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Are travelers substituting between transportation network companies (TNC) and public buses? A case study in Pittsburgh

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Abstract
Transportation network companies (TNC) provide mobility services that are influencing travel behavior in unknown ways due to limited TNC trip-level data. How they interact with other modes of transportation can have direct societal impacts, prompting appropriate policy intervention. This paper outlines a method to inform such policies through a data-driven approach that specifically analyzes the interaction between TNCs and bus services in Pittsburgh, PA. Uber surge multiplier data is used over a 6-month time period to approximate TNC usage (i.e., demand over supply ratio) for ten predefined points of interest throughout the city. Bus boarding data near each point of interest is used to relate TNC usage. Data from multiple sources (weather, traffic speed data, bus levels of service) are used to control for conditions that influence bus ridership. We find significant changes in bus boardings during periods of unusually high TNC usage at four locations during the evening hours. The remaining six locations observe no significant change in bus boardings. We find that the presence of a dedicated bus way transit station or a nearby university (or dense commercial zones in general) both influence ad-hoc substitutional behavior between TNCs and public transit. We also find that this behavior varies by location and time of day. This finding is significant and important for targeted policies that improve transportation network efficiency.

Keywords Transportation network companies (TNC) · Ride hailing · Shared mobility · Travel behavior · Uber · Lyft

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Introduction

Transportation network companies (TNC), such as Uber and Lyft, have grown quickly since they began offering ride-hailing services in 2010 and 2012 respectively. The two services have provided close to 4.5 billion rides in 2017 (Johana 2018; Kerr 2018). This period of rapid TNC growth coincides with a 7% decline in public transit ridership in the United States excluding New York City (Mallett 2018). During this same period, urban car ownership has also increased, both adding more vehicles to urban roadways and contributing to the observed reduction in transit ridership (Schaller 2019). These ridership trends threaten urban sustainability, public health, and transportation equity in the United States. Data-informed policies that consider emerging modes of travel are central to limiting rising congestion costs and improving mobility for vulnerable populations.

Up to this point, detailed TNC trip-level data has been closely guarded by privately held firms, thus limiting quantitative travel behavior analysis. For this reason, and to our best knowledge, the current literature that analyzes the relationship between TNCs and public transit is limited to survey-based methods, descriptive analysis, and longitudinal studies aggregated at the transit agency level. However, results can vary substantially by time and location, which may be related to a number of factors, such as the nature of the trips, land-use, and socio-demographics, to name a few. This paper proposes a novel method that analyzes the relationship (substitutional, complementary, no interaction) between TNCs and bus services in Pittsburgh at a neighborhood level during different times of day, and for various weather and traffic conditions. Data obtained from multiple sources coupled with natural experimental design are utilized at a 10 min resolution to observe system behavior at a scale not observed in the existing literature. Uber surge multipliers, which are used as a pricing strategy to balance supply and demand, are mined over a 6 month period and used as proxies for TNC usage (i.e., demand over supply ratio) at various points of interest throughout the city.

Widespread mode shift from public transit to TNCs can result in increased congestion simply due to large reductions in space efficiency. A recent study by Erhardt et al. (2019) found TNCs to be the biggest contributor to growing traffic congestion in San Francisco between 2010–2016. Henao (2017) also determined that less than 16% of TNC rides are shared and vehicle miles traveled (VMT) were over 180% compared to VMT without TNC services, further congesting urban roadways. Continued growth in U.S. congestion costs (Cookson 2017) highlight the importance of promoting sustainable, efficient modes of travel. The following study analyzes the relationship between public transit and TNCs to help inform sustainable policies and infrastructure investment in a changing transportation environment.

The remainder of this paper is organized as follows. The section "Literature review and research gap" reviews the current literature that analyzes the interaction between TNCs and public transit. Section "Conceptual design" discusses the design of the study and various required assumptions. Section "Data" discusses the data obtained for the analysis and the process used to assemble the multi-source data set. Descriptive statistics summarizes the current system with visualizations to help provide insights into system behaviors in Pittsburgh. Section "Methods" formulates the statistical model used to study the interaction between TNCs and local bus services. Section "Results" discusses model outcomes across various locations throughout Pittsburgh. Section "Multicollinearity and omitted variable checks" goes over the checks to ensure unbiased results. Section "Robustness testing" outlines various model robustness checks. And "Discussion and conclusions" discusses results and makes recommendations. Limitations of the research and future work are also discussed.

Literature review and research gap

Relationships between TNCs and public transit have been explored in previous studies, and generally, three relationships exist; substitutional, complementary, and no interaction. A substitutional relationship exists when travelers replace transit trips with TNCs. Currently, TNC user costs remain high compared to average transit user costs in the United States [$1.25–$2.50/mile for non-pooled service and $0.80–$1.40/mile for pooled services (Sperling 2018)]. However, the convenience, flexibility, and potential travel time savings of TNCs often outweigh higher user costs. A complementary relationship exists when TNCs facilitate increased transit ridership; possibly through first- and last-mile services, or by providing mobility services to regions that are either poorly served by public transit or during times when transit becomes less reliable (Steinmetz 2016). Additionally, TNCs can help smooth demand peaks during transit disruptions or high demand periods by providing alternative mobility services. Finally, the two modes might never interact due to different user populations and trip types. The current research generally employs two methods due to inaccessible trip-level TNC data. First, survey-based methods are used to study stated/revealed travel behavioral changes after the introduction of TNC services (Rayle et al. 2016; Lewis and MacKenzie 2017; Clewlow and Mishra 2017; Henao and Marshall 2018; Gehrke et al. 2018; Hampshire et al. 2017; Murphy and Colin 2016; Conway et al. 2018; Grahn et al. 2019). Second, various statistical methods (i.e., difference-in-differences, regression discontinuity, longitudinal studies) are used to analyze transit ridership changes after the introduction of TNCs to a region (Nelson and Sadowsky 2019; Graehler et al. 2017; Lavieri et al. 2018; Boisjoly et al. 2018; Hall et al. 2018; Babar and Burtch 2017; Jin et al. 2019). In a few select cases, research groups acquired trip-level TNC data, but these studies were often descriptive in nature (Brown 2018; Feigon and Murphy 2018).

Substitutional behaviors between TNCs and public transit are supported by several studies using both survey and statistical methods. Rayle et al. (2016) interviewed TNC users (n = 380) at several "hot spots" in San Francisco and found that 33% of users would have used public transit if TNCs were not available. The driving factor for the mode substitution was related to travel time. A similar intercept study (n = 83) was conducted for UberHOP[1] users in Seattle, Washington. The study found that 66% of users would have used either transit or some other form of non-motorized travel had UberHOP not been available (Lewis and MacKenzie 2017). Clewlow and Mishra (2017) administered an online survey (n = 4094) targeting seven major U.S. metropolitan areas and found a net change of − 6% in transit ridership among TNC users. In addition, 49–61% of the TNC trips would not have been made at all, or by either non-motorized travel or public transit if TNC services were not available. Surveys in Denver and Boston found 34% and 42% of trips would have been made by public transit had TNCs not been available (Henao and Marshall 2018; Gehrke et al. 2018). Hampshire et al. (2017) interviewed TNC users (n = 1214) in Austin, Texas about mode choices after Uber and Lyft suspended services in the city. Of the respondents, 3.7% switched to public transit for the referenced TNC trip. Nelson and Sadowsky (2019) used transit data at the agency level to study ridership changes before and after the arrival of TNCs. The study found transit ridership initially increased after the introduction of the first TNC. However, once a second TNC entered the market, ridership levels decreased to pre-TNC levels. Graehler et al. (2017) studied transit ridership changes for several North

[1] UberHOP is a fixed-route, flat-rate form of micro-transit that was piloted in Seattle, WA during 2015.

American cities between the years of 2002–2018 and found annual decreases of 1.3% and 1.7% for heavy rail and bus ridership, respectively. San Francisco, where Uber began services in 2010, has observed a 12.7% decrease in transit ridership.

Several studies have also highlighted complementary relationships between TNCs and public transit. A report released by the Shared Use Mobility Center in 2016 surveyed users (n = 4551) of transit and other shared mobility services across seven major metropolitan areas. The report concluded that TNCs were largely complementary due to the high proportion of TNC trips during late nights and weekends when transit services were poor or unavailable (Murphy and Colin 2016). Conway et al. (2018) and Grahn et al. (2019) use the 2017 National Household Travel Survey and conclude that TNC riders use public transit at increased rates compared to the general population, which might indicate that TNCs are filling transit service gaps, or are being used for first- and last-mile trips. Hoffmann et al. (2016) used TNC trip-level data in New York City and found a positive correlation between TNC and subway ridership. A 31% increase in TNC trips near subway stations with service disruptions was observed indicating that TNCs help smooth spikes in transportation demand. Lavieri et al. (2018) analyzed TNC trip generation data in Austin, Texas and found that TNCs are used more frequently in areas with poor transit service, thus filling a mobility gap. Boisjoly et al. (2018) studied transit ridership changes across 25 North American cities between the years of 2002–2015 and found a complementary but not significant relationship between the two modes.

The relationship between TNCs and public transit also varies by transit mode, time of day, and location. Clewlow and Mishra (2017) found that TNCs attracted people away from buses (− 6%) and light rail (− 3%), while an increase in commuter rail ridership (+ 3%) was observed. Brown (2018) used trip level data in Los Angeles and found that the majority of trips occur in population dense areas, which is likely due to high parking costs, low parking availability, and shorter trips. Feigon and Murphy (2018) observed that most TNC trips were generated in urban cores with mean trip distances of 2–4 miles. The same study found that 29–44% of Saturday TNC trips were a result of reduced transit services. Hall et al. (2018) concluded that the introduction of Uber decreased transit ridership by 5.9% in “small” MSAs and increased ridership by 0.8% in “large” MSAs.[2] In terms of transit agency size, small agencies saw a 6% increase in ridership while large agencies observed a 2.1% decrease. A similar study by Babar and Burtch (2017) found a 1.1% decrease in bus ridership after Uber market entry. Cities with high transit scores,[3] such as Pittsburgh, did not observe a decrease in bus ridership. The same study also found a 7.2% and 2.6% increase in commuter rail and subway ridership, respectively. Mucci (2017) also found that TNCs contributed to a 7% growth in light rail ridership and a 10% decline in bus ridership in San Francisco.

The absence of TNC data constrains current studies to specific cities and methods, which result in varied outcomes and conclusions. In general, there seems to be an aggregate substitutional effect between TNCs and public transit, especially for travel modes that share the roadways (i.e., buses, light rail). TNCs are heavily used in urban areas, which are the same areas that public transit performs well. However, it is hard to determine whether urban TNC trips are substitutional or complementary. Many TNC trips

[2] Small MSAs include all MSAs with populations less than the median MSA population while large MSAs have populations greater than the median MSA population.

[3] Transit scores were obtained from AllTransit. AllTransit provides transit scores at a city level for all different modes of transit.

originate at night or on the weekends, which are times when the level of service for public transit usually declines. Smaller transit agencies benefit more from TNCs, likely due to limited existing transit services.

The statistical studies previously mentioned address the long-term substitutional behavior between TNCs and public transit. We define their results as long-term behavior because monthly transit ridership changes are studied over periods of time that range from 4 to 16 years (Hall et al. 2018; Babar and Burtch 2017; Boisjoly et al. 2018; Graehler et al. 2017; Nelson and Sadowsky 2019). These studies all analyze slow changing trends and behaviors in the years following the introduction of TNCs.

The current literature analyzes changes in public transit ridership at the agency level and at a monthly resolution. However, many underlying drivers of mode substitution (e.g., trip type, socioeconomic status, origin/destination pair, built environment, etc.) vary by location and time of day. These features cannot be captured in an agency level analysis and are extremely important characteristics to consider for transportation policy design. Therefore, we employ a microscopic analysis that looks at bus ridership changes in the time intervals of a few minutes, and for different locations in the increments of a few hundred feet. Our intention is to fully examine the mode substitution that is likely to vary substantially by time and location. The improved granularity provides new insights into time-varying travel behavior across different populations and built environments. Such insights can be used to inform policies in a more strategic manner. For example, congestion fees can be applied to TNC trips in specific congested areas during commute times to promote more space efficient modes of travel. This type of targeted policy cannot be determined from monthly transit ridership changes that occur before and after the introduction of TNCs. This is because the cause of transit ridership change cannot be determined without trip-level information. The observed decline in monthly ridership might be driven by TNCs providing greater accessibility to transit-poor neighborhoods with no current congestion problems.

In other words, we study the short-term effects of TNC pricing on modal choices among TNC and buses in a relatively microscopic view, namely for specific points of interest in the city and 10-min time intervals. To our best knowledge, the spatio-temporal dynamics of the TNC/public transit interaction have not been addressed rigorously in the current literature except for one such study. This research, conducted by Jin et al. (2019), used buffer analysis and spatial cross-correlation between Uber pickups and scheduled transit services in New York City to conclude that Uber competes with transit during day time hours and complements transit during late night hours. However, this approach cannot be expanded to all cities where Uber data is not publicly available. In addition, our methodology differs through the use of real-time bus ridership data and modeling approaches, leading to differences in results and recommendations. The analysis in this paper adds to the existing literature in four distinct ways:

- The resolution of transit bus location and ridership data (10 min and by each bus stop) is much improved compared to previous research conducted at the MSA/transit agency level.
- The novel use of Uber and Lyft surge multiplier data to approximate demand in the absence of TNC trip-level data.
- Data from multiple sources are used to capture the effects of weather, traffic conditions, incidents, events, and bus level of service on bus ridership in Pittsburgh.
- An econometrics model is formulated to statistically analyze unusually high TNC demand events and the resulting changes in bus ridership for different locations and times of day.

Conceptual design

The research goal is to determine if bus and TNC users are making ad-hoc decisions between the two modes based on the real-time TNC fares. In other words, we define the "substitution" to be studied in this paper as a short-term behavior where travelers are making instantaneous choices between TNCs and buses. This definition of substitution excludes the long-term substitutional effect that has already taken place since the inception of TNCs several years ago. To accomplish this goal, we capture changes in bus ridership immediately after an abrupt rise in TNC fares, compare the ridership change at various locations and times throughout the day with control variables, and finally, attempt to interpret the change attributed to TNC fare increases. We consider the relationship substitutional if significant changes in bus boardings are observed during periods of elevated TNC costs. The intuition is that for some trips, generalized user costs are comparable between the two modes. We would expect to see an increase in bus boardings when the total generalized TNC trip costs overtake bus costs due to an increase in TNC fares. Alternatively, if an unusual number of bus riders request TNC services during a base fare period, we would expect to see a rise in TNC fares (due to increased TNC demand) and a decrease in bus boardings during the following time period. Both situations are considered substitutional because travelers are making instantaneous choices based on current costs. This study only analyzes the group of travelers making ad-hoc decisions between the two modes. Pre-planned substitutional behavior cannot be captured by our methods because an equilibrium between TNC riders and drivers has likely been achieved.

Elevated TNC fares are defined by a surge multiplier, which is a value that is multiplied by the base fare to increase user costs and driver profits. The surge multiplier increases in a specific location as the ratio of requested rides over the number of available drivers grows. The extra fare is designed to disincentivize additional ride requests in a specific location while, at the same time, incentivizing additional drivers to serve the area. When equilibrium is met, the surge multiplier drops to one,[4] meaning that no additional charge is applied to the ride.

For this analysis, surge multiplier time periods are viewed as the "treatment", or "shocks" to a group of travelers who are likely to make instantaneous choices between TNCs or buses for their upcoming trip. The intuition is that if the treatment is proven to be insignificant, then there is a strong signal that the group of travelers' instantaneous choices are not being influenced by real-time prices, resulting in a non-substitutional relationship (i.e., travel mode has been decided before opening the ridehailing app or waiting at the bus stop). The underlying assumption of the model is that travelers are making instantaneous choices based on the observed surge price. A traveler checks either the Uber or Lyft app to see the cost of their specific trip, then subsequently makes a decision based on the price of the current trip. The treatment effect from the surge multiplier will not affect travelers who are not making decisions between the two modes. We assume that any change—positive or negative—in bus boardings during a surge event is considered a substitutional relationship and has direct interaction with the surge treatment variable. This is because we use a set of control variables for other attributes that might cause changes in bus boardings. If the surge event was caused by travelers who do not typically use buses, then we would expect to see

[4] The minimum surge multiplier for Uber services is 1.2, which means that the rider fare is multiplied by 1.2, making the fare 20% greater. The minimum surge for Lyft is 25%, meaning that an additional 25% of the fare is charged to the rider.

no change in bus boardings. Observed changes in bus boardings will only be from a subset of bus users substituting trips because we compare changes in bus boardings.

Community events can also create higher than normal demand for all modes of travel which can cause a simultaneous increase in bus and TNC demand. Additionally, high bus demand can lead to overcrowding during peak periods, which might lead to a subset of travelers choosing other modes, such as TNCs, for comfort or convenience reasons. Both scenarios observe increased bus boardings during a surge event which are not caused by TNC fares. We control for community events through local and network traffic speeds. The increase in transportation demand during large events will likely increase congestion and reduce traffic speeds. Recurrent traffic speed variation is addressed through time-of-day fixed effects. For smaller events not captured through changes in roadway speeds, we assume that the event is not sufficiently large to trigger a surge event. In addition, the general assumption is that 6 months of data is sufficient to smooth out the occasional high transportation demand periods and capture typical time-of-day conditions.

The conceptual design highlighted above is not capable of tracking individual behaviors. Therefore, we rely on statistical signals to infer more aggregate behaviors at specific locations. Privacy concerns and privately held trip-level data prohibit analysis at the individual level. We realize that unobserved variables can cause fluctuations in bus boardings and/or TNC fares. To combat this, we employ a series of model robustness checks. We also assume that the large number of data points observed at the same location and time of day can adequately represent day-to-day conditions for this analysis.

Data

The Pittsburgh metropolitan statistical area population is 2.3 million people making it the 27 largest in the United States. The intense topography requires a diverse built environment requiring almost 450 bridges to span ravines, rivers, and valleys. In addition, much of Pittsburgh's transportation infrastructure is aging, thereby requiring numerous on-going and future construction projects causing significant traffic delays. Pittsburgh has a humid continental climate that is characterized by hot, humid summers and cold winters. Similar climates exist near and above 40 degrees latitude and east of the Mississippi River, which include the cities of Chicago, Cincinnati and Columbus, to name a few. Seven colleges/universities are located in the Pittsburgh area attracting students (in-state and out-of-state) during the academic year. Approximately 50% of Pittsburgh workers commute to the Central Business District each day (Daniels 2016), which is a small region representing only 410 acres. The same survey found that 34% of workers commuted to the Oakland neighborhood, which is home to both the University of Pittsburgh and Carnegie Mellon. Pittsburgh is known for its steel industry that was established in the late 19th century attracting a diverse population of immigrants to the region. Following the collapse of the steel industry in the 1980s, healthcare and higher education became the two largest economic sectors in the region. The results obtained in this analysis are unique to Pittsburgh, however, the diverse population and built environment that represent a typical U.S. post-industrial city provide various insights that can be translated to other metropolitan areas with similar characteristics.

The Port Authority of Allegheny County provides public transit services to the region and is the 26th largest transit agency in the United States in terms of unlinked passenger trips (Public Transportation Fact Book 2019). The Port Authority operates 97 bus routes, 3 light rail routes and 2 inclined planes in a 775 square mile service area. The service region includes 7000 transit stops and 52 park-and-ride lots. Approximately 85% and 12% of public transit riders use buses and light rail, respectively. Bus ridership increased by 3.3% from 2017 to 2018.[5] This trend might be due to three dedicated busways that serve the central business district from the east, west, and south directions. On average, the three busways account for 15% of weekday ridership.[6] For cities with populations greater than 100,000 inhabitants, Pittsburgh ranks 18th in overall proportion (17%) of commuters who use public transit as their primary commute mode.[7] Both Uber and Lyft began operating in Pittsburgh in the winter of 2014. This study focuses on locations with strong transit ridership throughout Pittsburgh in both inner-city and suburban areas.

Data from multiple sources were collected for the full duration of each day between September 2016 and March 2017 and aggregated at 10-min increments during the 6-month time period. Transit boarding data were obtained for each transit stop from the local transit agency. Uber surge multipliers were collected from the Uber API every 10 min for 45 points of interest throughout the Pittsburgh region. Lyft surge multipliers were also collected starting in November 2016 at the same locations. From the initial 45 locations, ten points of interest were selected to represent neighborhoods with diverse populations and built environments and that were spread out spatially throughout Pittsburgh. A minimum distance between each point of interest was desired to ensure that buffers did not overlap. The selected points of interest are also locations with strong bus ridership. During the time of analysis, the current surge multiplier at the location of the requester was displayed in the application along with the total fare. The surge multiplier was then directly stored for each location at each point in time. Uber surge multiplier data was used in our primary analysis due to their dominance in the ride-sourcing market at the time. Lyft data was used as a supplementary robustness check. Temperature and precipitation data were obtained from Weather Underground.[8] INRIX traffic speeds were used to control for transportation network conditions and events. Holidays were removed from the data set (Thanksgiving, the week between Christmas and New Year's Day, and Martin Luther King Jr. Day) as they are not representative of typical weekday conditions. School breaks were also removed for the two university locations (University of Pittsburgh and Carnegie Mellon University).

Since surge multipliers are specific point coordinates (defined by latitude and longitude), buffer zones are created to incorporate spatial forms of data into the analysis. The goal is to create an area around the point of interest where surge conditions are likely constant, or at least very similar. TNCs do not provide any information regarding the size or locations of surge regions. However, an analysis exploring surge correlation between two nearby points of interest can provide estimates for surge region area sizes. Surge multipliers for downtown points of interest located less than 1500 feet from each other were almost perfectly correlated. Slight differences in surge multipliers existed when distances increased to 1700 feet or more. A map of all points of interest, buffer zones, bus stops, and the spatial layout of Pittsburgh can be viewed in Fig. 1.

To provide additional context regarding the points of interest, some basic neighborhood characteristics were compiled in Table 1. For comparison, the population density,

5 https://www.portauthority.org/siteassets/services/service-request/2018asr.pdf.

6 https://www.pghcitypaper.com/pittsburgh/how-busways-can-lead-pittsburgh-into-an-equitable-public-transit-future/Content?oid=14594516.

7 U.S. Census Bureau, 2015 American Community Survey.

8 https://www.wunderground.com/.

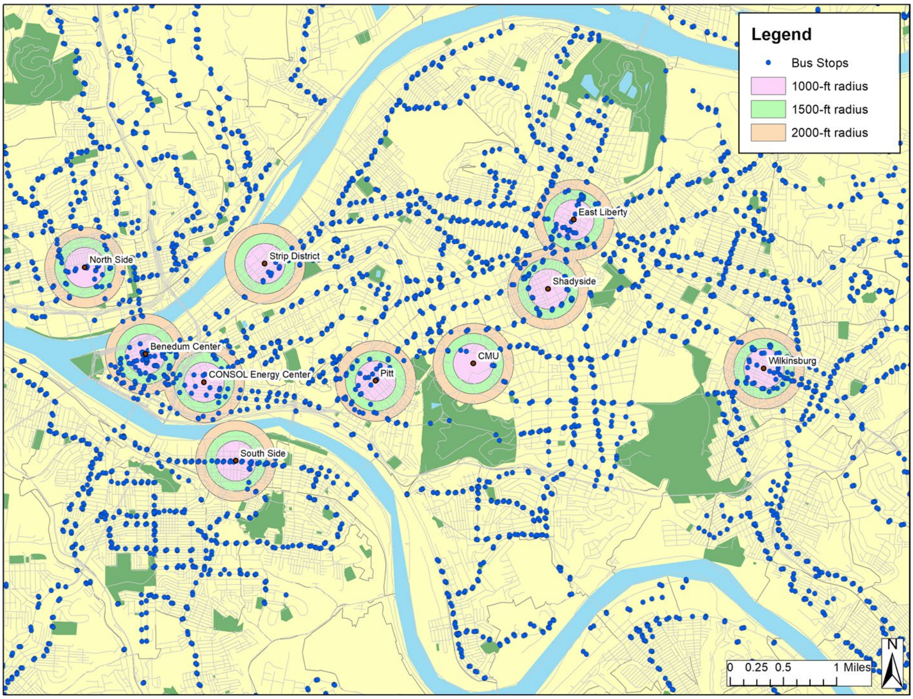


Fig. 1 Surge multiplier points of interest and buffer regions in the City of Pittsburgh

median income, and median age for the entire city of Pittsburgh were 5460 persons per square mile, $45k, and 34, respectively. The neighborhoods range from approximately 1000–20,000 people per square mile, highlighting the diverse built environments captured in this analysis. The median income also ranged from $24k–$100k. A few unique features were added to the table to provide some additional information not captured in census data.

A monotone spline function was used to estimate the surge multiplier for a common point in time among all points of interest. For example, the University of Pittsburgh location might have stored surge multiplier information at 5:08, 5:18, and so on. The spline function was fit to the surge multiplier data to estimate the surge value at 5:10 and 5:20. All time periods with no bus arrivals for a specific location during a 10 min time period were removed from the data set because no choice exists between the two modes of transportation. The busiest transit regions observed 1–5% of time periods removed, while the more residential areas observed 10–14% of time periods removed.

The Port Authority of Allegheny County utilizes automatic passenger counting (APC) and automatic vehicle location (AVL) technologies to monitor ridership information and bus trajectories in real-time. Vehicle information (vehicle id, route, and capacity, among others) is stored along with boarding and alighting data for each stop, stop information (address, stop id, latitude and longitude), and bus trajectory information (Pi et al. 2018). Coordinate information and time stamps for each on-boarding record are used to characterize transit system behavior throughout Pittsburgh for different times of day.

Hourly temperature, rain, and snow data were obtained from Weather Underground. These variables are used to control for weather conditions that might influence transit

Table 1 Points of interest information

Point of interest	Population density	Median income	Median age	Unique feature
Benedum Center	4470	$51k	30	Located in central business district where more than 150,000 people work. Financial district.
Carnegie Mellon	9150	$100k	33	Provides high frequency routes to nearby neighborhoods for students, faculty and staff.
CONSOL Energy	8800	$24k	30	Home of stadium for Pittsburgh Penguins. Located in a residential area between downtown and university locations.
East Liberty	9850	$33k	36	Contains a dedicated busway stop that serves downtown. Home to Google campus and other local technology companies.
North side	9790	$39k	41	Directly north across Allegheny River from downtown. Contains aviary, museums, and baseball and football stadiums.
Shadyside	11,700	$45k	29	Higher-income, residential neighborhood located near Chatham, Carnegie Mellon and Pittsburgh Universities.
South side	5150	$53k	32	Social hangout with numerous bars, restaurants, and concert halls.
Strip District	1110	$37k	36	Old industrial section being revitalized. Home to new condos, restaurants and bars.
University of Pittsburgh	21,100	$30k	29	Located near the University of Pittsburgh, the large university hospital and numerous restaurants and bars.
Wilkinsburg	6910	$27k	38	Contains a dedicated busway stop that serves downtown. Residential neighborhood.

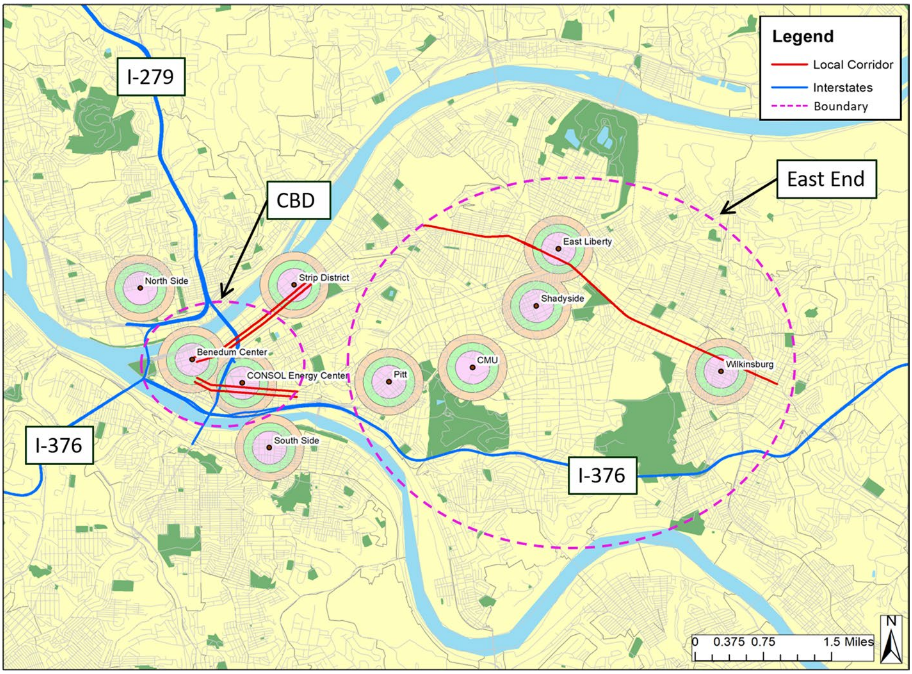
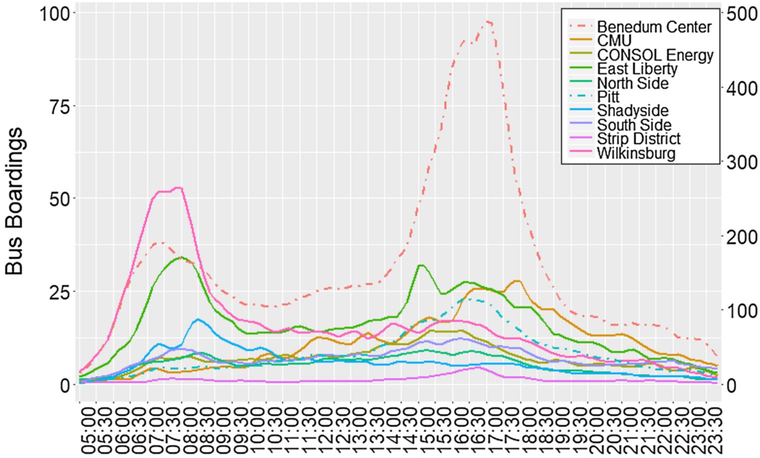


Fig. 2 Map of interstates and local roads used

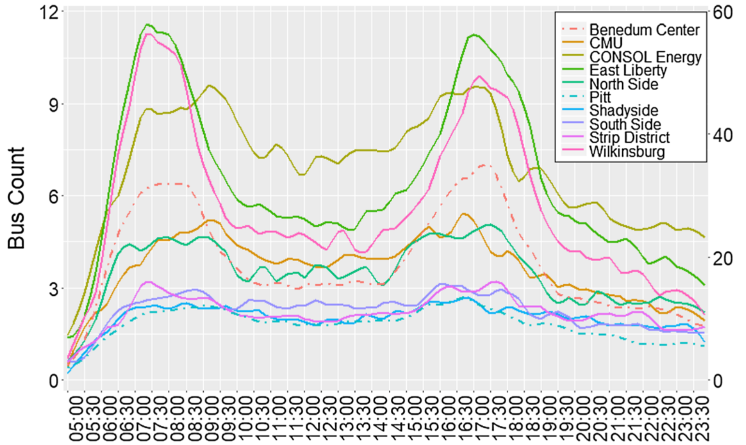
ridership. Linear interpolation methods were used to fill in weather conditions at 10 min increments between known values at 1 h increments.

INRIX traffic speeds were used to control for transportation network conditions. Real-time traffic speeds were compiled at road way segments throughout the Pittsburgh region. Network conditions were determined by selecting the major freeway system that feeds the city from each direction (North, South, East, and West). Inbound and outbound traffic speeds were calculated for each major freeway totalling six control variables. These roads are highlighted in blue in Fig. 2. Local corridors that directly feed the two main economic hubs of Pittsburgh (the Central Business District and the East End) were used as localized controls. These roads are highlighted with red in Fig. 2. Only the busiest local corridors were selected to maximize the number of records with real-time data.[9] All four local roadways highlighted directly entering the CBD are used to control for conditions at Benedum Center and CONSOL Energy Center (both locations are within the CBD boundary highlighted with a dashed line). The Strip District only considers the two local roadways directly serving the region. Both North and South Side neighborhoods do not have local controls (neither are within the CBD boundary). However, both regions are directly served by the interstate system, which are used as a set of traffic control variables. Wilkinsburg, East Liberty, and Shadyside locations use Penn Avenue (highlighted in red) as local traffic control variables. The University of Pittsburgh and Carnegie Mellon locations just use I-376 as a local control.

[9] Data is not collected for every time period due to limited probe vehicles.



(a) Mean bus boardings by location



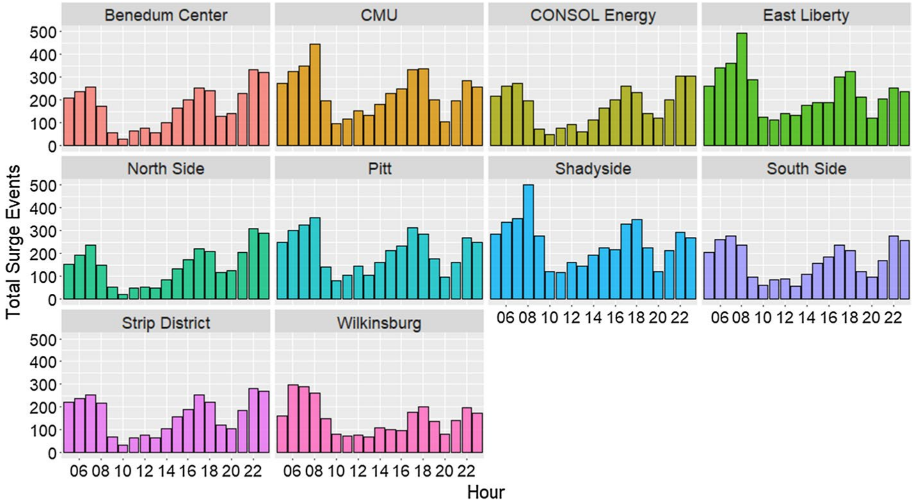
(b) Mean bus counts by location

Note: Due to their large magnitudes, boardings for the two locations (Benedum Center and Pitt) are represented by dashed lines and can be viewed using the secondary y-axis.

Fig. 3 Temporal patterns of transit boardings and bus services

Descriptive statistics

The points of interest represent a wide variety of neighborhoods and destination points. Some locations observe morning bus ridership peaks, some are bi-modal with bus ridership peaks during both morning and afternoon rush hour, and some produce only evening bus ridership peaks. Figure 3 plots the ten selected points of interest in terms of average bus boardings by time of day considering the full 6-month duration. A large variation in bus ridership is observed throughout the day for different locations. The number of buses serving the point



Note: Histograms represent the sum of all time periods when an Uber surge multiplier was observed, which indicate times when TNC demand is greater than TNC driver supply.

Fig. 4 Temporal Uber surge event patterns by location

Table 2 Daily bus demand and level of service statistics

Point of interest	Stop count	Weekday			Weekend		
		Bus count	Boardings	Mean*	Bus count	Boardings	Mean*
Benedum Center	46	2630	22,325	8.50	1079	6991	6.50
Carnegie Mellon	10	463	1367	3.00	296	832	2.80
CONSOL Energy	29	911	926	1.00	518	388	0.70
East Liberty	40	889	2177	2.40	377	892	2.40
North side	32	462	664	1.40	242	292	1.20
Shadyside	32	265	663	2.50	152	288	1.90
South side	19	289	816	2.80	164	439	2.70
Strip District	12	289	144	0.50	166	31	0.20
University of Pittsburgh	25	1203	5581	4.60	615	2000	3.30
Wilkinsburg	46	783	2077	2.70	303	800	2.60

*Average number of boardings per bus

of interest are also plotted to compare bus service levels. The Benedum Center and the University of Pittsburgh experience high volumes of bus ridership compared to other locations. To illustrate the temporal trends in boardings on one figure, high volume locations are scaled down by a factor of five. Boardings for these two locations (indicated by dashed lines) can be viewed using the secondary (right) y-axis.

Surge multiplier frequencies are plotted for each location in Fig. 4 for the 6-month period. All locations exhibit similar trends, in that surge events happen more frequently during late night and early morning hours. An increased number of surge periods are also observed during the evening commute peak at all locations. However, the counts vary from 200 surge

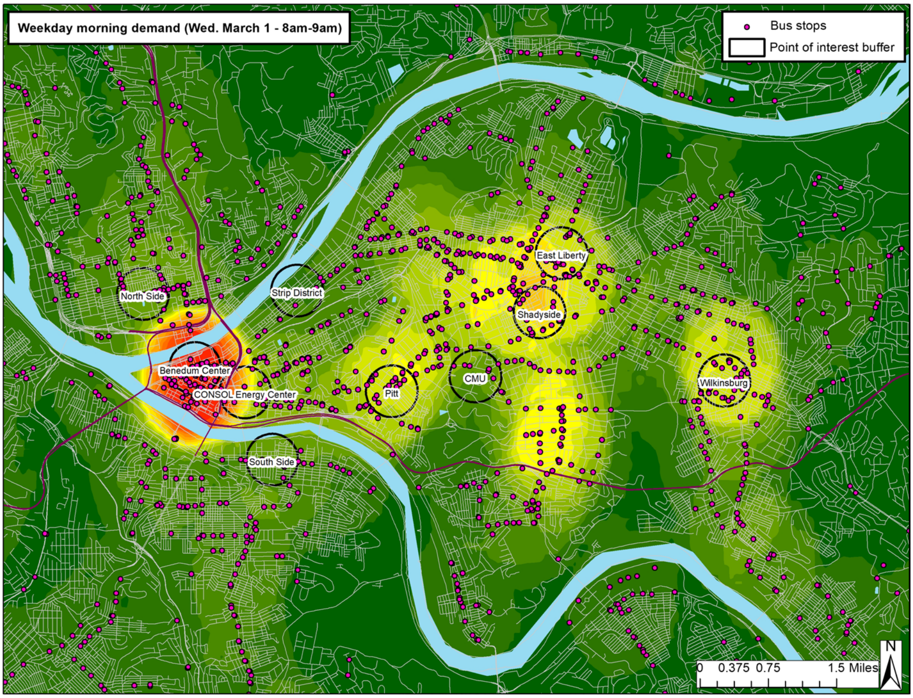


Fig. 5 Morning peak bus demand heatmap for Pittsburgh

events in Wilkinsburg up to 350 surge events in Shadyside. Neighborhood characteristics, zoning, and access to transit buses likely contribute to the observed differences.

Bus demand and service levels are tabulated to provide insights into neighborhood-level travel behavior. Table 2 provides the number of bus stops in each buffer region along with daily ridership and bus counts. Alternative bus level of service statistics (headways, operating hours, etc.) don't provide valuable insights because of the variety of routes (both low- and high-frequency routes with different operating hours) that serve each point of interest.

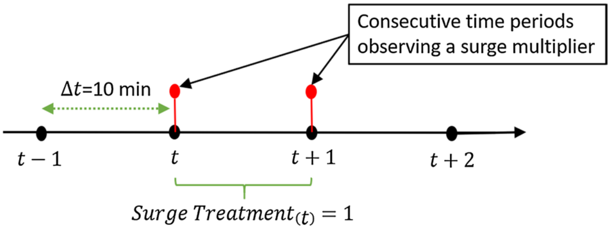
Figure 5 shows a typical weekday morning peak demand throughout the study area. One can see the heavy demand in the central business district area. Other high demand locations are captured with the points of interest selected for this study.

Methods

Uber surge multipliers are used as a proxy for unusually high TNC demand events with the assumption that in most cases, the number of TNC vehicles are stabilized over space. Unusually high TNC demand events are then compared with normal conditions (no surge present) in terms of bus boardings near the surge location. Local network traffic, incidents, bus levels of service, weather, and events are incorporated as control variables.

We define a "surge event" as two consecutive points in time when a surge multiplier was observed. By using two consecutive surge periods, random short duration surge

Fig. 6 Surge event definition



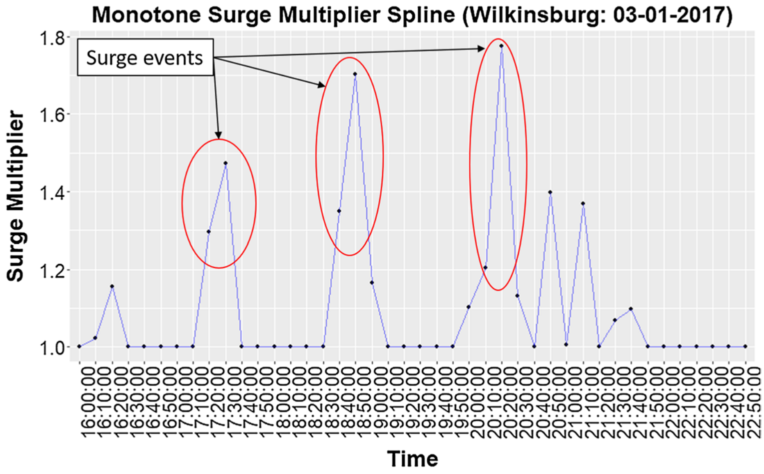


Fig. 7 Surge multiplier plot through time for one evening in Wilkinsburg

spikes caused by a brief lack of TNC drivers can be removed from the analysis. This filtering method will inadvertently also remove short duration, demand driven TNC events. However, these missing points will not affect the overall analysis due to the large number of surge periods over the 6 month period. The underlying assumption is that a sustained 10 min surge event is most likely a demand driven event because TNC drivers are provided time to relocate with higher profit incentives. A schematic of our surge definition is shown in Fig. 6.

Uber surge multipliers are plotted through time at one location (Wilkinsburg) during a weekday evening to provide a visualization of a "surge event" using actual surge multiplier data. In Fig. 7, it can be observed that three surge events occur on March 1, 2017 during the evening hours in Wilkinsburg. The other spikes in surge do not satisfy the requirement of observing a surge for at least two consecutive time periods, as those spikes may be attributed to random demand and supply conditions.

Total bus boardings are determined by summing all boardings for each bus stop within a buffer region for the 10 min following the listed time. For example, to determine bus boardings for 8:10 a.m., total boardings are summed between 8:10 a.m. and 8:20 a.m.. This allows us to capture ridership changes immediately after the observation of a surge event. The number of buses traversing each buffer is also calculated to help control for the number of bus arrivals. This is calculated by summing the number of unique bus vehicle ids during the given time period. The aggregate boarding behavior is then compared during surge and non-surge events. We assume that all travelers within a

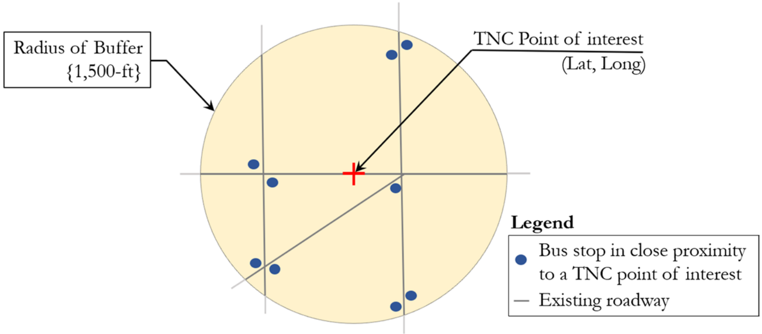


Fig. 8 Illustration of bus boarding calculation

region are within walking distance to a bus stop that can serve their specific trip needs. This is because the points of interest selected are all well-served by public transit. Figure 8 displays a visual representation of the buffer region and all considered bus stops.

A data filtering process is employed to remove time periods which might compromise our assumptions about system behavior. To isolate surge events and study their impacts, the data set was filtered to include three specific situations (1) time periods immediately before a surge event, (2) time periods when surge events initialize, and (3) all time periods when no surge multiplier is observed. The filtering process isolates the initialization of surge events to study changes in bus boardings during specific time windows. Surge time periods that occur in succession to the first observed surge multiplier are removed from the data set. For example, if no surge multiplier is observed at 8:00 a.m., followed by two surge multipliers at 8:10 a.m. and 8:20 a.m., only 8:00 a.m. (time period immediately before the surge) and 8:10 a.m. (time period of surge event initialization) are retained in the data set. We focus on the first surge multiplier for two reasons. First, we try to eliminate scenarios of reverse causation. For example, a large increase in bus ridership due to high TNC fares can result in overcrowding, thus causing travelers to use alternative modes (TNCs). Second, when subsequent surge multipliers are observed—likely with differing magnitudes—the attribution of bus ridership changes to the correct surge multiplier becomes difficult.

The interaction behavior is estimated using a linear regression model with a binary variable for surge periods. Independent regression models are used for each point of interest due to large differences in ridership patterns. The model includes a time-fixed effects variable for each time window, day-of-week, and month. The model can be viewed below in Eq. 1.

$$y_t = \beta(S_{(t)}) + \delta_t + \boldsymbol{\beta}\mathbf{X_t} + \varepsilon_t \tag{1}$$

where y_t represents the total transit boardings during time period t. $S_{(t)}$ is a binary variable that indicates the existence of a surge event with one and zero otherwise. δ_t represents the time-of-day fixed effect, and X_t is a matrix of control variables consisting of weather conditions (rain, snow, temperature), nearby traffic conditions (inbound and outbound network and local traffic speeds), number of buses traversing buffer region, and the average number of stops per bus. CONSOL Energy Center is the home of the Pittsburgh Penguins. The home game schedule was used to determine event nights, which take on the value of one during a home game and zero otherwise. However, local traffic congestion on event night also controls for this situation, which is a better indicator of periods of high transportation demand because only the event start time is provided in the schedule. For this reason, only local traffic conditions were used to control for large events at CONSOL Energy Center. Rain and snow variables take on a value of one if precipitation is observed, and zero otherwise. The temperature variable takes on a value of 1 if the current temperature is greater than 45 degrees (F), and zero otherwise. The network traffic speeds are continuous variables that represent the average observed real-time traffic speeds along a select roadway/corridor. Bus counts are used to control for the variation of real-time bus arrivals during a specific time period. The average number of stops per bus within a buffer region is used to control for local network characteristics and relative bus importance. During periods of congestion, the average number of stops will be reduced due to traffic, resulting in less ridership. Additionally, some buses might serve only one stop in the region, which indicates that the specific route is likely less important to the specific neighborhood. The goal of this variable is to differentiate between buses who barely serve the region and thoroughly serve the region, as the ridership is likely to grow with an increased number of stops.

Known variables that influence bus ridership (e.g., traffic conditions, weather, bus levels of service, seasonality, time of day, day of week, events, incidents) are included as control variables. We assume that causal relations are accounted for with these control variables. We also assume that the data set is sufficiently large to provide statistically significant results.

Three different surge multiplier thresholds (1.2, 1.4, and 1.6)[10] were used to define a "surge event". Thresholds are used to study how the magnitude of a surge event affects bus boarding behavior. All surge multipliers between the base fare (surge = 1.0) and the given threshold were removed from the specific analysis. For example, if the surge multiplier threshold is defined as 1.6, then all surge multipliers greater than 1.0 and less than 1.6 are removed from the analysis. This way, we can directly compare surge events ≥ 1.6 with periods of no surge. The comparison of bus ridership across surge threshold values is similar to a study by Cohon et al. (2016) that uses regression discontinuity to compare trip purchasing rates for different TNC fare levels.

Results

Four time periods are selected, and the model is run for each location during each time period. The time periods were morning peak (7 a.m.–10 a.m.), evening peak (4 p.m.–7 p.m.), evening/late night (7 p.m.–12 a.m.), and on weekend evenings (5 p.m.–10 p.m.). Weekdays consider Monday–Thursday while weekends consider Saturday and Sunday. Friday was omitted because it is similar to a weekend for TNC demand but is similar to a weekday for public bus demand. No significant changes in bus boardings were observed during morning time periods for the ten locations. However, four locations (Wilkinsburg, East Liberty, Carnegie Mellon, and the University of Pittsburgh) exhibited significant differences in bus boardings during evening peak and late evening hours.

The first set of results can be observed in Table 3 for weekdays between 4 p.m.–7 p.m. for the three surge multiplier thresholds (1.2, 1.4, and 1.6). The bus count variable is positive and significant, meaning that more boardings are observed when a greater

[10] The thresholds were chosen to match surge multiplier levels used by Uber at the time of the study.

Table 3 Regression results for Wilkinsburg

	Wilkinsburg (weekday 4 p.m.–7 p.m.)		
	Bus boardings		
	Surge = 1.2	Surge = 1.4	Surge = 1.6
	(1)	(2)	(3)
Intercept	5.961 (4.770)	8.058* (4.706)	7.851 (4.807)
Surge indicator	− 5.088*** (1.750)	− 6.875*** (2.106)	− 6.325* (3.702)
Bus count	1.417*** (0.078)	1.386*** (0.077)	1.395*** (0.077)
Ave. stop count	0.175 (0.363)	0.169 (0.361)	0.177 (0.361)
Temperature	0.371 (0.633)	0.528 (0.627)	0.494 (0.627)
Rain	0.651 (0.894)	0.342 (0.890)	0.439 (0.892)
Snow	− 0.210 (1.088)	0.098 (1.053)	0.161 (1.062)
North I-376 (inbound)	− 0.006 (0.024)	− 0.0003 (0.024)	− 0.001 (0.024)
South I-376 (outbound)	0.017 (0.027)	0.012 (0.027)	0.016 (0.027)
South I-279 (inbound)	− 0.075 (0.063)	− 0.103* (0.062)	− 0.108* (0.062)
North I-279 (outbound)	0.023 (0.041)	0.014 (0.040)	0.013 (0.041)
West I-376 (inbound)	− 0.043 (0.036)	− 0.048 (0.036)	− 0.043 (0.036)
East I-376 (outbound)	0.013 (0.047)	0.015 (0.046)	0.022 (0.046)
ES_Eastbound[a]	0.060 (0.106)	0.067 (0.105)	0.052 (0.106)
ES_Westbound[a]	0.112 (0.118)	0.131 (0.117)	0.128 (0.117)
Observations	1,343	1,370	1,372
R^2	0.401	0.399	0.399
Adjusted R^2	0.382	0.381	0.381

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

[a]Local roadway congestion in East End (See Fig. 2)

number of buses traverse the buffer zone in a given time period. The fall months are all positive and significant which translates to increased boardings during warmer months compared to January (intercept term). Significant negative bus boardings are observed during surge events for all of the surge thresholds. One defining neighborhood feature is the bus rapid transit (BRT) stop that directly connects Wilkinsburg to Pittsburgh's central business district. The BRT stop serves 47% of all morning boardings and 58% of all evening boardings in the buffer zone. If the BRT stop is removed from the analysis, no significant changes in bus boardings are observed. The result highlights the influence of a BRT stop on ad-hoc substitutional behavior, which is likely a result of occasional first- and last-mile mode substitution.

Significant changes in bus boardings are also observed in East Liberty during weekdays from 7 p.m.–12 a.m., which corresponds to a reduction in bus boardings during a surge period. Similar to Wilkinsburg, when the BRT stop is not included in the analysis, no significant change in bus boardings are observed. This highlights the potential ad-hoc substitutional behavior for first- and last-mile services from the BRT station. The regression results can be viewed in Table 4.

Significant changes in bus boardings are observed at the University of Pittsburgh during weekdays from 7 p.m.–12 a.m. However, changes were not significant at the surge

Table 4 Regression results for East Liberty

	East Liberty (weekday 7 p.m.–12 a.m.)		
	Bus boardings		
	Surge = 1.2	Surge = 1.4	Surge = 1.6
	(1)	(2)	(3)
Intercept	0.428 (5.366)	− 0.126 (5.143)	0.063 (5.128)
Surge indicator	− 2.949 (1.794)	− 2.674* (1.601)	− 3.322* (1.907)
Bus count	1.889*** (0.092)	1.862*** (0.090)	1.874*** (0.089)
Ave. stop count	0.145 (0.190)	0.140 (0.185)	0.133 (0.184)
Temperature	0.430 (0.462)	0.473 (0.446)	0.493 (0.443)
Rain	− 1.171 (0.726)	− 1.043 (0.712)	− 1.040 (0.700)
Snow	− 1.373 (0.957)	− 1.329 (0.903)	− 1.290 (0.909)
North I-376 (inbound)	− 0.006 (0.031)	− 0.009 (0.030)	− 0.008 (0.029)
South I-376 (outbound)	0.037 (0.045)	0.045 (0.044)	0.047 (0.044)
South I-279 (inbound)	− 0.050 (0.039)	− 0.050 (0.038)	− 0.048 (0.037)
North I-279 (outbound)	0.015 (0.044)	0.027 (0.042)	0.022 (0.042)
West I-376 (inbound)	0.014 (0.052)	0.002 (0.050)	0.004 (0.050)
East I-376 (outbound)	0.004 (0.047)	0.005 (0.046)	0.002 (0.046)
ES_Eastbound[a]	0.021 (0.055)	0.029 (0.054)	0.028 (0.053)
ES_Westbound[a]	− 0.078 (0.074)	− 0.085 (0.072)	− 0.098 (0.072)
Observations	1,118	1,156	1,165
R^2	0.469	0.469	0.473
Adjusted R^2	0.443	0.444	0.448

*p <0.1; **p <0.05; ***p <0.01

[a]Local roadway congestion in East End (See Fig. 2)

threshold of 1.4. Consistent coefficient magnitudes and signs provide confidence in the results, however, uncertainty remains due to varying levels of significance between surge thresholds. The regression results can be viewed in Table 5.

Significant changes in bus boardings were also observed at Carnegie Mellon on the weekends between 5 p.m.–10 p.m.. Many students rely on city bus services to and from campus. The Carnegie Mellon buffer only includes bus stops directly adjacent to campus, meaning that nearly all bus users considered in this analysis are affiliated with the university. The regression results can be viewed in Table 6.

Of the ten points of interest, four locations produced significant changes in bus boardings during periods of unusually high TNC demand. The significant results were only observed during specific times of day (evening hours). The observed results are likely due to a unique combination of built environment, existing bus services, and population characteristics present within the specific neighborhood. The presence of BRT stops in Wilkinsburg and East Liberty are key contributors to observed changes in bus boardings. The results at Carnegie Mellon are likely due to the relatively homogenous population affiliated with the university (tech savvy and well-educated). Previous literature has shown no aggregate substitutional effects in Pittsburgh (Babar and Burtch 2017), however, upon further

Table 5 Regression results for University of Pittsburgh

	University of Pittsburgh (weekday 7 p.m.–12 a.m.)		
	Bus boardings		
	Surge = 1.2	Surge = 1.4	Surge = 1.6
	(1)	(2)	(3)
Intercept	– 37.585*** (11.470)	– 39.612*** (11.131)	– 39.804*** (11.108)
Surge indicator	5.040* (2.615)	4.671 (3.022)	8.886*** (3.376)
Bus count	4.913*** (0.160)	4.865*** (0.158)	4.853*** (0.156)
Ave. stop count	9.651*** (0.661)	9.464*** (0.649)	9.577*** (0.650)
Temperature	– 2.110** (1.058)	– v2.490** (1.029)	– 2.462** (1.028)
Rain	0.472 (1.730)	0.874 (1.694)	0.610 (1.691)
Snow	4.828** (2.384)	5.754** (2.308)	5.482** (2.311)
North I-376 (inbound)	0.025 (0.066)	0.051 (0.065)	0.061 (0.064)
South I-376 (outbound)	0.093 (0.090)	0.075 (0.087)	0.055 (0.087)
South I-279 (inbound)	0.173** (0.077)	0.180** (0.075)	0.193*** (0.074)
North I-279 (outbound)	– 0.013 (0.089)	– 0.005 (0.087)	0.004 (0.087)
West I-376 (inbound)	0.016 (0.104)	0.010 (0.102)	0.029 (0.102)
East I-376 (outbound)	0.066 (0.102)	0.076 (0.100)	0.053 (0.100)
Observations	1567	1625	1638
R^2	0.695	0.694	0.693
Adjusted R^2	0.685	0.684	0.683

*p <0.1; **p <0.05; ***p <0.01

evaluation, potential ad-hoc substitutional behaviors were observed at a local scale. Local substitutional behavior can lead to network inefficiencies, especially during times of peak congestion, which highlights the importance of a high resolution, spatio-temporal analysis.

The previous results conclude that a significant change in bus boardings is observed for different surge thresholds. The above analysis compares all surge events above a certain threshold (treatment) to the time periods when no surge event is observed (control). To study how ad-hoc behavior varies as a function of the surge magnitude, a dummy variable was created for each different threshold level (1.2, 1.4, 1.6). The model was fit using three surge binary variables and the coefficients were plotted in Fig. 9 along with their respective 90% confidence intervals. By observation, we cannot conclude that surge coefficients are significantly different from one another. However, the data is limited for specific locations and times of day because surge events are rare.

Multicollinearity and omitted variable checks

A multicollinearity test to determine the level of correlation between independent variables was conducted by calculating variance inflation factors (VIF). Generalized variance inflation factors (GVIF) were calculated because the degrees of freedom for the time of day variable is greater than one. A widely used threshold in the research field is VIF < 5. Since GVIF is adjusted from VIF based on the number of degrees of freedom for each

Table 6 Regression results for Carnegie Mellon

	Carnegie Mellon (weekend 5 p.m.–10 p.m.)		
	Bus boardings		
	Surge = 1.2	Surge = 1.4	Surge = 1.6
	(1)	(2)	(3)
Intercept	– 20.162** (8.638)	– 14.684* (8.009)	– 15.392* (7.990)
Surge indicator	3.836** (1.661)	4.555** (1.853)	4.776** (1.901)
Bus count	4.436*** (0.269)	4.437*** (0.258)	4.465*** (0.252)
Ave. stop count	4.479*** (0.437)	4.334*** (0.404)	4.442*** (0.404)
Temperature	0.098 (0.952)	0.186 (0.897)	0.218 (0.895)
Rain	2.969 (1.837)	2.698 (1.737)	2.913* (1.744)
Snow	0.130 (1.984)	0.293 (1.884)	0.930 (1.851)
North I-376 (inbound)	0.074* (0.043)	0.096** (0.041)	0.097** (0.040)
South I-376 (outbound)	0.088 (0.065)	0.085 (0.062)	0.068 (0.062)
South I-279 (inbound)	0.013 (0.075)	– 0.020 (0.070)	– 0.025 (0.069)
North I-279 (outbound)	0.018 (0.084)	– 0.025 (0.080)	– 0.022 (0.079)
West I-376 (inbound)	– 0.123* (0.072)	– 0.132* (0.069)	– 0.125* (0.069)
East I-376 (outbound)	0.044 (0.052)	0.048 (0.049)	0.065 (0.048)
Observations	615	645	670
R^2	0.542	0.543	0.537
Adjusted R^2	0.504	0.507	0.502

*p <0.1; **p <0.05; ***p <0.01

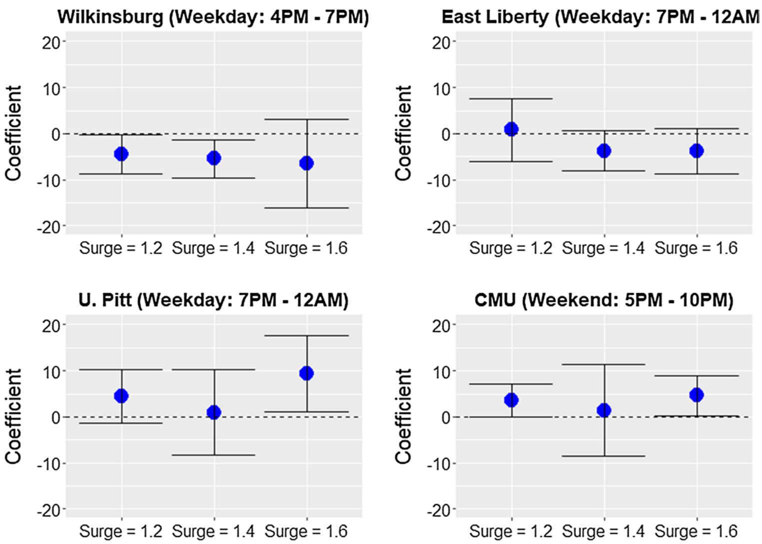


Fig. 9 Fitted coefficients with 90% CIs

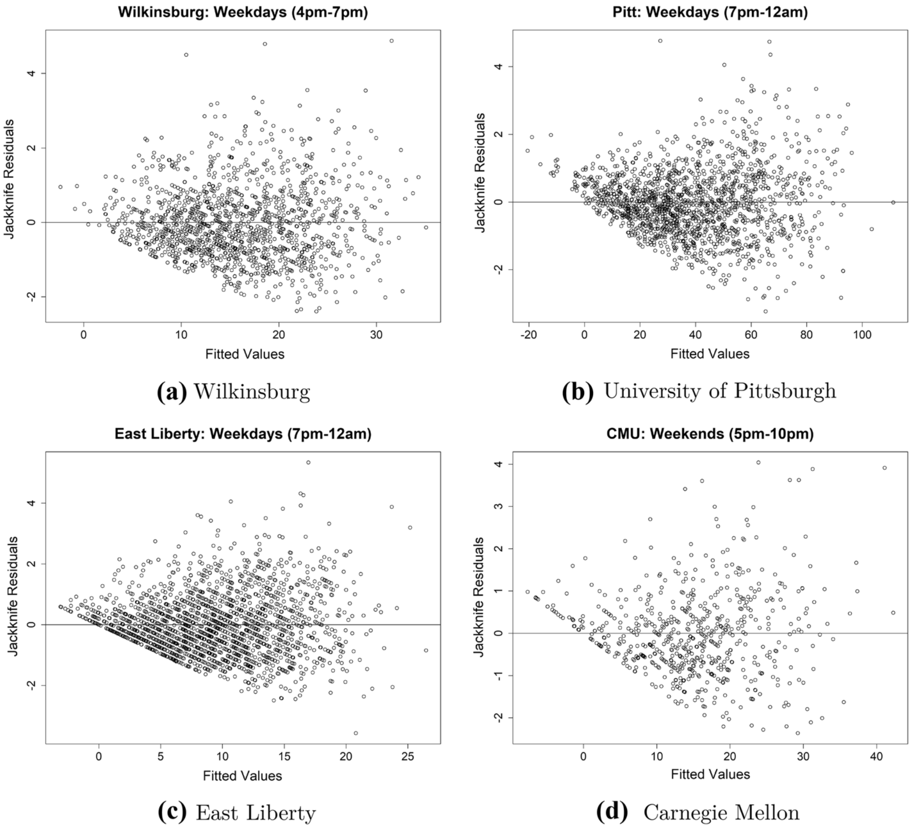


Fig. 10 Jackknife residual plots

variable, then squaring the GVIF value provides an accurate comparison to recommended VIF thresholds used in the literature. For the three cases highlighted in the above results, GVIFs were not greater than 1.5, meaning that VIF < 2.25. The low VIF indicates minimal collinearity in the models highlighted above.

A second check was conducted to assess the likelihood of omitted variable bias. Jackknife residual plots were used to check the assumption of zero conditional mean of the errors. In other words, a check was conducted to ensure that omitted variables that influence bus boardings are not correlated with any of the independent variables. The residual plots are shown for Wilkinsburg, University of Pittsburgh, East Liberty, and Carnegie Mellon in Fig. 10 during the times when significant changes in bus boardings were observed. The assumption of zero conditional mean of the error seems to generally hold across the four locations.

Robustness testing

Model robustness checks were conducted using three different strategies to address uncertainty and model design. These checks are in addition to varying the surge multiplier threshold, which is also considered a robustness check in this analysis. First, the actual size of the surge region is unknown. This region is determined by Uber/Lyft and is not public information. Point coordinates are used to mine surge multiplier information. We approximate the surrounding surge region by analyzing the correlation between different points at varying distances between one another. Second, we want to ensure that the indicator variable for a surge event is actually capturing the surge event itself. To address this modeling assumption, the surge indicator variables are shifted one time period prior when no surge multiplier is observed. It is expected that a shift in surge indicator variables would turn up insignificant results for bus boarding coefficients. Third, a propensity score weighted regression model was used to control for confounding variables. This was accomplished by weighting control group data points to produce similar propensity scores between both control and treatment groups.

Buffer radius sensitivity

A correlation analysis was conducted looking at surge multiplier correlation between various points of interest based on the distance separating the locations. Surge multipliers were almost perfectly correlated for the locations separated by less than 1500-ft. However, two locations separated by 1700-ft observed differences in surge multiplier values. It is also known that the size of surge multiplier regions determined by Uber and Lyft vary with urban density and other characteristics. Due to this uncertainty, two additional buffer radii—one larger and one smaller—were selected to evaluate model robustness.

Buffers with radii of 1000-ft and 2000-ft are used, in addition to the base case radius of 1500-ft, to determine total transit boardings for each time period. Both Carnegie Mellon and the University of Pittsburgh locations produced similar results for the treatment coefficient (significance, sign, and magnitudes) for all three buffer radii. Wilkinsburg produced similar results for a buffer radius of 2000-ft. Results for the 1000-ft buffer radius yielded no significant results for the surge treatment variable. Upon further analysis, the BRT station that provides direct service to the central business district was not included in the 1000-ft buffer. When the BRT station is not included in the analysis, the results become insignificant, indicating a clear interaction between TNCs and transit buses at BRT stations. The East Liberty location was similar to Wilkinsburg. Magnitudes and levels of significance for the surge treatment variables were similar for the 1500-ft and 2000-ft buffer radii. However, the 1000-ft radius case produced no significant results for the surge treatment coefficient. The same situation is observed for East Liberty in that the BRT station is not included in the analysis when the buffer radius is 1000-ft. The regression results for each location and buffer region can be viewed in the supplemental materials.

Surge treatment variation

The surge indicator variable was also shifted one time period prior to the actual surge event. This test is to ensure that the indicator variable was capturing the surge event. Since the surge treatment variable no longer indicates a surge event, we would expect the treatment variable to be insignificant. For the four locations, the treatment variable becomes insignificant for all surge thresholds. This observation provides us confidence that the treatment variable is capturing the surge event. Regression tables for the surge treatment variation tests can be viewed in the supplemental materials.

Propensity score weighted regression

A propensity score weighted regression model was formulated to further evaluate locations where significant bus ridership changes were observed. A weighted regression was chosen instead of using propensity score matching simply due to the number of data points defining a surge event. The number of surge events for a given 4-h time period varied between approximately 25–50 for the different locations. The goal of propensity score matching is to select the data points from both the treatment and control groups that produce a similar propensity score (probability of treatment). This way, the study is "randomized" in a way because both groups have a treatment probability of 0.5. However, in our case, most data points are removed, and we are left with few data points for the final analysis. For this reason, a weighted regression was used to evaluate model robustness. The method assigns data points with similar propensity scores between treatment and control groups larger weights.

The incoming and outgoing freeway conditions were omitted when calculating propensity scores because they were not important for predicting bus ridership. The standardized differences between the weighted and unweighted covariates were less than 0.1 in all cases, indicating a balanced model. The weighted linear regression results produced similar results for the treatment variable in terms of sign and magnitude for both the Wilkinsburg and East Liberty locations. The significance values for the East Liberty location were greater for the weighted linear regression. The weighted linear regression for the Carnegie Mellon location produced positive ridership changes for all surge thresholds, however, only the threshold at 1.6 was significant. The University of Pittsburgh produced similar results for surge thresholds of 1.2 and 1.6. However, a flip in sign was observed for a surge threshold of 1.4. Upon further evaluation, this result becomes positive and insignificant when using buffer radii of 1000-ft and 2000-ft (consistent with other models). The unique combination of a 1500-ft buffer radius and a propensity score weighted regression produced a chance result that is not robust. All propensity score weighted regression results are provided in the newly attached supplemental materials.

Analysis using Lyft data

Surge multipliers were collected over a 4.5 month period during the same time period (November 2016–March 2017) to compare TNC and transit bus interactions with Lyft users. We conduct the same analysis previously outlined in the "Methods" section; however, Lyft surge multipliers are used instead of Uber. The fixed-effects model was used for the four significant locations (East Liberty, Wilkinsburg, University of Pittsburgh, and Carnegie Mellon) and times of day outlined in the "Results" section. The treatment coefficient that indicates a surge event was insignificant for all scenarios. This result is likely due to small ridership numbers as opposed to any behavioral differences between Lyft and Uber users. However, if this same analysis was conducted on current data, different results might be observed because Lyft has grown significantly in previous years.

Discussion and conclusions

In this analysis, we assume ad-hoc substitutional behavior to be any change in bus boardings (positive or negative) during a surge event. Because we are only analyzing a sub-group of transit users making ad-hoc decisions, the sign of the coefficient isn't important. While it is true that a negative coefficient would indicate people are switching from buses to TNCs and opposite for a positive coefficient, the sign of the result might come down to timing and local conditions. For example, a bus load of commuters arriving at a BRT station during an evening commute is very different compared to students at Carnegie Mellon heading home after a weekend class meeting. In the first case, a larger than normal subset of commuters exits the bus and decides to order a TNC for last-mile services during base fares. This will cause a surge event and a reduction in bus ridership in the subsequent time window (i.e., a negative coefficient). In the Carnegie Mellon case, students might open a TNC app and observe very high fares, and subsequently wait for the next arriving bus (i.e., a positive coefficient). The point is that both scenarios are substitutional because travelers are making decisions between the two modes. The sign of the coefficient is helpful in determining the direction of substitution; however, the sign likely changes throughout the day even at the same location. Therefore, we focus our analysis to any significant changes at specific locations and conclude that both positive and negative signs represent ad-hoc substitutional behavior. In the case where no significant changes are observed, we assume that the two modes do not interact. This situation corresponds to pre-planned trips and/or different user groups for the two modes.

We assume that changes in bus ridership in real time are controlled by time-of-day effects, weather conditions, day of week, season, network and local traffic conditions, bus levels of service, and incidents. We compile surge event data with all control variables for 6 months for ten points of interest. We assume that the shock of a surge event directly affects the ad-hoc modal choices of travelers, and network conditions (i.e., incidents, congestion, trip purpose, etc.) do not change substantially from 5 min prior to the shock until 10 min after the shock. Several robustness checks are conducted (e.g., multicollinearity checks, residual plots, lagged treatment variables, varying buffer size, propensity score regression) to ensure consistent results, check for omitted variable bias (i.e., underlying factors that affect transportation demand), and to assess if the treatment variable is accurately capturing the surge event.

Data from multiple sources are used to assess the time-dependent relationship between buses and TNCs at various locations in Pittsburgh. The results from this analysis largely corroborate previous research in that no significant changes in bus ridership were observed during surge events for most locations and times of day. However, four locations did observe significant changes to bus boardings during select time periods. These results highlight the dynamic interaction between TNCs and public transit that changes by location and time of day.

Wilkinsburg observed reduced bus boardings immediately after a TNC surge event during the weekday evening commute (4 p.m.–7 p.m.). The presence of a BRT station that directly serves Pittsburgh's central business district contributes to these findings. When this transit station isn't included in the analysis, no significant change in bus boardings were observed. The East Liberty location observed a significant change in bus boardings during weekday evening/late night hours (7 p.m.–12 a.m.) during a surge event. The presence of a BRT station within the buffer region contributes to this result because no significant change is observed with the removal of the BRT station from the analysis. This result is similar to Wilkinsburg for workers who might return after 7 p.m. or individuals returning home from late night social events in downtown Pittsburgh. The university locations observed significant increases in bus boardings during surge periods on weeknights (7 p.m.–12 a.m. for the University of Pittsburgh) and weekend evenings (5 p.m.–10 p.m. for Carnegie Mellon). The positive coefficient for bus boardings during a surge event might indicate that students are more flexible with their travel plans. The fact that students at both universities are provided with transit passes might also play a role. Students are also likely to be more sensitive to price changes due to limited income.

To summarize, we find that BRT stations influence mode choice between TNCs and buses. Two locations—the only two with a BRT station located inside the buffer region—produced significant changes in bus boardings during surge events at specific times of day. The BRT is similar to commuter rail in that high volumes of commuters utilize the service during weekday commutes. Previous research has highlighted a possible relationship between the two modes (Babar and Burtch 2017; Clewlow and Mishra 2017), and the observed results corroborate previous findings. The study also finds that an ad-hoc substitutional relationship exists near university locations. Both University of Pittsburgh and Carnegie Mellon produced significant results during specific times of day—weekdays 7 p.m.–12 a.m. for the University of Pittsburgh and weekends from 5 p.m.–10 p.m. for Carnegie Mellon. The underlying causes of these results are more challenging but could be related to neighborhood population characteristics, lack and/or cost of parking, among others. And finally, we find that the relationship between TNCs and buses varies by location and time of day. This result emphasizes the need for high resolution data and analysis techniques for efficient policy design and infrastructure investment.

To explore these findings further, a joint model was constructed to analyze how universities and BRT stations might influence ad-hoc mode choice between TNCs and buses. New distance-based covariates were created as a proximity measure for each point of interest and the nearest university and BRT station. However, spatial features—roadway traffic congestion and incidents—were removed because these variables were unique to each neighborhood. Since each point of interest observes different bus use behavior throughout the day, an interaction term was used for the location and time-of-day controls. The fitted distance metrics—proximity to universities and BRT stations—were insignificant and very small (0.001). This result highlights the complexity and multitude of factors that come into play in travel decision making. For example, BRT user behavior doesn't vary linearly as the distance from the BRT station increases. There is likely some threshold where travelers no longer consider the BRT, and this threshold varies with population characteristics and the built environment.

The results highlighted in this analysis are specific to Pittsburgh. However, many other U.S. cities might observe more significant interactions based on their constituents and built environment characteristics. We find that the relationship between TNCs and public transit is location and time dependent. Effective policies must consider these relationship dynamics when trying to promote sustainable modes at specific locations and times of day.

The measure of TNC usage in this analysis is through a proxy (surge multiplier). This is not ideal, but in the absence of TNC trip-level data, this method can help approximate TNC usage in time and space. It is important to note that many locations might observe high TNC demand without a surge multiplier due to many drivers currently located in the same location. We cannot detect these situations with methods outlined in this paper. We are also not able to detect pre-planned or long-term substitutional behavior because it is likely that an equilibrium between TNC users and drivers has already been met. We also use the first instance of a surge event to define the treatment variable for a "surge event".

All subsequent surge time periods are removed due to the complicated dynamics that are challenging to decouple. This design limits the data and the types of events we can detect.

This research and the previous literature both highlight the fact that commuter type services (e.g., commuter rail, bus rapid transit) could pair well with TNCs for first and last mile services. This would depend on the type of commuter service, the built environment, cost and access to parking, and fares, among others. It is also important to note that locations (or times of day) will not observe the same behavior simply due to the presence of a BRT station. The varying travel behavior in time and space is highlighted in this research. While this is an important first step, the underlying drivers that influence heterogeneous travel behavior are extremely important features to consider when designing transportation policy. From this point, we highlight two future directions that can both help inform policies and designs that can improve network efficiency. First, a more thorough analysis of data and/or surveys that are specific to regions near large commuter transit stations. A better understanding of how people arrive, depart, and make choices as part of a multi-modal trip can help isolate areas where future TNC/transit partnerships might be viable. Second, further analysis that studies travel behavior in the face of emerging technologies and modes of travel. What are the factors that influence mode choice and how do socioeconomics and the built environment fit into the decision making-process?

Supplemental materials

The full estimation results for each location and time of day can be found at Github (https://github.com/rgrahn/tnc_public_transit). Data sets and statistical analysis are also provided. The data files included are: (1) mapping between individual buffers and bus stops, (2) Hourly weather data, (3) sporting events data, (4) incidents data. The INRIX data is not provided because we have an NDA in place. The raw transit ridership and surge multiplier data are too large to post on Github. They can be provided upon request.

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