge: It is difficult to estimate the relative contribution of different factors because…

1. We can observe speeds everywhere, but volumes only sporadically
2. The volume-speed relationship is non-linear
3. The source of traffic on a link may come from far away.



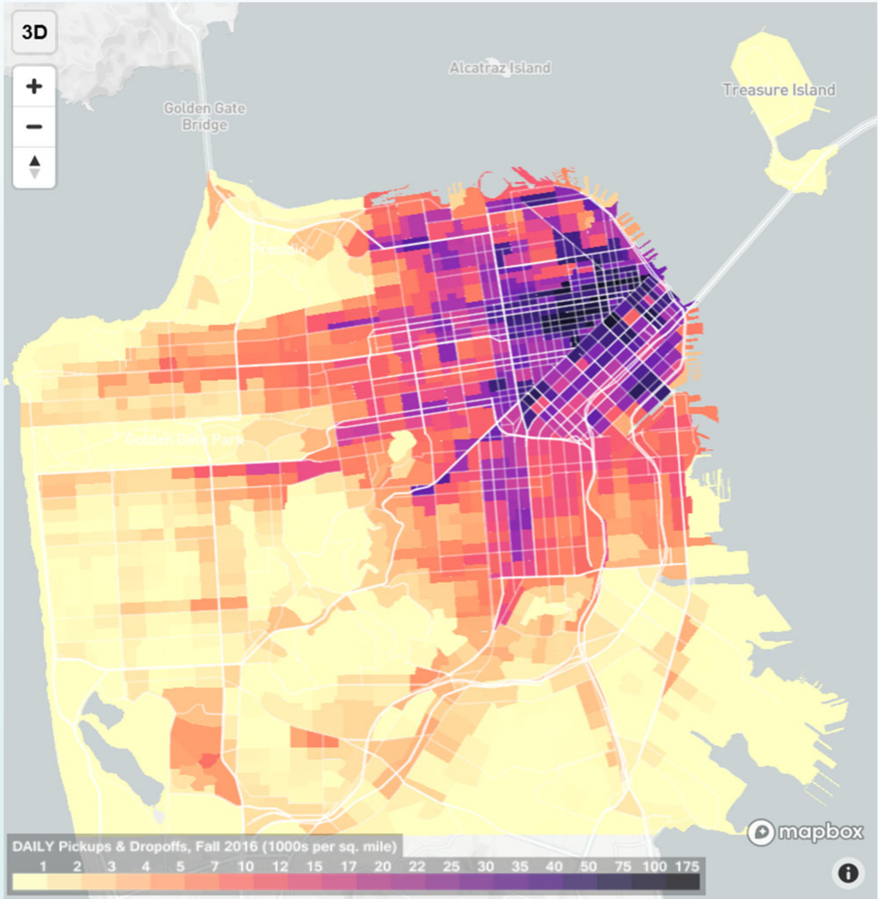
M. Grabau, M. Davis, Travel Demand Modeling for Planners

Approach: Use an activity-based travel model to conduct control experiments, separating the effect of different contributing factors

Summary of Scenarios Tested.

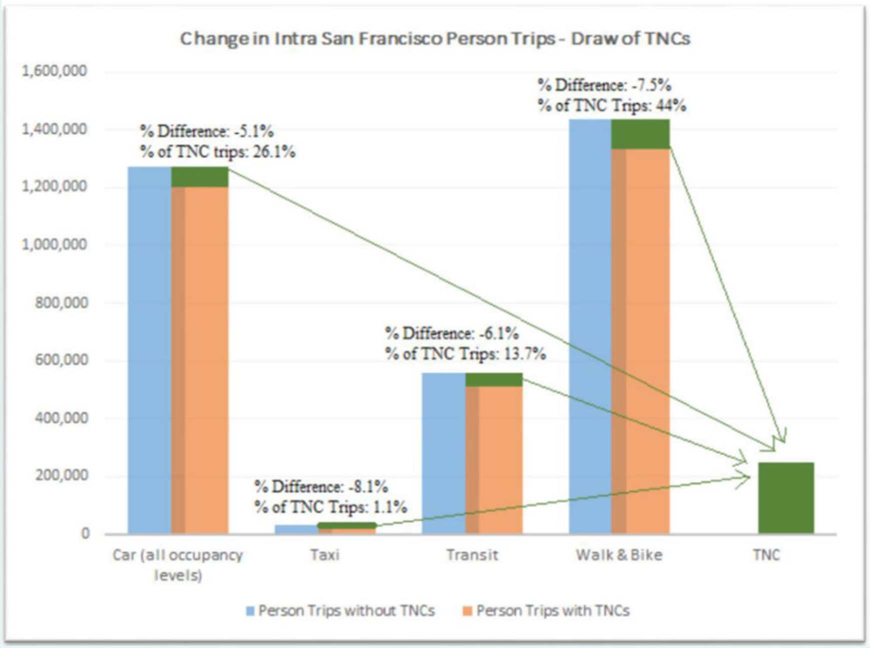
Scenario	Network	Population	Employment	TNC Volumes	TNC PUDO
2010 Base Case	2010	2010	2010	No	No
Network Change	2016	2010	2010	No	No
Population Change	2016	2016	2010	No	No
Employment Change	2016	2016	2016	No	No
TNC Volume	2016	2016	2016	Yes	No
TNC PUDO	2016	2016	2016	Yes	Yes

Some Details



Tncstoday.sfcta.org

- Ride-hailing was not in the most recent travel survey.
- We did have access to observed ride-hailing pick-up and drop-off locations and deadheading traces.
- Estimated mode shift by assuming ride-hailing draws proportionally to mode shares by O-D and TOD



Results: About half of the congestion increase is attributable to population & employment growth, and half to ride-hailing

Scenario	Percent Change from 2010 Base Case				
	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
Network Change	0%	0%	0%	1%	0%
Population Change	4%	6%	–1%	8%	2%
Employment Change	8%	11%	–3%	15%	5%
TNC Volume	15%	21%	–5%	27%	7%
TNC PUDO	15%	22%	–6%	30%	8%
Total Change	15%	22%	–6%	30%	8%

Lessons:

- Simulation is valuable as a “third way of doing science, in contrast to both induction and deduction.”
- Questions remain about how to best incorporate new data sources that may be less rich than a travel survey.

Axelrod, Robert. “Advancing the Art of Simulation in the Social Sciences.” In *Handbook of Research on Nature-Inspired Computing for Economics and Management*, edited by Jean-Philippe Rennard, 90–100. Hersey, PA: Idea Group, 2006.

Models across many cities

Transportation Research Part A 161 (2022) 68–87

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Why has public transit ridership declined in the United States?

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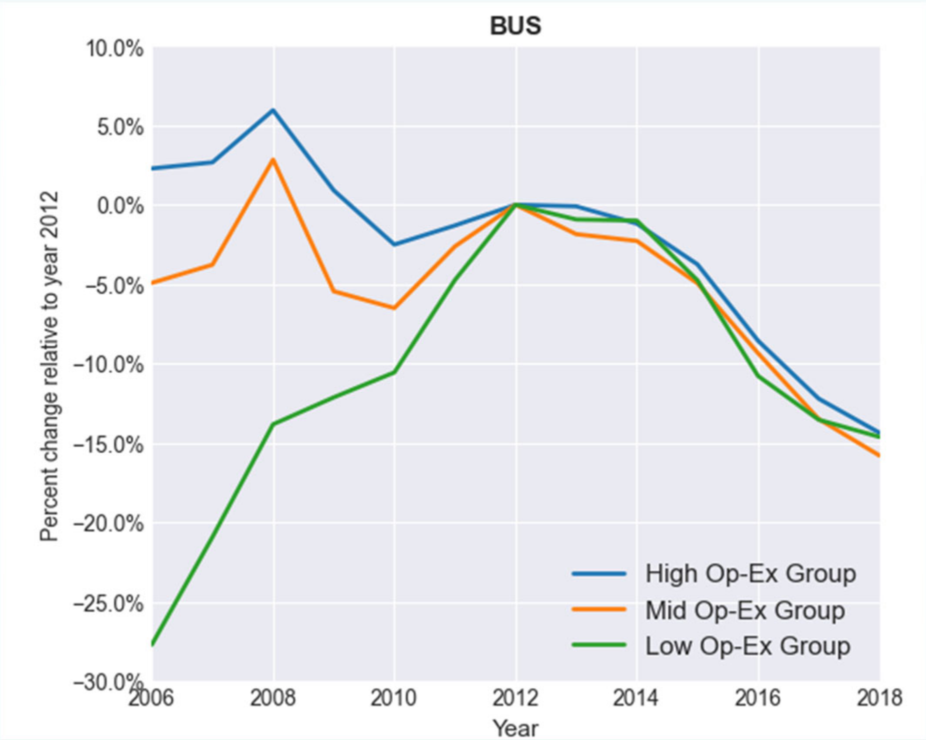
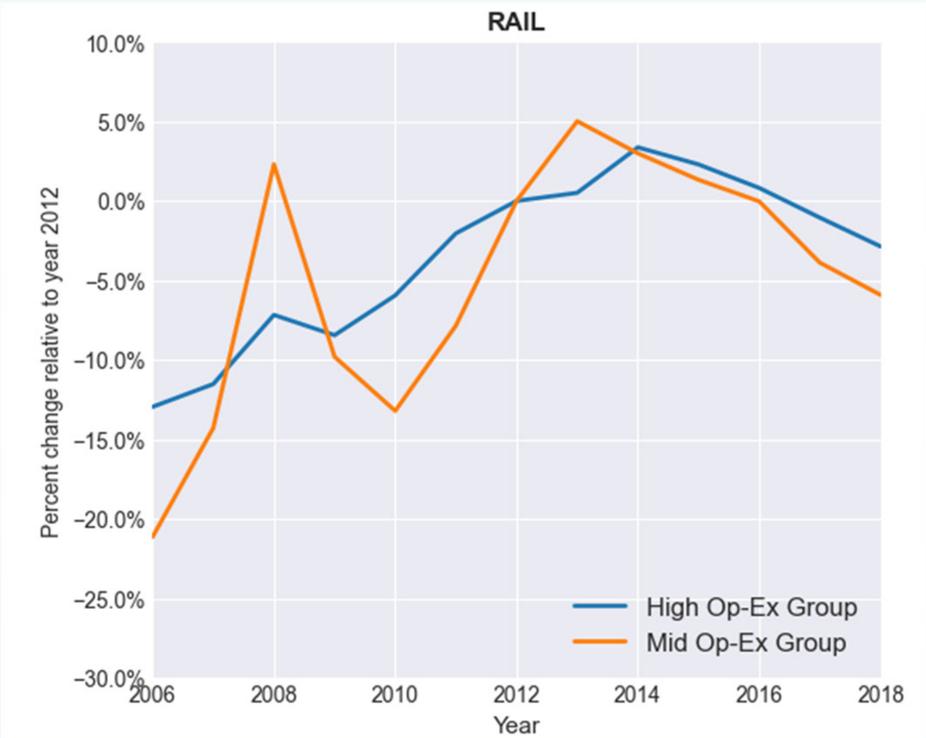
Why has transit ridership declined?

Motivation: Between 2012 and 2018 bus ridership in the US declined 15% and rail ridership declined 3%. Why?

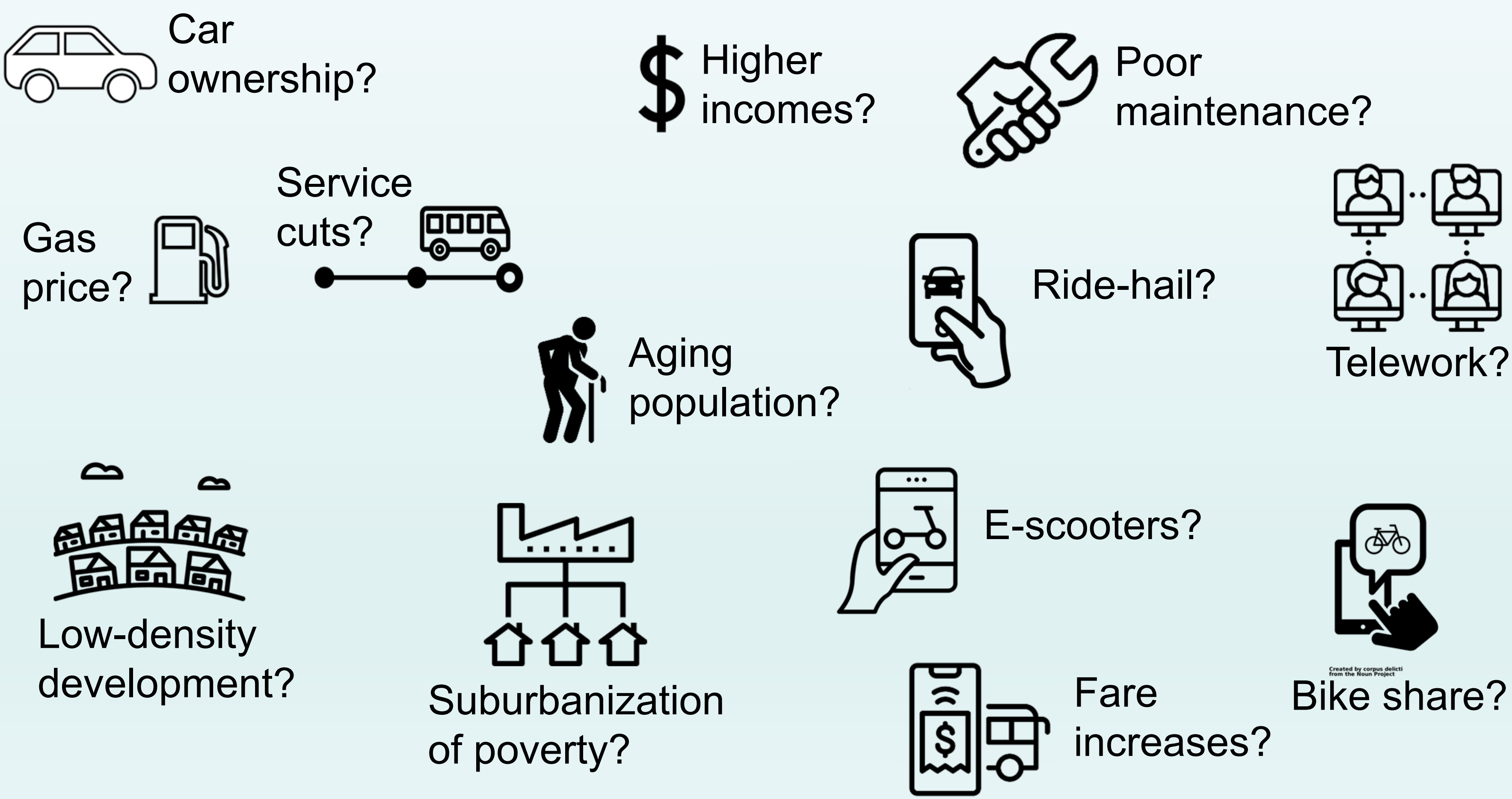




The decline is:

- Widespread
- Especially steep from 2014-2018
- During a period of economic growth
- In contrast to most other countries

Challenge: In any single city, local factors may dominate, so the results may not apply elsewhere.

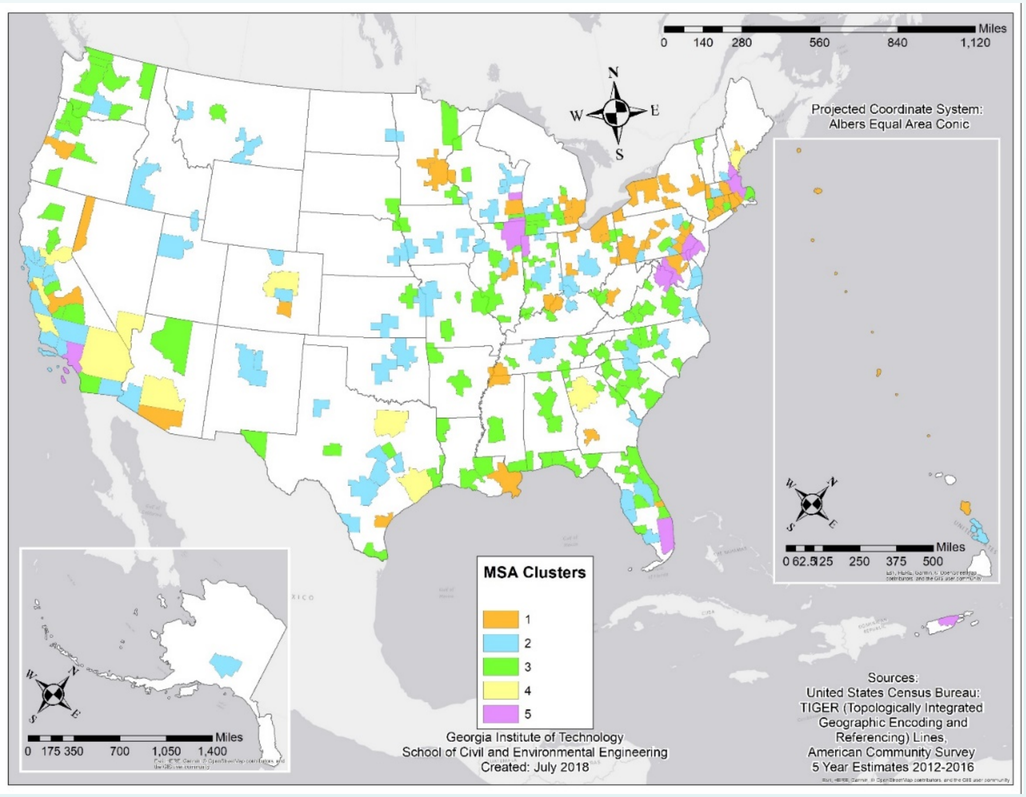


Approach: Consider change in bus & rail ridership in each of 215 MSAs annually from 2012-2018.

With many factors changing at once, we need a way to distinguish the effect of each. We can do so because they change at different rates in different places.

Estimate a fixed-effects panel model of the total bus/rail ridership in each MSA

Apply the estimated coefficients to the observed change in each variable to calculate the contribution of each factor to the change in ridership.



Results: Estimated Sensitivities

R-squared = 0.54

Fixed-effects panel model of the log of bus and rail ridership in each MSA (part 1)

Description	Transf.	Coeff.	t-statistics
Service			
Vehicle Revenue Miles (Bus)	Log	0.449	14.66
Vehicle Revenue Miles (Rail)	Log	0.662	16.05
Major maintenance event		-0.133	-1.89*
Network restructure		0.047	1.35**
Fare			
Average Fare (in 2018$) (Bus)	Log	-0.579	-16.29
Average Fare (in 2018$) (Rail)	Log	-0.346	-4.3
Land Use			
Population + Employment	Log	0.218	2.78
Percent of total employees living and working in Transit Supportive Density in an MSA		0.399	1.39**
Gas Price			
Average Gas Price (in 2018$)	Log	0.143	7.77

** Not statistically significant at 90% confidence interval

* Statistically significant at a 90% confidence interval but not at a 95% confidence interval

Results: Estimated Sensitivities

R-squared = 0.54

Fixed-effects panel model of the log of bus and rail ridership in each MSA (part 2)

Description	Transf.	Coeff.	t-statistics
Median Per Capita Income (in 2018$)	Log	-0.071	-1.19**
% of Households with 0 Vehicles		0.002	0.78**
% Working at Home		-0.008	-2.86
New Competing Modes			
Effect of the Presence of TNCs on Bus Ridership			
At MSAs where transit operating expenses exceed 300M		-0.019	-4.71
At MSAs where transit operating expenses are less than 300M		-0.033	-12.66
Effect of the Presence of TNCs on Rail Ridership			
At MSAs where transit operating expenses exceed 300M		0.002	-0.46**
At MSAs where transit operating expenses are between 30M to 300M		-0.023	-3.85
Presence of Bike Share		-0.011	-1.51**
Presence of Electric Scooters		-0.039	-3.28

** Not statistically significant at 90% confidence interval
* Statistically significant at a 90% confidence interval but not at a 95% confidence interval

Contributions to bus and rail ridership change: 2012-2018

estimated elasticity * observed change in value, summed across entities

Description	Bus Ridership: Change in Average Value	Bus Ridership: Effect on Ridership	Rail Ridership: Change in Average Value	Rail Ridership: Effect on Ridership
Service				
Vehicle Revenue Miles	5.5%	3.1%	12.5%	10.3%
Network Restructure	0.02	0.1%**		
Major Maintenance Event			0.05	-1.0%*
Subtotal		3.3%		*9.3%*
Fare				
Average Fare (2018$)	5.7%	-0.6%	10.7%	-2.6%
Subtotal		-0.6%		*-2.6%*
Land Use				
Population + Employment	6.6%	1.5%	6.0%	1.4%
% of Pop+Emp in Transit Supportive Density	-0.8%	-0.1%**	-0.8%	-0.007%**
Subtotal		1.4%		*1.4%*
Gas Price				
Average Gas Price (2018$)	-28.2%	-3.6%	-28.5%	-3.7%
Subtotal		-3.6%		*-3.7%*

** Not statistically significant at 90% confidence interval

* Statistically significant at a 90% confidence interval but not a 95% confidence interval

Contributions to bus and rail ridership change: 2012-2018

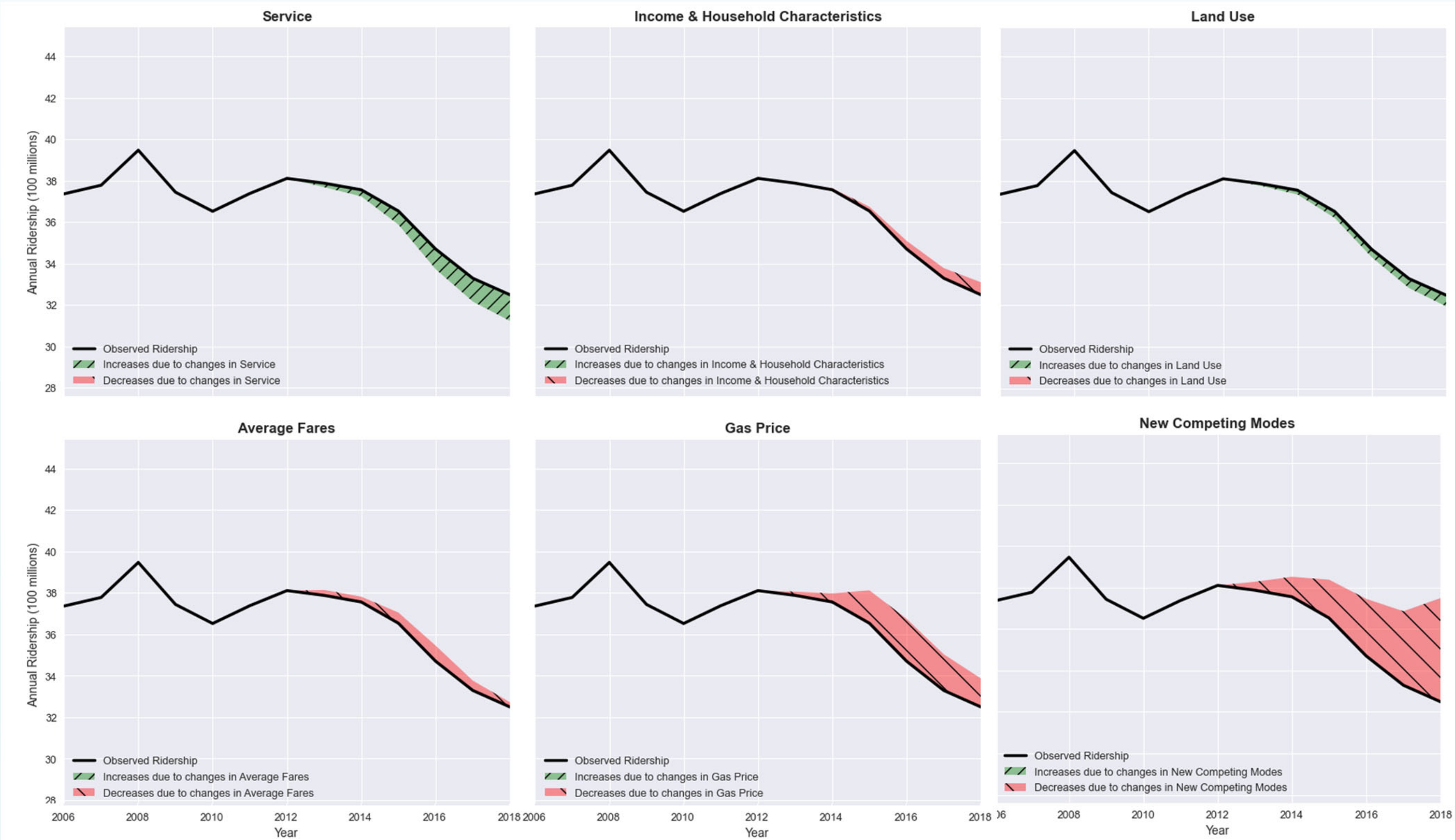
estimated elasticity * observed change in value, summed across entities

Description	Bus Ridership		Rail Ridership	
	Change in Average Value	Effect on Ridership	Change in Average Value	Effect on Ridership
Household & Income Characteristics				
Median Per Capita Income (2018$)	10.3%	-0.7%**	10.5%	-0.8%**
% of Households with 0 Vehicles	-8.9%	-0.2%**	-9.8%	-0.2%**
% Working at Home	29.5%	-0.8%	28.1%	-0.9%
Subtotal		-1.7%		*-1.9%*
New Competing Modes				
Years Since Ride-Hail Start	4.27	-10.6%	5.04	0.8%**
Bike Share	0.69	-0.8%**	0.57	-0.7%**
Electic Scooters	0.34	-1.6%	0.6	-2.4%
Subtotal		-13.0%		-2.3%
Total Modeled Ridership		-14.1%		0.2%
Total Observed Ridership		-14.7%		-3.0%
Unexplained Change		-0.7%		-3.2%

** Not statistically significant at 90% confidence interval

* Statistically significant at a 90% confidence interval but not a 95% confidence interval

Contributions to bus ridership change relative to 2012



Contributions to rail ridership change relative to 2012

Lessons:

- To generalize, we would like to move beyond single-city analyses.
- We would ideally like to do so using more sophisticated models than presented here.
- Sometimes, aggregate models are useful for informing how disaggregate models should behave.

Modeling the big picture

INDUCED TRAVEL DEMAND: MEASURING THE CONTRIBUTION OF ADDITIONAL LANE MILES ON THE INCREASE IN U.S. VEHICLE MILES TRAVELED FROM 1980 TO 2019

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the College of Engineering at the University of Kentucky

By

Brandon Ivanchak

Lexington, Kentucky

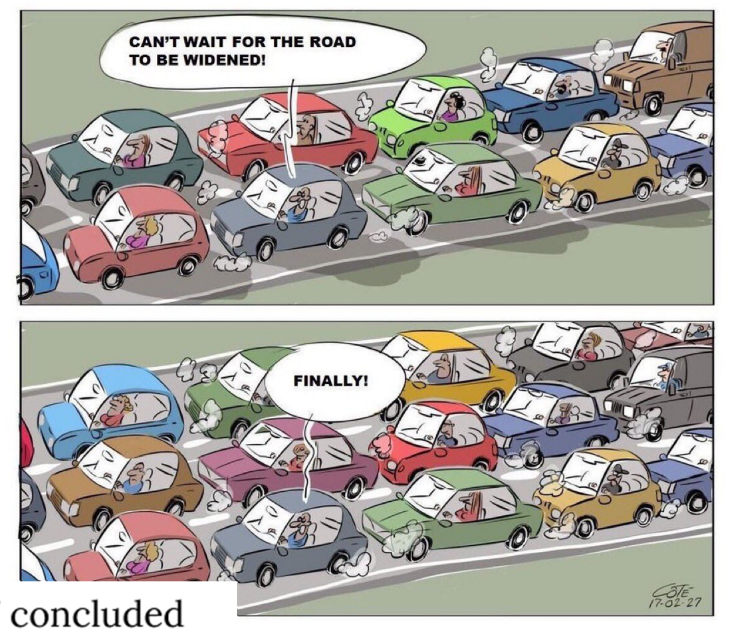
Director: Dr. Greg Erhardt, Professor of Civil Engineering

Lexington, Kentucky

2022

How much did induced demand contribute to VMT growth?

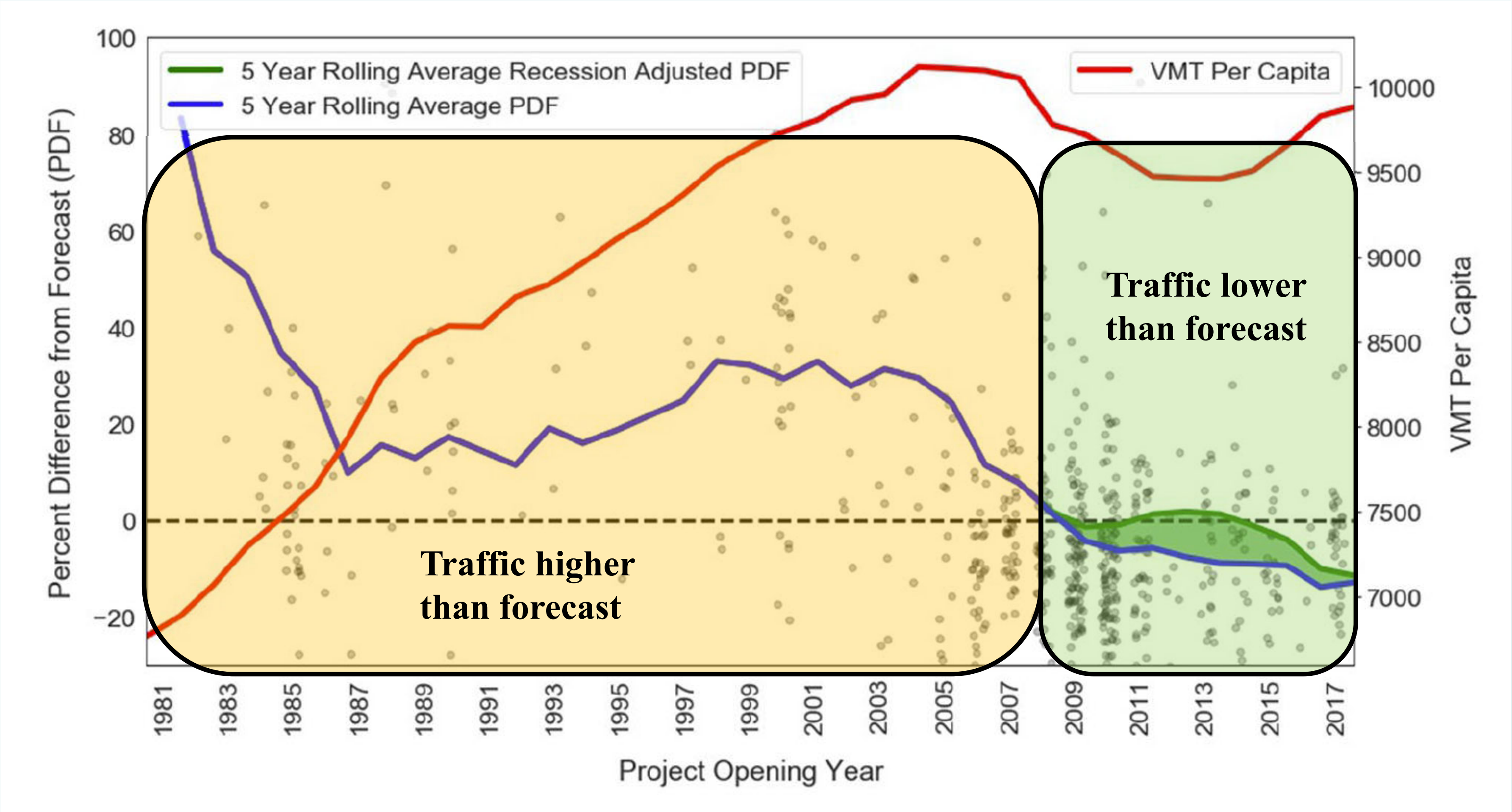
Motivation: Some critics suggest that expanding roads is futile because of induced demand, and that travel models do not adequately reflect his. Are they right?



A 2011 paper called "The Fundamental Law of Road Congestion" concluded "increased provision of roads or public transit is unlikely to relieve congestion" because every time new lane-miles are added, trip miles driven increase proportionately. The more highways and roads we build, the more we drive. (The flip side is also true: in the rare cases when highways are temporarily out of commission, such as the case with the Alaskan Way Viaduct in Seattle, traffic doesn't get much worse.) And TDMs have been totally ignorant of it.

Gordon, Aaron. "The Broken Algorithm That Poisoned American Transportation." *Vice*, August 24, 2020.

The average difference from forecasts changes in both direction and magnitude in the 2000s



Hoque, et al. 2021 "The Changing Accuracy of Traffic Forecasts." *Transportation*.

Challenge: Empirical estimates of induced demand are highly aggregate with data limitations.

US estimates of the elasticity of VMT w.r.t. lane miles.

Short run : 0.28-0.59 Long run: 0.53-1.12

Induced demand elasticity estimates from earlier IV-based studies.

Study	Sample	Identification strategy	Estimator	Elasticity range	Time period
Internal instrument					
Fulton et al. (2000)	Counties in the US Mid-Atlantic (1969–1996)	Lagged growth in highway capacity	FE 2SLS FE	0.56–0.59 0.46–0.51	Short run Short run
External instruments					
Noland and Cowart (2000)	US urbanized ureas (1982–1996)	Urbanized land area inverse population density	2SLS FE 2SLS FE	0.28 0.90	Short run Long run
External instruments					
Cervero and Hansen (2002)	Urban counties in California (1976–1997)	Measures of geography, politics, and air quality	3SLS FE	0.79	5 year
External instruments					
Duranton and Turner (2011)	US Metropolitan Statistical Areas (1983–2003)	The 1947 US Interstate Highway system plan and mapped rail and exploration routes from 1835 to 1898	OLS FE 2SLS ML	0.82–0.86 0.95–1.12 0.94–1.03	10 year 10 year 10 year
Internal instruments					
Melo et al. (2012)	US urbanized ureas (1982–2010)	Lagged levels and differences of the dependent & independent variables	GMM	0.98	Long run
External instruments					
Hsu and Zhang (2014)	Urban employment areas in Japan (1990–2005)	Japan's 1987 National Expressway Network Plan	OLS FE 2SLS ML FE	1.02–1.17 1.13–1.14 1.24–1.34	3–5 year
Internal instruments					
Graham et al. (2014)	US urbanized ureas (1985–2010)	Lagged levels and differences of the dependent & independent variables	PS RE OLS FE GMM	0.77 0.76 0.53 0.61	Long run Long run Long run Long run

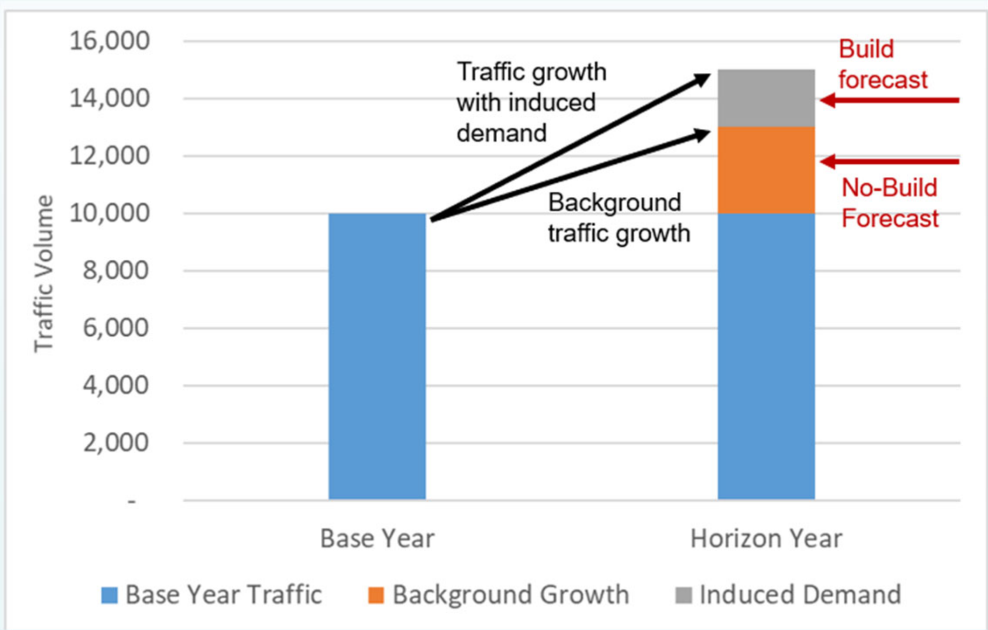
Hymel 2019. "If You Build It, They Will Drive: Measuring Induced Demand for Vehicle Travel in Urban Areas." *Transport Policy* 76.

Approach: Aggregate estimation compared to travel model application.

Estimate a fixed-effects panel model of the car VMT in each state as a function of lane miles and other control variables

Apply the estimated coefficients to the observed change in each variable to calculate the contribution of each factor to the change in ridership.

Future: Compare to scenario tests in travel models.



Results: Between 1980 and 2019, lane miles increased 13% resulting in an 11% increase in car VMT.

Model Estimation

Dependent variable is log of Car VMT	Model Summary	
	Coefficient	T-Stat
LN (lane miles)	0.483	10.073
LN (population)	0.891	38.085
LN (per capita income)	0.561	23.840
LN (retail gas price)	-0.050	-6.481
Share of population in fringe/small metro	0.856	4.302
Share of population in non-metro	0.441	2.017
Auto and truck registrations per capita	0.072	2.866
Employed per capita	1.956	21.483
Constant	-15.991	-38.757
R^2	0.901	

Model Application

	1980-2019	
	Change in VMT due to variable	Change in variable
Lane miles	11.23%	12.86%
Population	55.78%	44.99%
Per capita income	52.28%	78.79%
Retail gas price	-7.45%	105.13%
Share of population in fringe/small metro	6.14%	3.90%
Share of population in non-metro	-1.88%	-2.95%
Auto and truck registrations per capita	1.30%	12.78%
Employed per capita	-3.64%	0.78%
Car Vehicle Miles Traveled	-	109.21%
Unexplained Change	-4.54%	-

Lessons:

- Future step to validate the sensitivity of ABMs vs the estimated elasticities.
- Aggregate estimation is more limiting in this case, but an ABM could be applied or estimated across this period.
- Limiting factor may be data on past networks.

Models for project ranking

SHIFT
KENTUCKY AHEAD

How to evaluate 1,200 projects efficiently?

Motivation: Provide a means of raking ~1200 projects for inclusion in the state highway plan.

Priority	Score
Safety	25%
Congestion	20%
Economic Growth	20%
Benefit /Cost	20%
Asset Management	15%
TOTAL	100%

Priority	Score
Safety	20%
Congestion	10%
Economic Growth	15%
Benefit/Cost	15%
Asset Management	10%
SUBTOTAL	70%
District Priorities (KYTC)	15%
Local Priorities (ADD/MPOs)	15%
TOTAL	100%

Approach: Separate working groups for each component to develop a data-driven approach.

Previous Component Improvements

Safety

- Roadway - Updating Project Type Improvements.
- Crash History – Included all crashes and incorporated Severity Aspect

Congestion

- Updating with field sampled real data as a measure of congestion.

Economic Growth

- Improving the travel time modeling inputs for TREDIS economic modeling software.
- Incorporating Job Access potential.

Benefit / Cost

- Using Crash Severity in order to better inform related costs and improving travel time modeling methods.

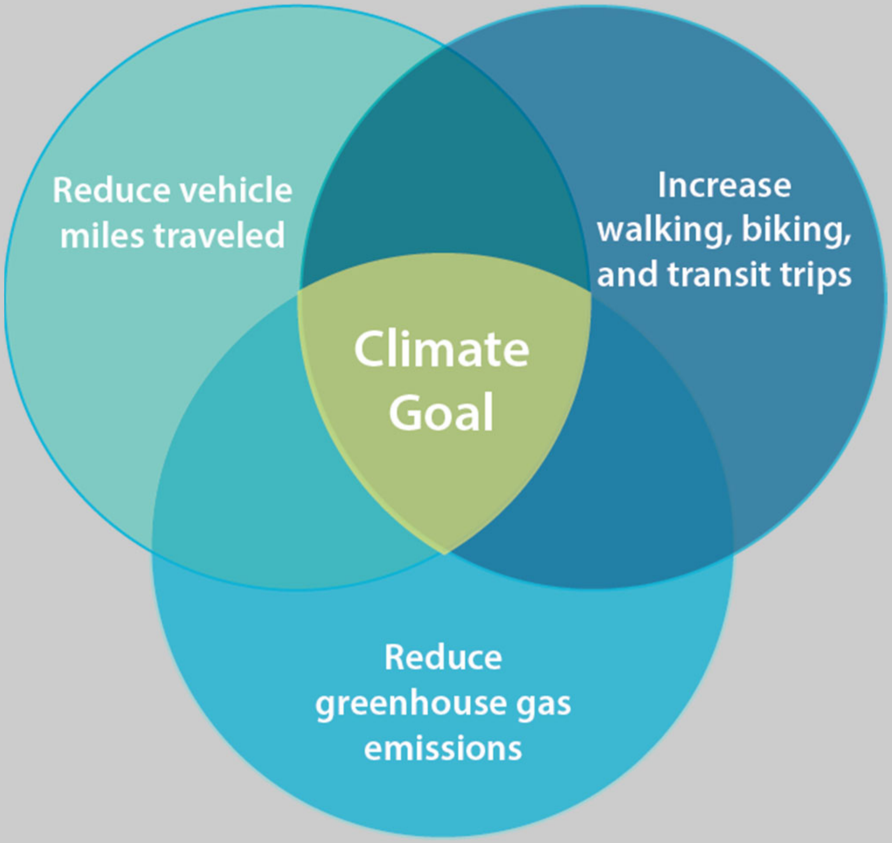
Asset Management

- Incorporating OMS data to identify reoccurring issue locations within a project.
- Including NHS importance in the bridge metric.
- Addition of new Criticality Measure.

Lessons:

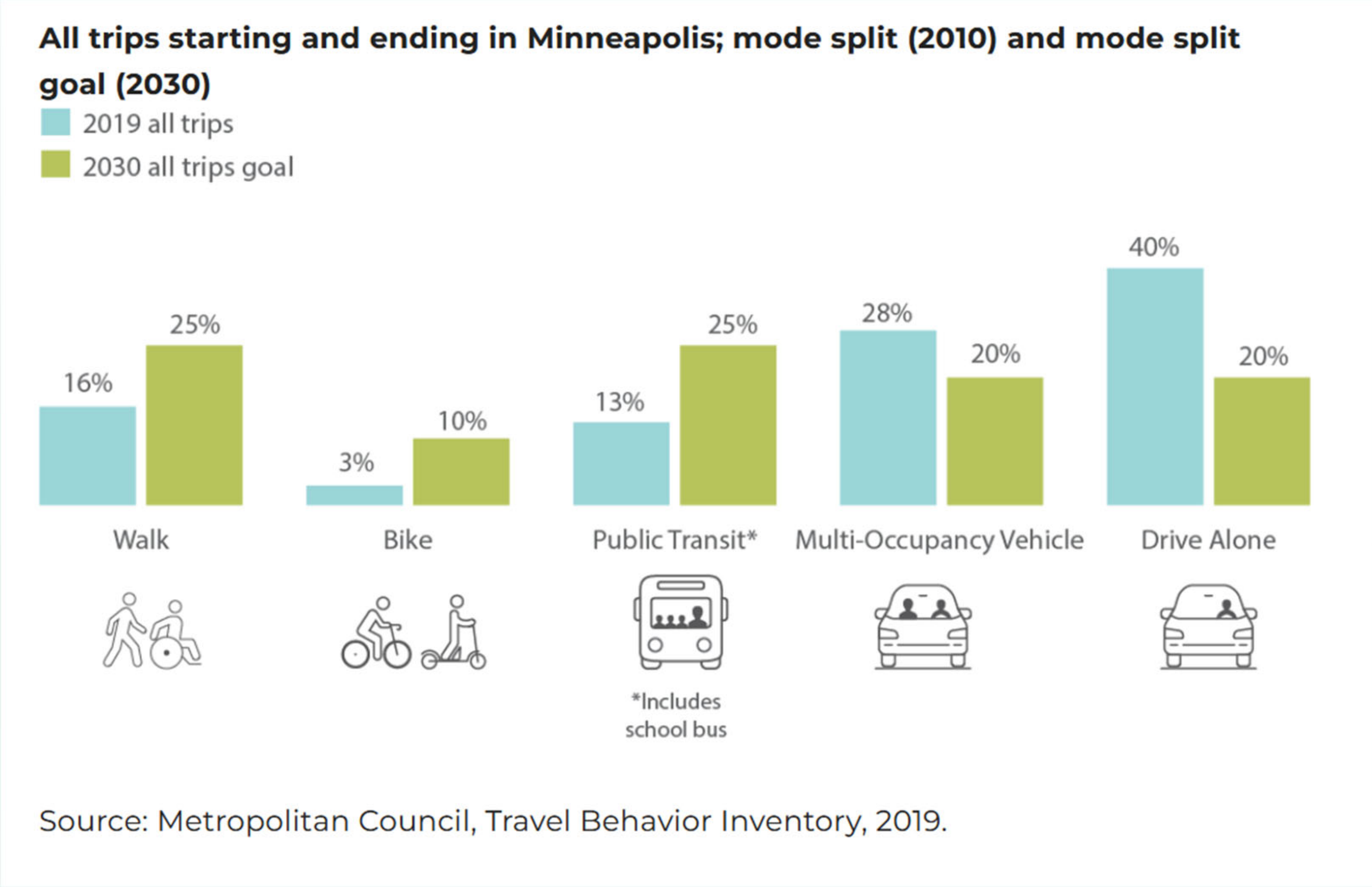
- Legislators generally appreciate the rankings and also appreciate the opportunity for a “local boost”.
- Room for improvement in the scoring.
- Travel model is useful for 2-3 of 5 categories.
- Models impose a substantial burden on DOT planning staff due to runtime (1 hr) and staff time.

Models to set targets



Which trips have the most “mode shift potential”?

Motivation: Metropolitan Council seeks to set targets for VMT reduction and identify how to effectively meet those targets.



Challenges

Metropolitan Council maintains an activity-based travel model. However, the forecasts are inherently uncertain and the models often predict future changes much smaller than the proposed targets. This can lead to a debate on the limitations of the forecasting methods themselves that distracts from a focus on the solutions to regional problems.

ActivitySim

An open platform for activity-based travel modeling

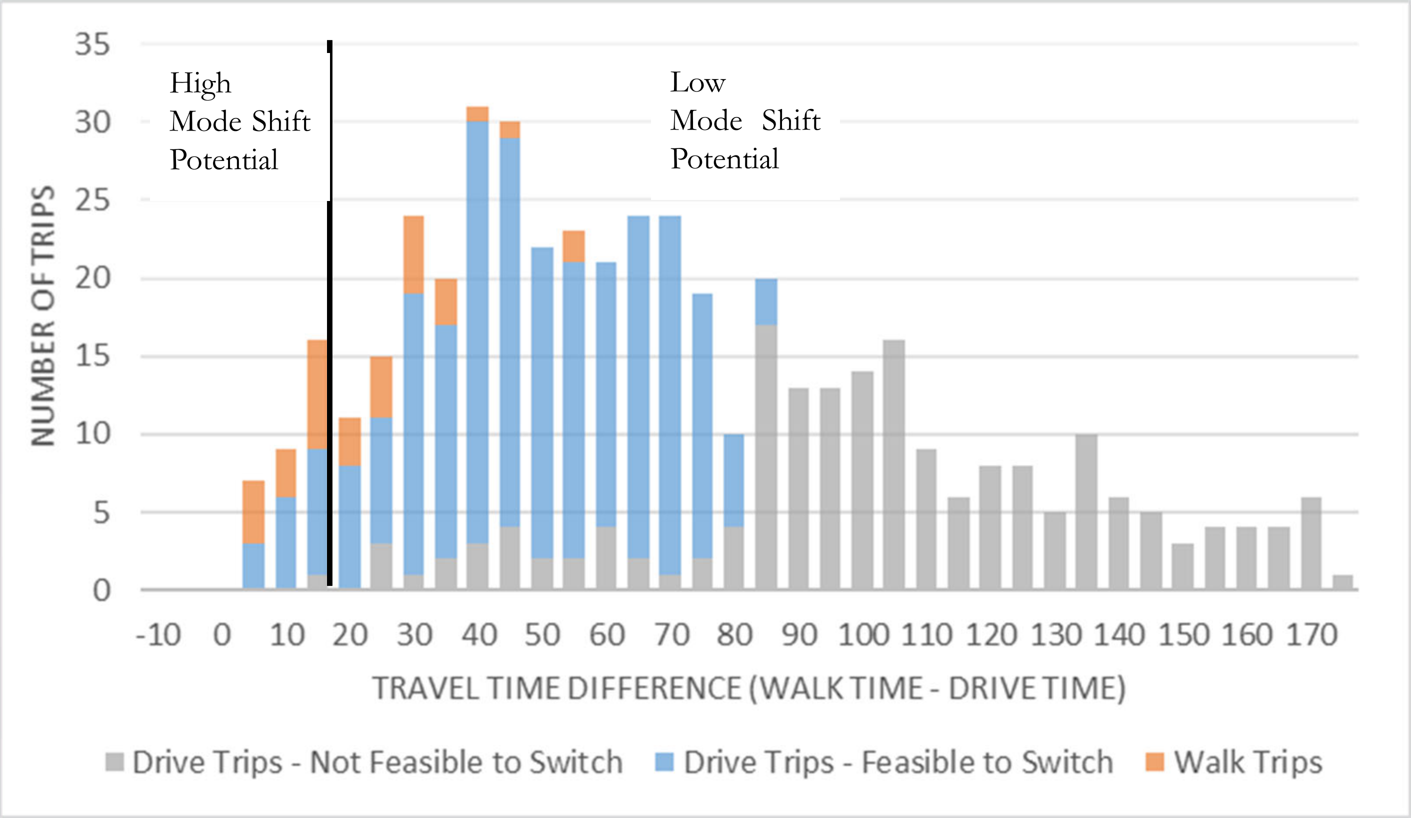
Approach

Instead of creating synthetic trips from a travel forecasting model, the study will analyze the **500,000+ real-world trips reported by residents in the 2019 and 2021 Travel Behavior Inventory surveys**[2] for which detailed origin and destination coordinates[3] are available. The study will develop two key measures: **mode shift potential**, the percent of trips and vehicle miles traveled that can be shifted to other modes; and the **time cost** to individuals and households of shifting modes.

Feasible Mode Shifts: Trips that could feasibly switch to a non-auto mode, defined as lacking barriers to doing so.

Potential Mode Shifts: Trips with a high potential to switch to a non-auto mode, defined as feasible trips with a best non-auto time within a user-specified time cost of the auto travel time.

Expected Results



Use this analysis to determine the degree to which the proposed targets can reasonably be met.

Identify to what extent the mode shift potential **varies across geography, demographic groups, and trip types**. Use this to identify the markets of trips likely to switch.