HOW ARE UBER/LYFT SHAPING MUNICIPAL ON-STREET PARKING REVENUE?

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ABSTRACT

Autonomous Vehicles (AVs) will impose challenges on cities that are currently difficult to fully envision yet critical to begin addressing. This research makes an incremental step toward quantifying the impacts that AVs by examining current associations between transportation network company (TNC) trips—often viewed as a harbinger of AVs—and parking revenue in Seattle. Using Uber and Lyft trip data combined with parking revenue and built environment data, this research models projected parking revenue in Seattle. Results demonstrate that total revenue generated in each census tract will continue to increase at current rates of TNC trip-making; parking revenue will, however, start to decline if or when trips levels are about 4.7 times higher than the average 2016 level. The results also indicate that per-space parking revenue is likely to increase by about 2.2 percent for each 1,000 additional TNC trips taken if no policy changes are taken. The effects on revenue will vary quite widely by neighborhood, suggesting that a one-size-fits-all policy may not be the best path forward for cities. Instead, flexible and adaptable policies that can more quickly respond (or better yet, be proactive) to changing AV demand will be better suited at managing the changes that will affect parking revenue.

Keywords: Ride-hailing, transportation network companies, autonomous vehicles, parking, public finance and budgeting

INTRODUCTION

Fifteen years ago, autonomous vehicles (AVs) were more fiction than science. Today, AVs have driven millions of miles but continue to face design, planning, and financial challenges (Brodsky, 2016; Glancy, 2015). AVs have the potential to drastically change transportation and shape the equitable distribution of the new infrastructure required to accommodate them, reshuffle city development patterns, and alter land valuation, leading to strains on government finances. While a proliferation of research has explored the technological aspects of AVs, few cities are yet planning for or considering how AVs may impact various elements of city and suburban life (Freemark et al., 2019; Glancy, 2015; Mitteregger et al., 2019; Terry & Bachmann, 2019). This article seeks to study a specific effect: parking revenue in the age of AVs and its potential impacts on municipal budgets. Little work to date (see for example Clark, Larco, and Mann (2017); Clark and Lewis (2018); and Mitteregger et al. (2019)) has investigated the budgetary impacts of AVs on municipal budgeting and finance. One limit to current research on AV effects in their limited deployment; while 2016 marked the first exclusively AV freight delivery and the first introduction of a fully autonomous ride-hail (Uber) fleet (Davies, 2016), the current level of AV deployment is not yet sufficient to evaluate how they might actually impact city environments and budgets. Instead, researchers and policymakers have relied on transportation network companies (TNCs) such as Uber and Lyft to proxy for forthcoming AV technologies.

This article uses TNCs as a proxy for future AV use. Like AVs, TNCs eliminate the need to park at a destination. Previous researchers have used chauffeur services—similar to TNCs—to examine travel behavior responses to eliminating driving to and parking at destinations (Harb et al., 2018). Using Uber and Lyft trip data along with built environment and parking revenue data from the city of Seattle, this research asks: what is the association between TNC trips in a neighborhood and parking revenue? Findings yield implications for city budgets and parking and AV policy moving forward.

The remainder of this article arranged as follows. First, it provides an overview of the pertinent literature surrounding TNCs, AVs, and parking. Second, it reviews the data and methods used to answer the above research question. The paper concludes with a discussion of the results and implications for policy.

BACKGROUND

Effects of AVs on Municipal Budgets

Clark, Larco, and Mann (2017) provide some of the first explorations of potential impacts of AVs on city budgets. However, this study proposed directional impact and did not quantify the magnitude of these impacts. Clark and Lewis (2018) provide some limited budgetary impacts in three case study cities across a number of revenue categories, but this study is not based on an empirical evaluation of what is currently happening on the ground. Mitteregger et al. (2019) examine the case of Vienna, Austria and the projected fiscal impacts on that city. Maciag's (2017) article in *Governing Magazine* is one of the few articles in the popular press to question empirically how AVs might impact local government budgets. In his study of 25 large U.S. cities, Maciag finds that parking revenues (meters, garages, fines/fees) account for an average of $129/capita in revenue. He notes that city "[t]otals were much larger in cities assessing special taxes on parking operators, deploying traffic cameras or those receiving substantial shared revenues from states in the form of gas taxes or vehicle registration fees" (Maciag, 2017). This implies that the degree to which a city relies on parking- and enforcement-related revenues will impact how much a city's budget will be affected by the shift to AVs.

A handful of policy guides distributed in the last few years offer initial suggestions for how cities can adapt to an autonomous future. Glus et al.'s (2017) "Driverless Future: A Policy Roadmap for City Leaders" provides an overview of how cities may shift over the coming decades as a result of AVs and provides recommendations on how cities might plan for these changes. They state that "Cities have a window of opportunity to shape how the autonomous vehicle is used and must act now to define policies that minimize risks and maximize the benefits of driverless technology" (Glus et al., 2017, p. 2). And while the authors provide a range of recommendations, they only briefly mention the financial impacts of AVs. Fagnant and Kockelman's (2015) study examines "traffic safety, congestion, and travel behaviors," and while they suggest coming changes to costs and revenues for local governments' budgets, they offer little beyond demonstrating a need for planning and research. Lewis et al. (2017) provides a roadmap for leaders at all levels of U.S. government, but only briefly addresses changes in costs and revenues and does not provide the level of detail needed to be actionable by local leaders. Connery (2016) provides an overview of the impacts of AVs on the municipal bond market, with a focus on the investment risks of General Obligation (GO) bonds related to AVs. The National League of Cities (2017) issued a local government "policy preparation guide" that provides some guidance to cities on preparing for autonomous vehicles. They provide an overview of AV technology and answer common questions cities have about AVs. The guide calls for proactive policies by cities and coordination across jurisdictional boundaries—particularly using metropolitan planning organizations to coordinate regionally. Similar to other reports, the National League of Cities offers the broad sense that cities need to plan for investments and that changes to expenditures and revenues are coming; however, it offers little specific advice or insight on where within the budget these changes may happen. The City of Seattle issued its own guide, called the "New Mobility Playbook," which indicated a need to diversify revenue sources to respond to widespread AV adoption (Seattle Department of Transportation, 2017). In this report, the city laid out steps that they will take to prepare for all types of new mobility that are hitting the streets, including AVs. Seattle's work makes it clear the city is aware change is happening, but again does not project the magnitude of change. Public officials nationwide need to also be aware that AVs will impact both sides of their budget (expenditures and revenues). In sum, the existing literature provides very limited insight into how to start fiscal and budget planning for AVs.

Parking Demand in an Autonomous Future

Many argue that, today, city requirements err on the side of requiring way too much (free) parking, rather than using any localized analysis or market mechanisms (Shoup, 2017; Willson, 2013). Studies of TNCs hint at a range of possible futures for parking demand in an autonomous future. Anecdotal evidence from across the country suggest falling parking revenues alongside the rise of TNCs (Bergal, 2017b, 2017a; Maciag, 2017; Morris, 2018; Williamson, 2018). Correspondingly, surveyed TNC users report hailing a ride to avoid parking congestion and prices (Clewlow & Mishra, 2017; Henao, 2017). While some suggest that TNC use could reduce driving trips and therefore parking demand—particularly at high-trafficked destinations such as airports, sports arenas, and bar and nightlife areas (Henao & Marshall, 2019)—one could also expect to see *more* TNC trips in areas of high parking demand as people seek to avoid parking in such areas. For example, Brown (2019) finds a negative association between off-street parking density—where ostensibly parking is easier to find as supply is greater—and the number of Lyft trips per capita. TNC trips are also associated with built environment characteristics beyond parking: research repeatedly notes connections between density and ride-hail travel (Brown, 2019; Mahmoudi Jina & Zhang Lei, 2009; San Francisco County Transportation Authority, 2017). Mixed land uses are also associated with higher demand for for-hire vehicles (including taxi, Uber, and Lyft) (Mahmoudi Jina & Zhang Lei, 2009).

Like TNCs, AVs hold the potential to dramatically affect parking demand and therefore revenues. As Clark and Lewis (2018) and Maciag (2017) note, AVs *will* reduce parking revenue, though the time horizon of this decline remains uncertain. Some estimates of AV adoption predict fully-functional autonomous and shared ride-hailing-service (Lyft without a driver) within 20 years. While two decades may seem like a sufficient time horizon for cities to plan and adapt to AVs, research also finds that few cities are preparing or planning for these technologies (Freemark et al., 2019). What are cities to do if and when shifts from personal driving to hailing AV fleets decimate parking revenues so that garages and meters are no longer sustainable sources of revenue, or even sufficient to repay debts incurred to build the parking infrastructure in the first place? In the following sections, we discuss, ask, and answer the following research question: what is the association between local TNC demand and parking revenue in the City of Seattle between 2013 and 2016?

DATA AND METHODS

Data

This research utilizes parking revenue and TNC trip data in conjunction with data on the local built environment to examine the association between TNC trips and parking revenue in the City of Seattle between January 2013 and December 2016. January 2013 represents the start of Uber operations in the City of Seattle at volumes sufficient to track in our data (at least 5 trips in a tract per time period (e.g. 11am-3pm)); December 2016 represents the most recent data that Uber was willing to provided trip data to this study. Lyft data are also included in TNC trip data beginning in 2013 when the company began operations in Seattle. The data used in this research are described in depth below.

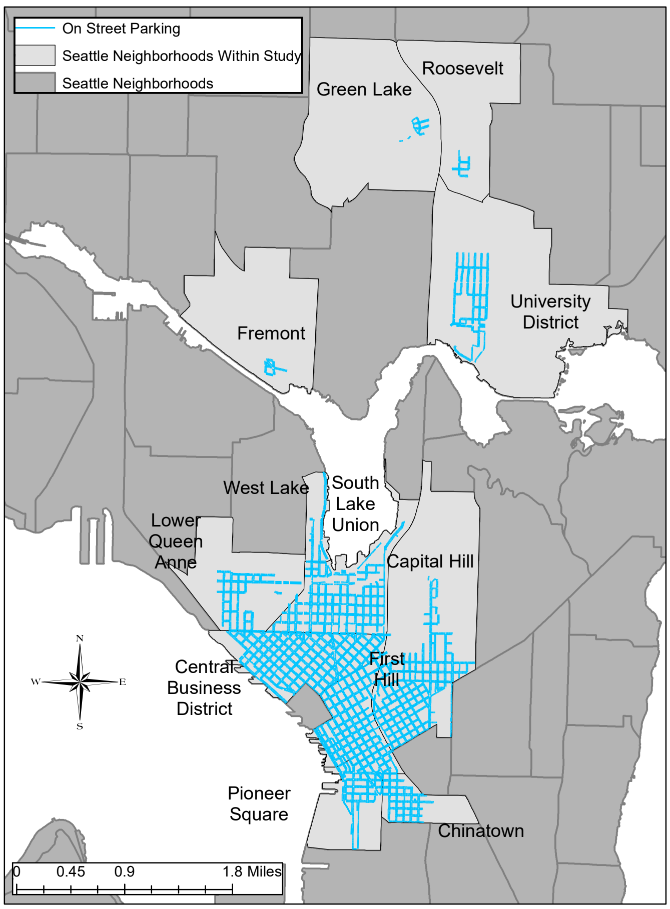
Unit of Analysis

Before discussing each dataset used in the analysis, it is first important to understand how the data are aggregated. The size of the dataset, primarily the parking data from the Seattle Department of Transportation (SDOT) (detailed more below), created challenges in geospatial and statistical analysis. The parking occupancy dataset totaled approximately 500GB in size and the parking transaction dataset about 60GB. We therefore collapsed each dataset to allow for quicker computing times and provide clearer findings interpretations. Transaction-level data were aggregated to the census tract and into three observations time periods, bounded by paid parking hours of 8am-7pm, Monday to Saturday: morning (8am-10am), afternoon (11am-3pm), and evening (4pm-7pm). We further separated data by month, day, and year. For example, all individual parking transactions were summed across all Monday mornings (8-10am) in January 2015. In sum, aggregating individual observations across six days of the week and times three time periods per day produced 18 monthly observations per tract. The resulting study sample size is 24,598 time periods.

Parking Revenue

There are about 1.6 million parking spaces in Seattle, which amounts to about five parking spaces per household and nearly 30 parking spaces per acre, on average, throughout the city. On-street parking accounts for approximately one-third of these parking spaces, with the rest in private garages, surface lots, and driveways. The Seattle parking supply, in all its forms, is ample and the city parking supply is more similar to less dense cities such as Des Moines, Iowa (which actually has fewer parking spaces per acre than Seattle), than it is to the more densely populated East Coast cities of New York and Philadelphia (Scharnhorst, 2018). Figure 1 shows the paid on-street parking areas of Seattle that are included in this study.

Figure 1: Map of Study Area



SDOT provided two datasets used in analysis. The first data are transaction-level data for all on-street parking in the city. Each parking transaction records the transaction location, the number of minutes purchased, and the total cost of those minutes. The second dataset from

SDOT is block-level parking occupancy by minute during the study period. All parking data were aggregated to the census tract using ArcGIS and Stata. We use parking data to calculate parking revenue per tract for each unit of observation (aggregated to time block of day (e.g. 11am-3pm), on day of week (e.g. Monday), in a month (e.g. January), in a year (e.g. 2015)). The total parking revenue per tract and time period is used in all analyses. We also used parking data to estimate median parking occupancy at the tract level for each time period. Finally, we estimated the average rate paid per hour by dividing the total revenue generated by the total number of hours paid for in the tract. Average hourly rate is subject to a degree of inaccuracy, however, as people can pay for more meter time than they use (i.e., depart a meter before their time has expired) or pay for less than they actually use (i.e., park at a meter without paying). We assume that this pattern of over/underpayment is evenly distributed across all parking areas. Hourly parking rates are adjusted up and down by the city periodically to maintain target occupancy levels. We controlled for average hourly parking rates in each time period to account for these changes in rates. We control for the neighborhood location of all parking meters in analysis to account for non-measured or non-observed heterogeneity across neighborhoods.

TNC Data

We obtained data from both Uber and Lyft to measure TNC use in Seattle. For each time period between 2013 and 2016, we calculated the number of pick-ups, drop-offs, and the total number of both kinds of trips. The two models specified in this paper use different TNC trip dependent variables: 1) the total number of trips (pick-ups and drop-offs combined) in a tract during the specified time period; and 2) the number of pick-ups in a tract separate from the number of drop-offs in order to determine if the association between parking revenue varied meaningfully for TNC pickups versus drop-offs.

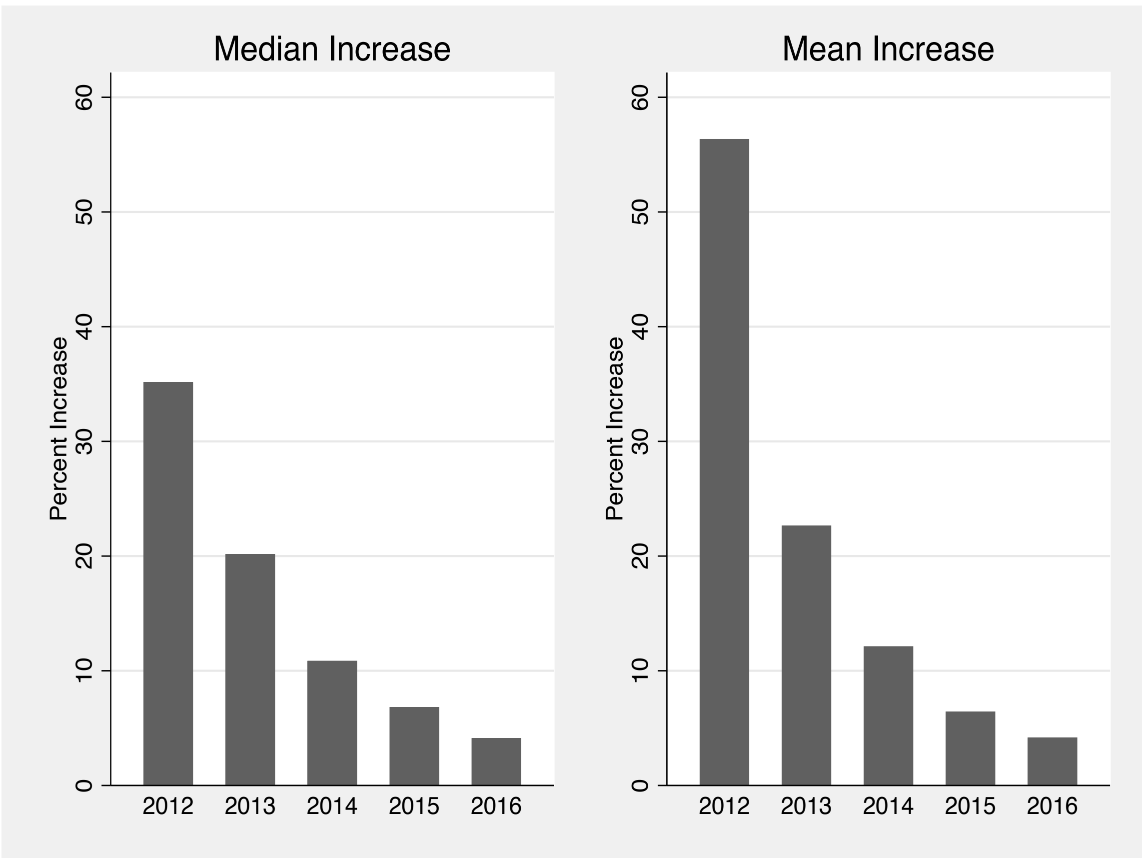
TNC use has grown exponentially since both Uber and Lyft began service in Seattle. Figure 2 shows the average monthly growth rates for each year of TNC travel in Seattle during the study period. Exponential trip growth led us to include a squared trip volume variable in the models. We would not expect trips to be linear at any point in the short or medium term given the exponential growth patterns of TNCs since their arrival in Seattle. Post-estimation tests also reveal that the inclusion of the squared terms yields less information loss (based on AIC statistics), further supporting the decision to include these variables in the models.

Built Environment Data

Parking revenue and TNC trips may also be related to the built environment context.
We gathered five-year American Community Survey (ACS) data (2013-2016) including car ownership, population density, and median household income by census tract to reflect previously found associations between TNC travel, resident, and the built environment characteristics (see Brown, 2019). Because research also finds that social and leisure trips are a top trip purpose for TNC users—and that users may substitute personal driving for TNCs (Henao & Marshall, 2019)—we include a measure of local entertainment activity in analysis. Specifically, we collected beer, wine, and liquor license address data from the State of Washington and aggregated number of establishments by census tract. Finally, we included the average price of all grades of retail gasoline from the U.S. Energy Information Administration (2019). Controlling for the price of gasoline accounts previous findings that higher gasoline prices are associated with fewer aggregate vehicle miles traveled, i.e., driving (Manville et al., 2017).

We collected land use data from the city of Seattle and used ArcGIS to calculate the share of each land use type by tract. Because land uses change over time, we created land use variables for each year included in the analysis. Land use codes are highly specific and include hundreds of specific use designations. To condense the number of uses into more manageable and interpretable groups for analysis, we aggregated land uses of similar types into five broad categories: commercial, industrial, residential, mixed, and all other uses.

Figure 2: TNC Month-over-Month Percent Increase in Number of Trips



Methods

We analyzed parking revenue is analyzed as a dependent variable in two Poisson regression models with robust standard errors. Poisson regression models account for the non-normal distribution of the dependent variable, following the advice of Wooldridge (2002) and Gould (2011). The models—which control for TNC trips and the built environment variables described above—produce forecasts of two separate measures of on-street parking revenue as a function of the covariates. We use robust standard errors because Poisson assumes the mean and variance are equal, but using the "Huber/White/Sandwich linearized estimator of variance is a permissible alternative to log linear regression," and as Gould (2011) demonstrates this produces a less biased estimator. In addition, a Poisson model retains observations of zero revenue rather than omitting them as a log linear model would do. Typically when we think of using a Poisson model we are conditioned to think of its use only four count data, but as Silva & Tenreyro (2006, p. 645) point out "what is more important, y_i does not even have to be an integer—for the estimator based on the Poisson likelihood function to be consistent."

We use two models to estimate and forecast parking revenue to allow for variation in the parking revenue dependent variable. Model 1 uses total tract revenue in a tract for a time period as the dependent variable and measure of revenue. Model 2 uses the average revenue per parking space in a tract in time period as the dependent variable.

RESULTS

Findings present a mixed message of how TNC trips are associated with on-street parking revenue in the City of Seattle. In addition, the forecasting efforts in this article provide some insight into how AVs might further shape parking revenue stream for cities. Table 1 shows three columns for each model. The first column shows the beta coefficients, the second column shows the robust standard errors, and the third is the percent change in the dependent variable with a one-unit change in the independent variable. The third column is used in the discussion of results to ease interpretation.

Table 1 shows the results from Models 1 and 2, which have specified associations between parking revenue, the built environment, and TNC trips. Model 1—the relationship between total parking revenue in a census tract during a time period—shows that for each 1,000 additional TNC trips taken in a census tract, revenue would increase by about 8.2 percent, all else equal; this relationship is, however, moderated negatively in the squared term, decreasing revenue by 4.7 percent. The results indicate that at approximately 4.7 times the average number of TNC trips per day in 2016, parking revenue will start to decline. The level at which revenue starts to decline is about half as much as the maximum observed value for number of trips in a time period—meaning we could be closer to revenue decline that would seem apparent at first blush.

Model 2—the relationship between average parking revenue per parking space in a census tract during a time period—shows that for each 1,000 additional TNC trips taken in a census tract, all else held constant, parking revenue per space increases by about 12.9 percent; the squared term in Model 2 mediates the growth by -0.8 percent for each 1,000 trips taken. The results indicate that at approximately 4.2 times the average number of TNC trips per day in 2016, parking revenue will start to decline.

Table 1. TNC Trips and Parking Revenue, Poisson Regression Models Results

	(1)			(2)		
	DV=Total Parking Revenue	se	% change in expected count for unit change in X	DV=Parking Revenue Per Space	se	% change in expected count for unit change in X
All pickups and dropoffs (in 1000s)	0.05969**	[0.00892]	6.2	0.12155**	[0.00767]	12.9
All trips squared (in 1000s)	-0.00529**	[0.00087]	-0.5	-0.00828**	[0.00079]	-0.8
Average cost to park on-steet per hour	0.01723*	[0.00676]	1.7	0.39431**	[0.00634]	48.3
On-Street Parking Median Occupancy Rate	0.01621**	[0.00029]	1.6	0.02520**	[0.00027]	2.6
Paid Parking Spaces in Tract (in 100s)	0.18502**	[0.00190]	20.3			
Number of Vehicles -Cars, Trucks, Vans (in 100s)	-0.04550**	[0.00116]	-4.4	-0.00620**	[0.00119]	-0.6
Number of Beer/Wine selling establishments	0.00621**	[0.00017]	0.6	-0.00155**	[0.00020]	-0.2
Average cost per gallon of Gasoline	0.02746*	[0.01323]	2.8	0.04075**	[0.01188]	4.2
Median Household Income (in $1000s)	-0.00509**	[0.00029]	-0.5	-0.00292**	[0.00031]	-0.3
Population Density (1000 people/sq mile)	0.00844**	[0.00056]	0.8	-0.00021	[0.00038]	0
Zoning & Land Use (Commercial is Ommitted Category)						
% Residential	-0.00256**	[0.00032]	-0.3	0.00163**	[0.00023]	0.2
% Industrial	0.00445**	[0.00027]	0.4	-0.00053*	[0.00022]	-0.1
% Mixed Use	-0.00849**	[0.00032]	-0.80	0.00002	[0.00024]	0
% Other Zoning/Use	-0.00608**	[0.00028]	-0.6	-0.00004	[0.00026]	0
Time of Day (Omitted Group: Morning [8-10am])						
Afternoon (11-3)	0.41492**	[0.01519]	51.4	0.34369**	[0.01431]	41
Evening (4-7)	-0.48570**	[0.01672]	-38.5	-0.59416**	[0.01698]	-44.8
Day of the Week (Omitted Group: Monday; no paid parking Sundays)						
Tuesday	0.09235**	[0.01410]	9.7	0.07000**	[0.01209]	7.3
Wednesday	0.08941**	[0.01410]	9.4	0.05537**	[0.01206]	5.7
Thursday	0.07398**	[0.01433]	7.7	0.02332	[0.01229]	2.4
Friday	0.09260**	[0.01411]	9.7	0.01904	[0.01220]	1.9
Saturday	0.11279**	[0.01332]	11.9	-0.00977	[0.01287]	-1.0
Year Trend	0.01220	[0.00836]	1.2	-0.06735**	[0.00745]	-6.5
Constant	-17.52513	[16.86488]		140.96893**	[15.04188]	
Observations	24,598			24,598		
Psudo R-squared	0.8567			0.6607		
Robust standard errors in brackets ** p<0.01, * p<0.05						

Both models highlight an important role for land use in the associations between TNC trips and parking revenue. In model 1, all land use variables have statistically significant differences from the omitted commercial category. Increasing the share of land devoted to residential, other uses, and mixed use by one percentage point decreases parking revenue by 0.3, 0.6, and 0.8 percent, respectively, compared to the commercial land uses. Increasing land devoted to industrial uses by one percent would increase parking revenue by 0.4 percent compared to the commercial. In model 2, only residential and industrial uses have a statistically significant difference from commercial land uses. Increasing the share of land in the tract devoted to residential land use would increase the average per space revenue by 0.2 percent compared to commercial land. An increase in land devoted to industrial uses by one percent decreases average per space revenue by 0.1 percent.

Other built environment characteristics are likewise associated with parking revenues. More parking spaces in a tract are naturally associated with more total revenue collected; we omitted the number of parking spaces in model 2 because we would not expect the number of spaces in a tract to impact per space revenues. In Model 1, for each 100 additional spaces in a tract, revenues would be expected to increase total revenue by 20.3 percent during each time period. This finding demonstrates that increasing parking supply could increase revenue, all else equal.

The variable controlling for the number of vehicles owned by tract residents indicates, in Model 1, that for each 100 additional owned vehicles is associated with about a 4 percent decline in parking revenue. In Model 2, 100 additional vehicles would decrease the average per space revenue by 0.6 percent. The number of vehicles may be colinear with neighborhood median household income (with a statistically significant positive correlation at r=0.61), which is also associated with reduced parking revenue, potentially altering these results for both models. For each $1,000 increase in median household income in a census tract, results show a decrease in total tract parking revenue of about 0.5 percent. Model 2 indicates that each $1,000 increase in median household income would increase average revenue per parking space by 0.3 percent.

For each additional establishment that sells beer and wine within a census tract, total revenue for on-street parking (Model 1) increases by almost 0.6 percent. The average revenue for each space, Model 2, decreases by 0.2 percent for each additional establishment.

The association between the cost of fuel and parking revenue is statistically significant in both models. In model 1, the results indicate that each additional dollar per gallon fuel prices increase parking revenue increases by 2.8 percent. While in model 2, a one dollar increase in fuel price increased revenue by 4.2 percent. This result that not necessarily comport with earlier research and is likely due to the relatively small range of values of fuel prices that did not vary widely during the study period—interquartile range of $2.35 to $3.57.

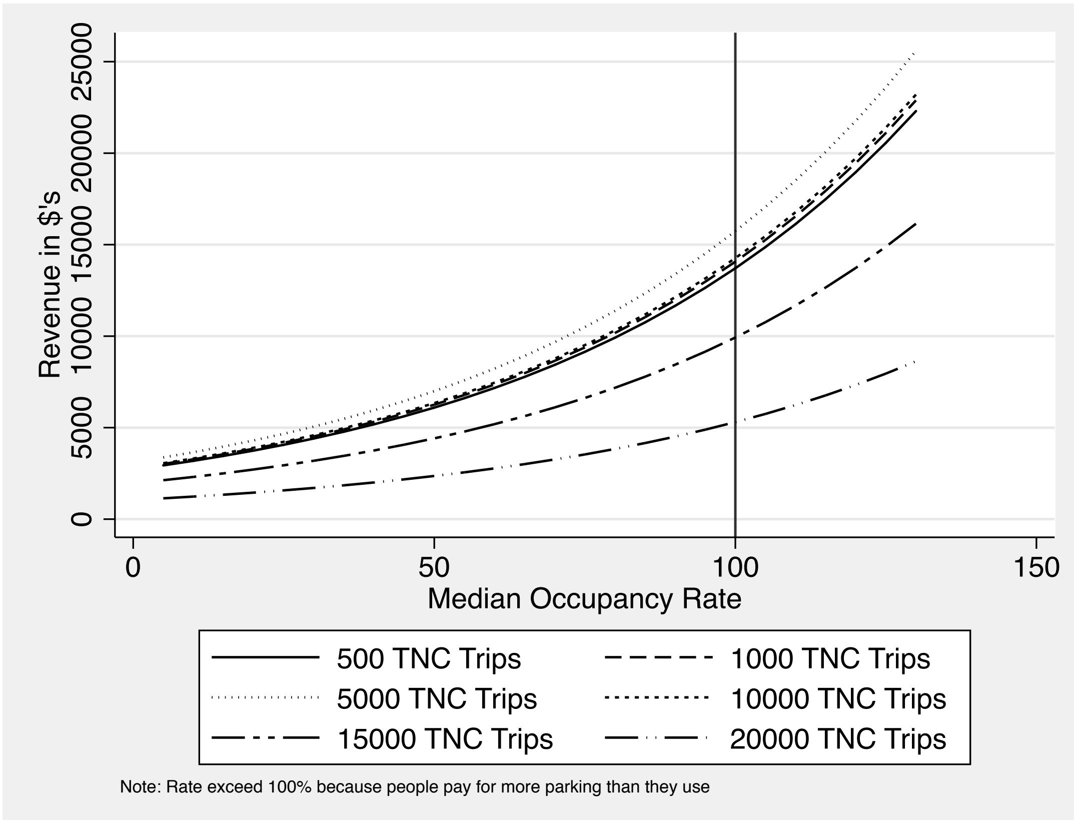
Finally, results show that each 1,000 additional people per square mile in a tract, total on-street parking revenue (model 1) increases by 0.8 percent. The average revenue per space is not statistically associated with population density.

Revenue Implications

Controlling for TNC trips, Model 1 results show that parking revenue is expected to increase by 13.3 percent when the average hourly parking rate increases by $1. Model 2 predicts that average revenue per parking space in a tract increases by 43.2 percent for each $1 increase in average hourly rate. This finding, however, does not account for potential travel behavior and/or parking occupancy changes stemming from increased hourly prices.

Results in both Models 1 and 2 indicate that revenue would increase by 2.2 to 2.3 percent for each one percent increase in parking occupancy. Figure 3 illustrates the relationship between parking occupancy and total parking revenue (Model 1) over several different levels of total TNC trips. The curves are all similarly sloped and changing over the range of values. While this estimate reflects constant parking prices, City of Seattle policy dictates that parking prices would change in response to falling occupancy, which is what we might expect in the long-term when more trips do not require parking.

Figure 3. On-Street Parking Occupancy Rate Effects on Revenue by Number of TNC Trips



Forecasting the Future

Understanding that expected revenue generation changes depend on the number of trips modeled, we next examine a range of potential parking revenue outcomes across a range of possible TNC trip volumes. The relationship between TNCs and parking revenue is most easily understood by examining Figure 4, Figure 5, and Figure 6, which show how revenue changes over a range of possible trip volumes, holding average cost of parking and occupancy fixed at current average values. We include two vertical lines as points of reference in Figure 4 and Figure 5; the solid vertical lines represent the mean number of TNC trips taken during 2016 during that time of day (though the models include data from 2013-2016), which ranged from about 1,200 trips in the morning to about 2,300 trips in the evening. The dashed vertical line represents the maximum number of trips observed, which ranges from about 6,600 in the mornings to around 15,000 trips in the evening. Importantly, this means that the revenue-TNC relationship to the left of the dashed vertical line is based on observed data, while everything to the right of that dashed vertical line is a forecast of what we might expect if the number of TNC trips increase.

Figure 4 shows that total parking revenue varies across time of day; the predicted effects of TNC trips, however, maintains relatively constant despite total revenue fluctuations. Jointly, Figure 4 and Figure 5 show that the total number of TNC pickups and drop-offs are associated with more parking revenue, but only up to a point; total parking revenue is predicted to fall as total TNC trips hit various thresholds depending on time of day. At the 2016 mean value for total TNC trips (1,782 trips), the model predicts an average revenue of $5,665 per tract in a time period. At the maximum observed value (15,134 trips) the model predicts a revenue of $3,807, or about $1,858 (33%) less. At thirty-thousand TNC trips the model predicts revenue to be only $266 , or about $5,399 (95%) less than what would be expected at the latest date of our data, on average. The results from the analysis predict that revenues peak at about $5,870, or at about 8,500 trips.

Figure 4. TNC Trip Effects on Total Parking Revenue

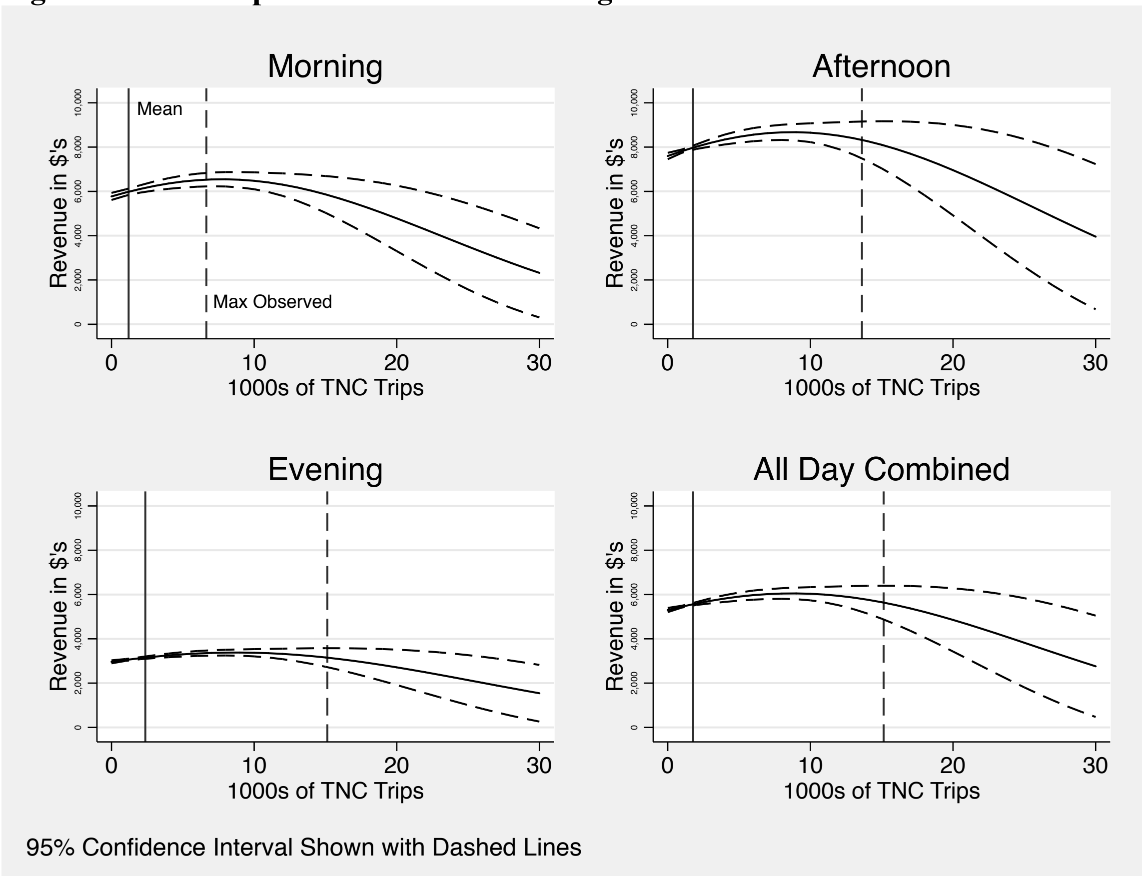


Figure 5 shows the relationship between the number TNC trips and the average revenue generated for each parking space in a census tract. At the 2016 mean value for total TNC trips (1,782 trips) the model predicts an average parking space generates about $1,536 in a time period. At the maximum observed value (15,134 trips) the model predicts a revenue of about $1,201, or about $335 (22%) less. At thirty-thousand TNC trips the model predicts revenue to be about $28, or about $1,508 (98%) less than what would be expected at the latest date of our data, on average. Notably, the revenue peaks at about half of the maximum observed value.

Figure 6 breaks predicted effects of TNC trips on parking revenues across the 18 Seattle neighborhoods that charge for on-street parking. This figure is based on results from Model 1 and reflects total revenue generated in a tract. Figure 6 largely shows that neighborhoods with higher levels of on-street parking revenue will see more dramatic changes in revenue moving forward.

Figure 5: TNC Trip Effect on Average Per Parking Space Revenue

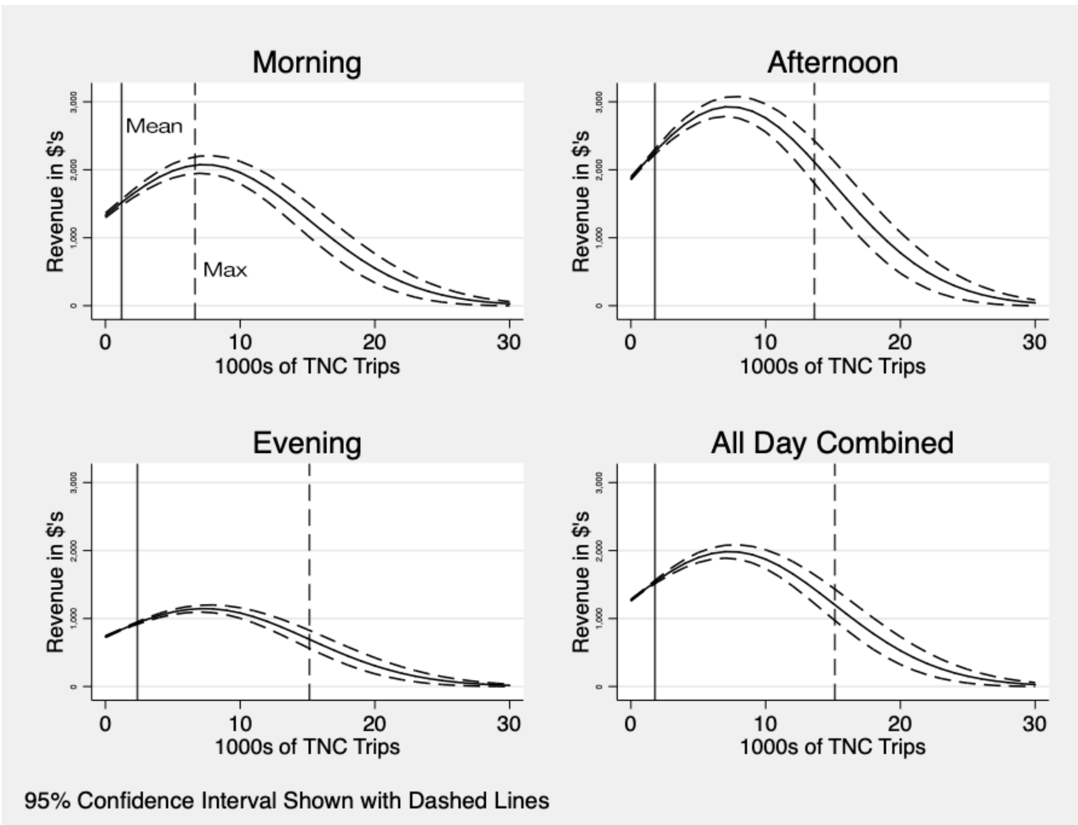
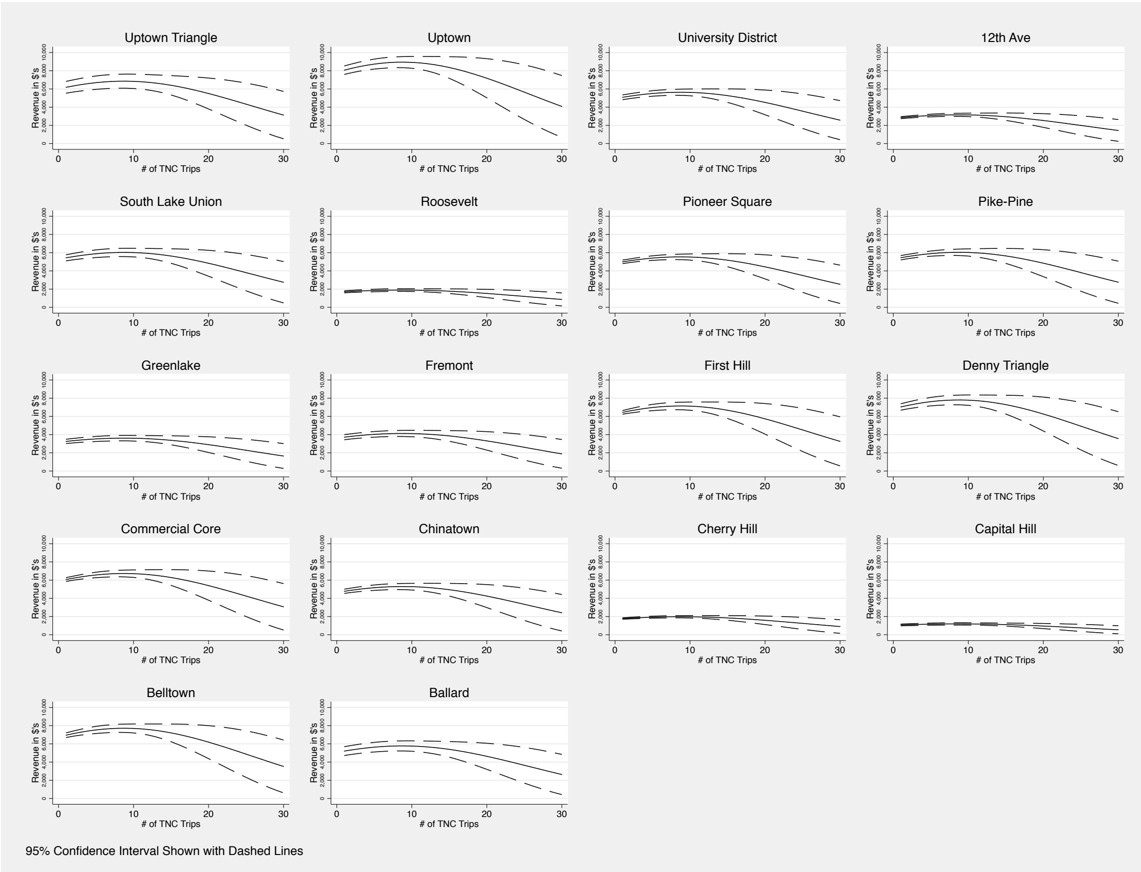


Figure 6. TNC Trip Effects on Parking Revenue by Neighborhood



Notably, these graphs represent what revenue would look like if no policy action is taken to change parking prices. Seattle, like many cities around the country, is frequently adjusting parking rates to achieve a parking occupancy rate between 70 and 85 percent (Baruchman, 2018). As more TNC trips occur, parking occupancy may fall; in response, Seattle parking policy would dictate reducing parking prices, which would in turn further affect these total revenue figures.

CONCLUSION

The results of the analysis suggest that, while cities might not expect falling parking revenues at current rates of TNC use, they should prepare policies to adapt to an uncertain, and likely autonomous, future. While Seattle, like many cities, does not set parking rates to maximize revenue, parking revenues are nevertheless critical to financial stability within the city budget. In the fiscal year 2018 budget, parking meter revenue represented a little more than three percent of total General Fund revenue—or about $44 million (City of Seattle, Washington, 2018). The share of total general fund revenue that parking generates has remained reasonably constant over the last 5 years (City of Seattle, Washington, 2018).

Findings from this article suggest that—at least at present trip levels—TNC use will not tank total or per-space parking revenue in cities. Model 1 results do indicate, however, that as trip volumes increase, revenues may decline. Model estimates show parking revenues will decline if or when TNC (or potentially AV) trips are about 4.7 times the average number of daily trips taken in 2016. In model 2, revenues begin to decline at 4.2 times the 2016 average number of daily TNC trips. But the results also indicate that we are close to peak parking (revenue) based on the observed maximum TNC trip levels. This suggests that, while some travelers may substitute TNCs for driving to avoid high-cost or scarce parking (Henao, 2017), modal substitution is not yet resulting in parking revenue losses overall, although it is getting close. At present the findings suggest that—rather than a fixed number of travelers traveling to and from neighborhoods by a different modal mix—*more* people are traveling to and from neighborhoods using a combination of modes, including TNCs and driving personal vehicles. These findings suggest that, in sum if not for individual travelers, TNCs and driving may be complements and enable more people to travel to/from locations on preferred routes, times, and modes. It is impossible to know from these data which TNC trips substitute for driving, which are new trips, or which transport people who previously traveled by other modes or at other times of the day. Additional research is needed to further understand the potential mode shift dynamics at play.

The results from this article assume no policy action by cities. Current parking policy in the City of Seattle aims to maintain a parking occupancy rate between 70 and 85 percent (Baruchman, 2018). If occupancy does begin to fall at much higher levels of TNC (or AV) use, cities will have to consider policy alternatives. One choice would be to lower the price of parking to reflect diminishing parking demand for parking. This action would further erode parking revenues, but may also run counter to many cities' aims of encouraging car-alternative travel. Alternatively, cities could maintain parking prices but reduce their supply of on-street parking and repurpose on-street spaces for other uses such as parklets, loading spaces, or non-auto parking spaces. This action, too, would likely reduce total parking revenue, but may have ancillary benefits such as managing congestion (loading spaces), facilitating micromobility (non-auto parking), or enhancing the streetscape and useable outdoor space (parklets). Cities have begun experimenting with alternative uses for traditional parking spaces: Washington, DC recently piloted a study evaluate an on-demand curb space reservation system for commercial pick-up and drop-off activity that would include TNCs but also food deliveries and commercial deliveries (District Department of Transportation, 2019); Boston is experimenting with pilots in similar ways as well, with some success (Short, 2019). By eliminating on-street parking spaces as demand for street parking declines, using an on-demand reservation system that charges for curb space use, Washington, DC and Boston are providing examples of how cities are beginning to seek out sources of revenue replacement and reduced congestion.

Total parking revenues are highest in commercial areas, and model results show that increasing residential, mixed, or other land uses relative to commercial uses slightly reduces total parking revenue all else equal. This suggests that parking revenues are highest in commercial areas, even when accounting for TNC travel. This may indicate that cities should, in the longer-run, focus on these higher revenue commercial areas for more revenue opportunities since they are projected to have larger revenue impacts. Finding replacements for these revenues, such as those pilot projects in Washington, DC or Boston, could provide some relief but may not be a panacea.

Model results for both total and per-space revenue results show that land uses, like other features of the built environment including population density, have relatively small associations with revenue compared to the broader temporal and transportation context: time of day, day of week, number of TNC trips, parking occupancy, and parking price all have strong associations with parking revenue. This finding presents a policy opportunity across land use types. Policymakers and planners can adjust parking policies or prices by time of day or day of week to attain desired occupancies or outcomes; other researchers suggest setting occupancy goals rather than attempting to maximize revenue, which may actually underutilize parking (Pierce et al., 2015).

City budgets are not in immediate danger of losing parking revenues due to TNC adoption and parking demand will not disappear overnight, or even in the medium term. Nevertheless, cities should begin to work through scenario planning to understand revenue implications as more TNC trips—and eventually AVs—are taken in the coming years. Future research will need to do a dynamic analysis that assesses the changes in parking rates in response to higher TNC use, and how those changes paired with one another could impact parking revenues.

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