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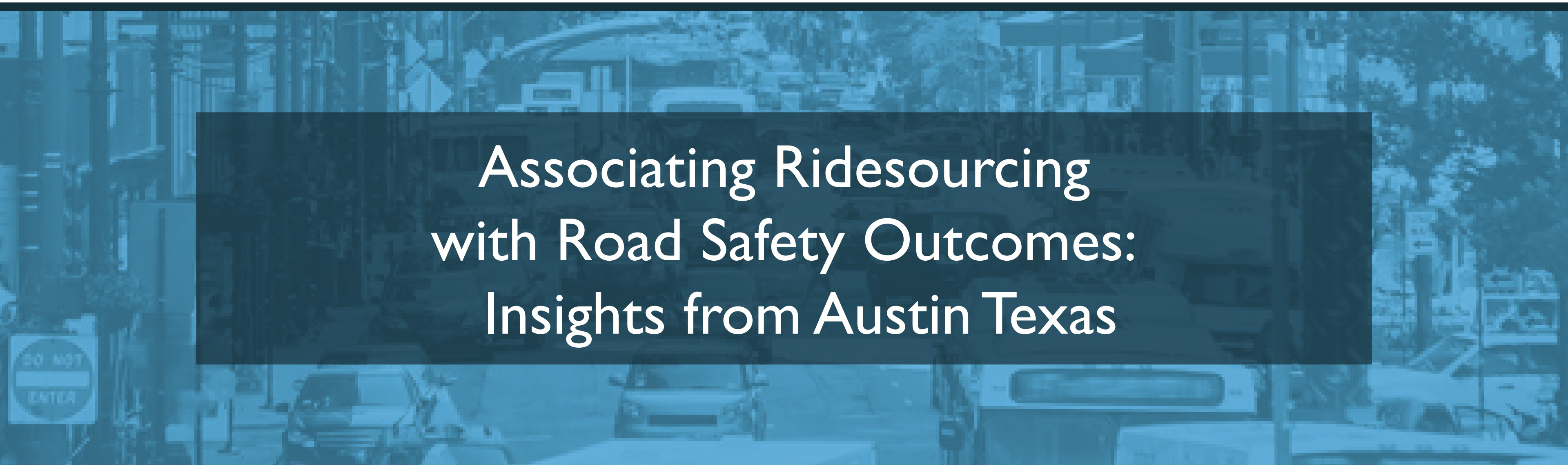

Associating Ridesourcing with Road Safety Outcomes: Insights from Austin Texas

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Introduction

United States Stats

37,133 traffic fatalities in 2017 (NHTSA)

29% from drunk driving

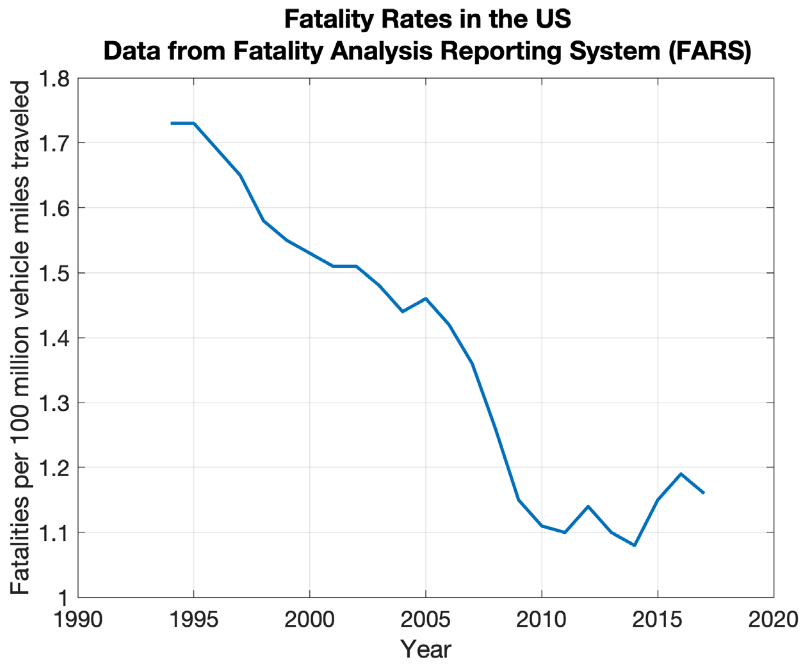
220 children under 14 years old

Vision Zero Programs

Reduce Crashes & NO Fatalities

Why?

- Loss of productivity
- Loss of human capital
- Loss of income

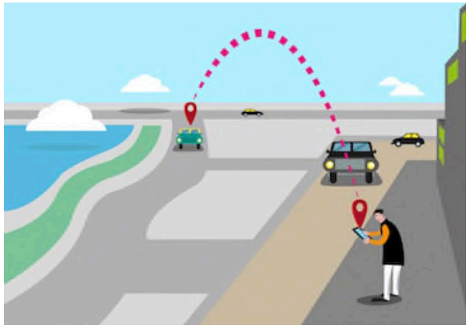


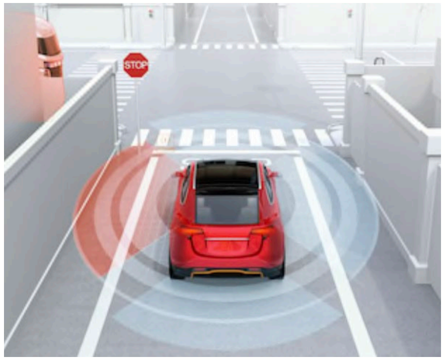
NHTSA (2019) Fatality Analysis Reporting System
https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars

Road Safety Interventions

- Speed limit reduction & traffic calming measures (10%-15%) Elvik, 2001
- Seatbelt laws enforcement (up to 9%) Carpenter and Stehr, 2008
- Educational programs and behavior changes
- Vehicle safety standards and intelligent systems
- **More mode options !**

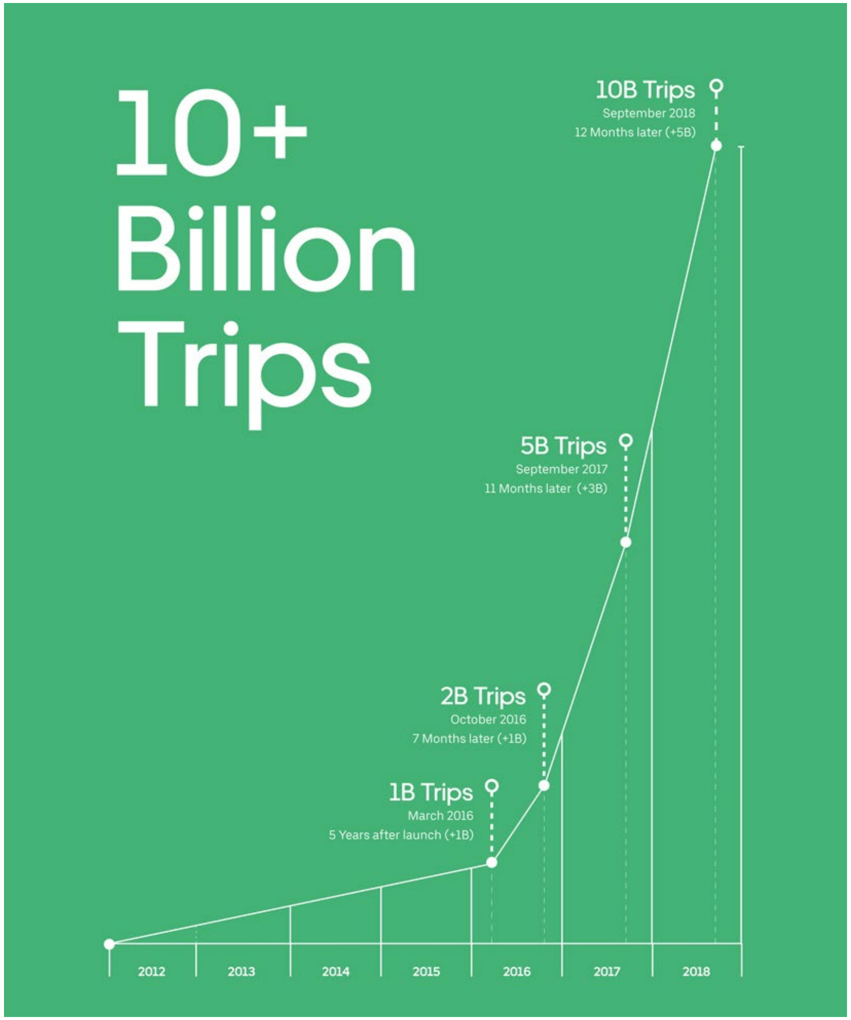
Dills and Mulholland, 2018





Introduction: Ridesourcing

What is Ridesourcing?
Uber and similar e-hailing services



Uber IPO Prospectus, 2019

Role of Ridesourcing in Vision Zero

Why would ridesourcing use be associated with road crashes?

- Ridesourcing associated with reduction of alcohol-involved crashes and driving under the influence offences

Supported by Morrison et al. 2017 & Dills and Mulholland, 2018

- Drivers cruising contributes to congested city centers and associated with increase in crashes

Supported by Barrios et al., 2018


Miami Herald

SOUTH FLORIDA

DUI arrests in South Florida plummet. Uber, Lyft, millennials among the reasons why

BY CHARLES RABIN JULY 31, 2018 01:07 PM

Research Objective

Research Goal

Uncover effects of ridesourcing use on: road crashes,
injuries,
fatalities,
DWI offence rates.

Contributions

- **First empirical study** that uncovers such effects while accounting for intensity of ridesourcing demand using real-world data from Travis County TX.
- Assist planners and engineers with **developing roadmaps for ridesourcing-related interventions** to meet vision zero goals.

Existing Literature: Overview

Reference	Method	Dependent Variable	Ridesourcing Indicator	Controls	Spatial-Unit	Time-Unit
Greenwood and Wattal (2017)	**DiD** / OLS/ QMLE	Alcohol-related motor vehicle deaths, all driving fatalities, alcohol-related in high demand and holidays	UberX and Uber Black **launch dates**	Age, college graduates, population, median income, population living under poverty, law enforcement population	Townships (State of California, US)	Quarter (2009-14)
Brazil and Kirk (2016)	**DiD**	Total, alcohol-involved, weekend and holiday traffic fatalities	Uber launch date	State laws, state beer tax, unemployment rate	Metropolitan area county (100 US largest)	Month (2009-14)
Martin-Buck (2016)	**DiD**	Alcohol-related fatalities, DUI and other arrests	Uber and Lyft launch dates	City population, unemployment rate, light-rail transport availability and use	City (273 US cities of >100,000 population)	Month (2000-14)
Morrison et al. (2017)	ARIMA	All-injury, alcohol-involved, serious injury and fatality crashes	Uber launch, cease, and resume dates	n.a.	City (Portland, OR, Las Vegas NV, Reno NV, San Antonio TX)	Week (2013-16)
Dills and Mulholland (2018)	**DiD**	Fatal accidents per thousand persons (total, alcohol-involved, night-time) Arrests per thousand persons (Assaults, motor vehicle thefts, DUIs, Liquor law violations)	UberX launch date	State driving laws, state beer tax, age, race, unemployment rate, population density	County (all US, or only Uber entry)	Month (2007-15)
Barrios et al. (2018)	**DiD**	Total/drunk/pedestrian-involved/non-drunk crashes and fatalities	**Intensity of rideshare use** (Uber and Lyft google search), Single and pooled ride service	Population, per capita income, vehicle ownership, public transportation use, VMT, new car registrations, quality of drivers	City (US places with population greater than 10,000)	Quarter (2010-17)
Huang et al. (2018)	**DiD** / ARIMA	Road traffic deaths	Uber launch date	Age, sex, birth province	South African province	Week (2010-14)

Existing Literature: Methods Summary

- Seven studies determining relationships between ridesourcing entry and road fatalities (and/or injuries)
- 6/7 studies use difference-in-difference approach
  - 2 groups over two time periods
  - Treatment group: **Uber/Lyft entry**
- 2/7 studies use time-series forecasting (ARIMA)
- Control (depends on studies focus)
  - Vehicle Miles Traveled
  - Population
  - Others
- Analyses time units: week, month, quarter
- Analyses spatial units: city, county, metropolitan statistical area

Existing Literature: Major Findings

Study	Findings
Greenwood and Wattal (2017)	**Significant drop in the rate of alcohol-related fatalities in California** after the introduction of Uber X.
Brazil and Kirk (2016)	Ridesourcing services deployment is **not associated with any of the categories of traffic fatalities** examined.
Martin-Buck (2016)	Ridesharing services **significantly reduce fatal alcohol-related automobile crashes and DUI/DWI arrests for several cities.**
Morrison et al. (2017)	The resumption of ridesourcing led to a significant 62% **decrease of alcohol-involved crashes in Portland**.
Dills and Mulholland (2018)	**Reduction in fatal traffic crashes**, after certain number of months operating, and DUI arrests.
Barrios et al. (2018)	**Fatalities and fatal crashes increase 2-3% with ridesourcing arrival** and such trends persist over time.
Huang et al. (2018)	For provinces served by Uber, no significant **reductions in road traffic deaths were observed in South Africa**.

Data

Data	Measures	Time Unit	Spatial Unit	Source	Timeline
Safety Outcomes	crashes injuries fatalities DWI offences	time of day	X,Y coords	Austin PD	2012-17
Ridesourcing	trip origins and destinations	time of day	X,Y coords	RideAustin	2016-17
Total Trips	Origin-Destination Trip Index	month	Census tract	StreetLight Data	2012-17
Demographic Economic Data	med. household income population density employment density % of 0 vehicle ownership	year	Census tract	American Community Survey	2012-17

Approach

Data Preprocessing

- convert to consistent units: tract-month
- uncover correlations between variables
- conduct trends and before/after analyses

Spatial Dependence Models

- spatial error, lag, SARAR models with fixed effects
- variable significance

Results

- interpretability >> prediction accuracy
- data-driven policy
- potential safety impacts

Spatial Dependence Models

Spatial Lag and Error Models
Spatial AutoRegressive w additional AutoRegressive error structure (SARAR)

SARAR accounts for both neighboring effects and omitted spatially correlated covariates

$$y_{\mathrm{it}} = \lambda \sum_{i \neq j} w_{ij} y_{jt} + \beta x_{it} + a_i + \gamma_t + u_{it} \quad [1]$$

$$u_{it} = \rho \sum_{i \neq j} w_{ij} u_{jt} + \varepsilon_{it} \quad [2]$$

SARAR specification from Anselin and Florax, 1995

λ and ρ spatially autoregressive coefficients

disturbance term u_{it} follows spatial autoregressive process in [2]

w_{ij} weights based on binary contiguity, where $w_{ij} = 1$ when the intersection of the boundaries of i and j spatial units is not empty, ow $w_{ij} = 0$

a_i spatial unit fixed-effect, γ_t time unit fixed-effect,

β vector of parameters to be estimated, x_{it} vector of explanatory variables

Interpreting Spatial Dependence Models

- Logarithmic (natural) transformation of road safety outcomes and ridesourcing

Addresses right skewness via normalization

- Panel data

Capture intertemporal dependence of events

- Fixed effects (both time and space)

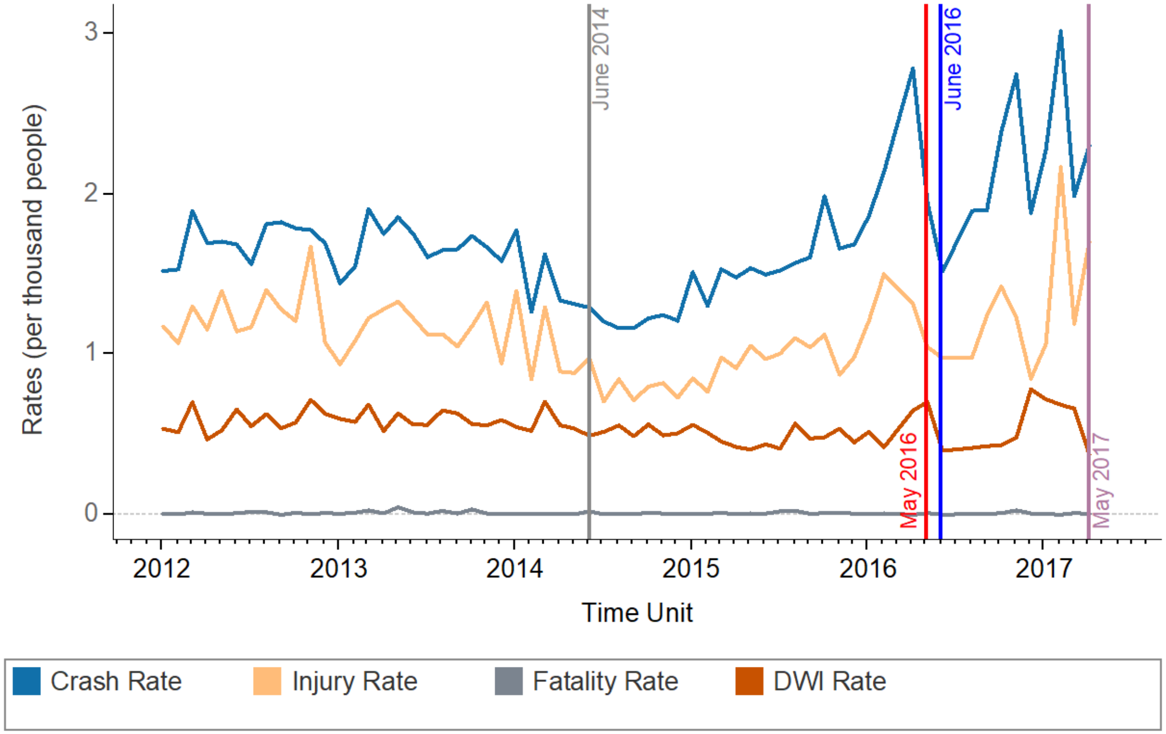
Eliminate bias from unobserved factors that are changing over time unit but constant over census tract and vice versa

- Spatial Dependence

Comparing the spatial lag and spatial error models, the former suggests road safety crashes in one spatial unit predict an increased likelihood of road crashes in neighboring places; the latter suggests that we might have omitted spatially correlated covariates that would affect inference

Crash Rates in Travis County TX

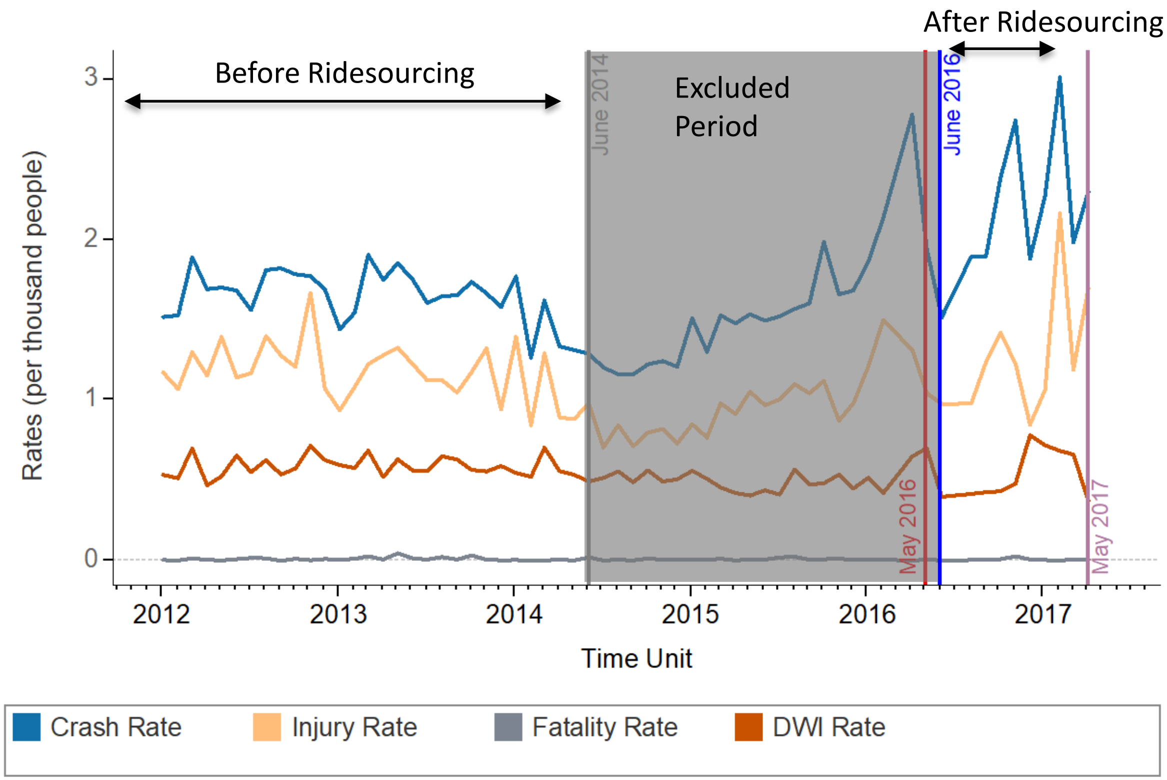
Safety Outcome Rates Time-Series Aggregated for Travis County



Crash Rates in Travis County TX

Timeline

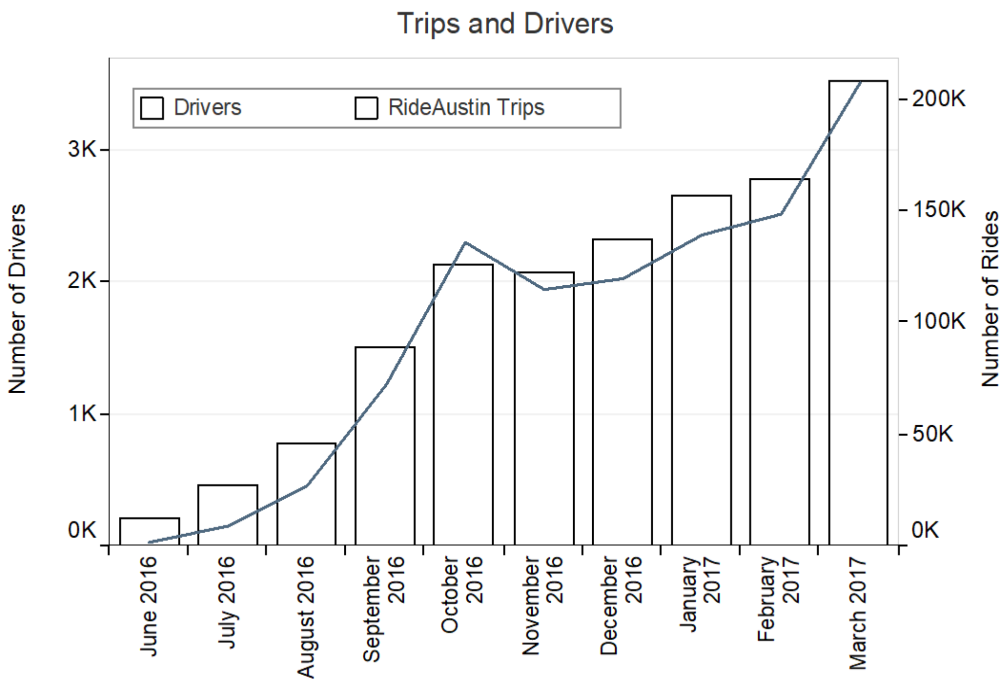
- June 2014 Uber/Lyft launch in Austin
- May 9, 2016 Uber and Lyft exit
- June 6, 2016 RideAustin launch & data available
- May 29, 2017 Uber and Lyft return



Ridesourcing Exposure in Travis County TX

Ridesourcing Exposure: Origins and Destinations per Census Tract

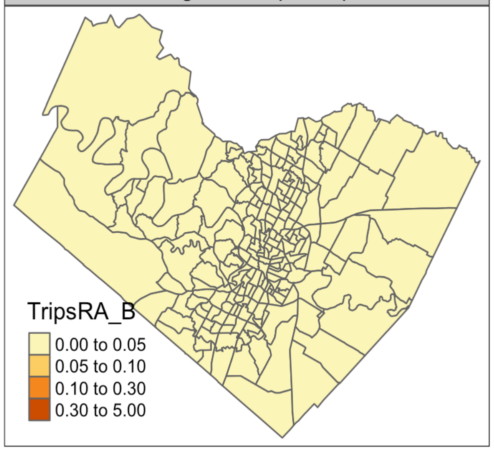
- Timeline: June 6 2016 – April 13 2017



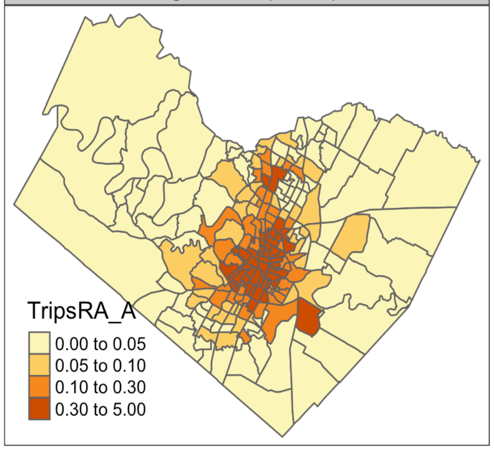
Spatial Analytics in Travis County TX

Ridesourcing Use Rates

Before: Avg. RA Trips/Population

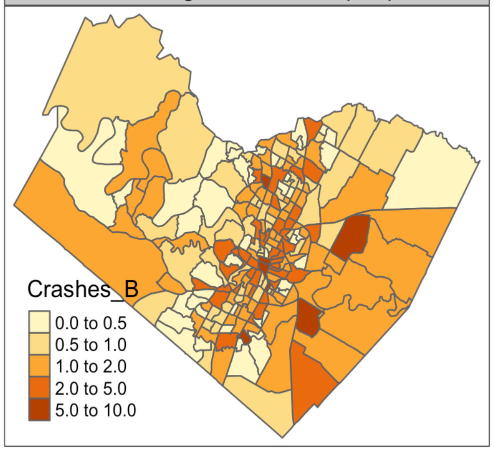


After: Avg. RA Trips/Population

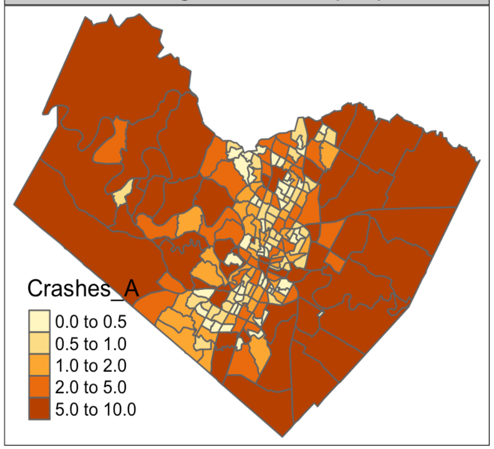


Road Crash Rates

Before: Avg. Crashes/1K people



After: Avg.Crashes/1K people



Road Safety Before & After Ridesourcing Launch

	Tract-Month-Year Units without Ridesourcing Mean (Std. Deviation)	Tract-Month-Year Units with Ridesourcing Mean (Std. Deviation)
Crashes (per 1,000 people)	1.65 (3.22)	2.20 (11.54)
DWI Offences (per 1,000 people)	0.59 (1.35)	0.53 (2.56)
Injuries (per 1,000 people)	1.17 (2.97)	1.38 (9.93)
Ridesourcing Rates (per 1,000 people)	0	0.28 (1.05)
Median Household Income ($)	63,744 (32930)	71,068 (34002)
OD Trips Index/Population	6.27 (8.31)	7.60 (14.91)
Gas Price ($/gallon)	3.36 (0.19)	2.00 (0.08)
Population	4,847 (2,620)	5,314 (3,029)
Percent of Zero Vehicle Ownership	3.33% (3.78%)	3.02% (3.47%)
Percent of employment	72.03% (11.78%)	72.10% (10.93%)
Records	72.50%	27.50%

Ridesourcing Associated with Road Safety Improvements

Results of spatial dependence modeling

	Crashes	Injuries	DWI Offences	Fatalities
Ridesourcing coefficient	-0.013	-0.025	-0.036	-0.0009
Reduction % for 10% increase in ridesourcing trips	0.12%	0.25%	0.36%	insignificant
P-value	$p<0.05$	$p<0.001$	$p<0.0001$	$p>0.1$
Adjusted std. errors	0.007	0.009	0.007	0.002
Census tract and month-year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	8720	8720	8720	8720

- Potential **benefits of ridesourcing**: reducing injuries and property loss; reducing court costs, insurance rate increases, loss of income due to DWI offences reduction.
- **Magnitude** of ridesourcing effects on improving road safety **is lower compared to infrastructure improvements.**

Findings Discussion

- RideAustin trips10% increase is found associated with a 0.36% and 0.25%, 0.12% decrease in DWI offences, road injuries, and crashes respectively.

- No statistically significant association at conventional levels between RideAustin use and fatalities.

- Analysis is not limited by the use of dichotomous variable to describe ridesourcing availability.

- Potential benefits of implementation of ridesourcing, primarily due to DWI offences reduction.

Future Directions

- Address data limitations
  - Test alternate travel demand measures
  - Effects might not manifest immediately from ridesourcing use
  - Results only correspond to Travis County, other regions need to be examined for robustness

- Ongoing research
  - Uncover which populations and subpopulations are influenced to the greatest degree, based on household income and employment
  - Identify key drivers of where public health benefits of ridesourcing can be maximized

Thank you!

Streetlight Trip Index: Backcasting

Traffic time series analysis

Unavailability of OD traffic data for each census tract in Travis County for the whole period of the analysis (January 2012-June 2014 and June 2016-April 2017)

Solution: time series, autoregressive integrated moving average model ARIMA(p, q, d)
In our analysis $p = 1, q = 0,$ and $d = 1.$
The transfer function is the average monthly $ per gallon gas price.

The autoregressive order of the model ARIMA(p, q, d) dictates the number of the lagged values $x_{i,t-1}$ that have an impact on $x_{i,t}$ OD trips. The order of the moving average direction q is the number of the lagged error terms used in the model, and d is the fractional integration parameter used to force stationarity.

The chosen model was based on comparisons of R squared adjusted and Akaike's Information Criterion.

Final Model Results

	Log(1+Crashes)		Log(1+Injuries)		Log(1+Fatalities)		Log(1+DWI)	
	β		β		β		β	
SARAR Panel Model								
Percent of	-0.029		0.326		-0.108	*	0.034	
Employment	[0.159]		[0.2024]		[0.0515]		[0.158]	
Median HH Income	$-1.80\ 10^{-6}$	.	$-1.13\ 10^{-6}$		$0.59\ 10^{-6}$	.	$-1.97\ 10^{-6}$	*
	[$1.02\ 10^{-6}$]		[$1.40\ 10^{-6}$]		[$0.33\ 10^{-6}$]		[$1.00\ 10^{-6}$]	
Percent of Zero	-0.922	**	-0.899	*	0.121		-0.103	
Vehicle Ownership	[0.293]		[0.410]		[0.099]		[0.294]	
Population Density	$3.89\ 10^{-6}$	**	$2.86\ 10^{-6}$		$-1.23\ 10^{-6}$	**	$1.73\ 10^{-6}$	
	[$1.46\ 10^{-6}$]		[$1.78\ 10^{-6}$]		[$0.41\ 10^{-6}$]		[$1.27\ 10^{-6}$]	
OD Trips	$1.13\ 10^{-8}$		$8.55\ 10^{-7}$		$0.135\ 10^{-6}$		$1.13\ 10^{-6}$	.
	[$5.60\ 10^{-7}$]		[$8.04\ 10^{-7}$]		[$0.21\ 10^{-6}$]		[$0.59\ 10^{-6}$]	
Log(1+TripsRA)	-0.011	.	-0.024	**	-0.001		-0.036	***
	[0.006]		[0.009]		[0.003]		[0.008]	
λ	0.359	***	0.186		-0.296	***	0.136	
	[0.058]		[0.129]		[0.089]		[0.170]	
ρ	-0.290	***	-0.141		0.272	***	-0.092	
	[0.075]		[0.146]		[0.073]		[0.186]	
LM: lag (df=1)	28.09	***	6.67	*	1.26		11.23	*
LM: error (df=1)	25.74	***	6.203	.	1.27		10.36	.
Hausman test (df=6)								
chi-squared	205.6	***	110.31	***	10.32	.	7.57	*