

# Integrating Shared Mobility Services with Public Transit in Areas of Low Demand

Natalia Zuniga-Garcia<sup>a,\*</sup>, Krishna Murthy Gurumurthy<sup>a</sup>, Cesar N. Yahia<sup>a</sup>, Kara M. Kockelman<sup>a</sup>, Randy B. Machemehl<sup>a</sup>

<sup>a</sup>*The University of Texas at Austin, Department of Civil, Architectural and Environmental Engineering, 301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, United States*

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## Abstract

The increasing demand for shared mobility services has led to multiple Public-Private Partnerships (PPPs), where public transit agencies and mobility providers work together to increase transit service coverage. However, several partnerships have failed due to the lack of demand and budget constraints. Furthermore, the limited data-sharing agreements restrict the analysis and dissemination of outcomes. This paper analyzes the integration of shared-mobility services into the public transit system using data from pilot programs in Austin, Texas. The use of Transportation Network Companies (TNCs) and microtransit service is evaluated as first-mile-last-mile (FMLM) solutions. The associated TNC, microtransit, and bus transit demand are analyzed using ridership data, and the trip characteristics are discussed and compared. Then, after controlling for confounding variables through matching, a difference-in-differences (DID) model is used to infer the effect of microtransit on bus transit demand. Specifically, by evaluating bus ridership before and after implementing the microtransit program, the DID model estimates the change in bus demand attributed to microtransit. The results suggest that the TNC services, focusing only on FMLM, were not as popular as microtransit services offering FMLM and intrazonal trips. Even though the microtransit trips were longer and, in some cases, the driver response times were higher than for TNC trips. Also, the DID model demonstrates that the microtransit service did not substantially impact the bus transit ridership, suggesting that the trips were mainly used for intrazonal door-to-door trips and not for FMLM trips. A further discussion highlights the need for performance metrics beyond demand and costs to capture the benefits of these partnerships for improving mobility, safety, and customer experience.

**Keywords:** public-private partnerships, public transportation, ridesourcing, microtransit, on-demand transit, difference in differences.

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\*Corresponding author

Email addresses: [nzuniga@utexas.edu](mailto:nzuniga@utexas.edu) (Natalia Zuniga-Garcia), [gkmurthy10@utexas.edu](mailto:gkmurthy10@utexas.edu) (Krishna Murthy Gurumurthy), [cesaryahia@utexas.edu](mailto:cesaryahia@utexas.edu) (Cesar N. Yahia), [kkockelm@mail.utexas.edu](mailto:kkockelm@mail.utexas.edu) (Kara M. Kockelman), [rbm@mail.utexas.edu](mailto:rbm@mail.utexas.edu) (Randy B. Machemehl)

## 1. Introduction

Public transit agencies are evaluating the incorporation of on-demand shared mobility options to increase current transit service coverage. While traditional fixed-routes face challenges to provide efficient and high-quality services in areas with low or sparse demand, alternative on-demand shared modes can supplement fixed-routes and provide flexible service (Mishra et al., 2020). In several cities, public transit authorities have started implementing Public-Private Partnerships (PPPs) to provide services in conjunction with Transportation Network Companies (TNCs) and microtransit companies; examples include Boston, San Francisco, and Austin (Blodgett et al., 2017; Feigon et al., 2018).

Compared to TNCs, microtransit requires higher operating costs and significant subsidies. However, the use of TNCs raises accessibility and equity concerns. In particular, TNCs are not subject to regulations by the Americans with Disabilities Act (ADA), and the TNC service can not be used by riders that do not have a smartphone (Lader and Klein, 2018). While incorporating these options seems to provide more public transportation solutions and alleviate transit first-mile-last-mile (FMLM) access and egress concerns, TNCs and microtransit partnership pilot programs have failed due to the lack of ridership and budget constraints (Westervelt et al., 2018). Therefore, more research is needed to understand the effective integration of shared mobility with the public transit system. This research compares TNCs and microtransit services using information from two pilot programs in Austin, Texas.

### 1.1. Background

Ridesourcing or TNCs, such as Uber, Lyft, and Didi, provide pre-arranged or on-demand transportation services for compensation (Shaheen et al., 2016). These services are expanding at a rapid pace and increasing their market share (Yahia et al., 2020). After its establishment in 2009, Uber completed 140 million annual trips during 2014, and this number increased to a total of 5.22 billion trips worldwide in 2018 (Smith, 2019).

On the other hand, microtransit services are defined as privately owned and operated transit systems (using large vans or minibusses) that can offer fixed and flexible route services (Shaheen et al., 2016); examples include Via, Chariot, and Bridj. While on-demand transit services have existed for decades, emerging microtransit services (enabled by technology similar to the mobile smartphone applications pioneered by TNCs) have gained popularity in recent years (Lucken et al., 2020; Pike and Kazemian, 2020).

The increasing demand for shared mobility options led to the introduction of multiple pilot programs. Public transit agencies partner with mobility providers to integrate these services into the transit system (Westervelt et al., 2018). Lucken et al. (2020) survey of 62 PPPs in the U.S. showed that they typically offer four service model types: FMLM (32 percent), low-density (39 percent), off-peak (8 percent), and paratransit (21 percent). The FMLM model includes trips with start or end at a fixed-route or fixed-stop location. Low-density models serve trips with starts or ends outside a fixed-route service area and can also be used for FMLM trips. Off-peak services are offered to fill the fixed-route temporal gaps, and paratransit trips serve a specific population (e.g., senior citizens). Although several pilot programs have tested these different service models, there are limited analyses of the outcomes, mainly due to the lack of openly-available data. Some partnerships between public

transit agencies and private companies restrict the data exchange agreements; this limits the types of analysis that the agencies or external sources can provide (Pike and Kazemian, 2019; Terry and Bachmann, 2020).

### 1.2. Objective and Contributions

This research analyzes the integration of TNCs and microtransit with local fixed-route bus service in areas with low demand in Austin, Texas. Data from two pilot programs are used, including PPPs offering the FMLM and low-density service models in the same geographic location during different periods. The study area corresponds to four zones where land use and road networks make it difficult to provide cost-effective bus service. Previous fixed-route buses in the area were replaced before introducing the pilot programs due to low ridership. These four areas present different socioeconomic attributes, allowing for further comparison of the influence of various characteristics. The PPPs analyzed are described as follows:

1. The first pilot program is a partnership with RideAustin, an Austin-based TNC. It lasted approximately six months and consisted of free TNC trips to bus transit users from the designated areas. The service was designed to solve FMLM accessibility, and it was used for trips where either the origin or the destinations occur at a fixed set of stops.
2. The second pilot program, currently operating, consists of a geofenced microtransit service in a partnership with Via called “Pick-Up.” In this case, the service has the same cost as a bus ride, but it includes intrazonal door-to-door trips rather than only FMLM trips (i.e., the trips are not restricted to a fixed set of stops).

The analytical framework is divided into two main tasks. The first task includes an analysis of the bus, TNC, and microtransit demand and compares their primary service characteristics in each of the four zones. The second task develops a causal analysis to estimate the effect of microtransit service on public transit. In particular, the impact of microtransit is evaluated by measuring the change in monthly bus ridership attributed to the implementation of the microtransit program. To this end, a difference-in-differences (DID) study is implemented using bus ridership and microtransit demand information.

The contributions of this work include (i) a comparison of the characteristics of two shared-mobility services offered in the same area during two different periods, (ii) an analysis of the effects of these services on bus demand across four zones with heterogeneous socioeconomic characteristics, and (iii) a causal study implementation to measure the integration of microtransit into the transit system. The main results show that the microtransit service did not result in significant changes in the bus ridership, which suggests that it was mainly used for intrazonal trips and not for FMLM.

### 1.3. Outline

Subsequent sections of the paper are organized as follows: Section 2 provides a literature review of the principal aspects of TNCs and microtransit and their integration with public transit systems; Section 3 describes the dataset; Section 4 presents the methodology describing the DID method; Section 5 includes the empirical analysis and provides results and discussion; and finally, Section 6 contains conclusions and final remarks.

## 2. Literature Review

Public transit provides an efficient means of travel that can serve captive riders who do not have access to alternative modes. Travelers, however, are unwilling to walk longer than about a quarter-mile ([El-Geneidy et al., 2014](#)) to reach their transit stops or their destinations from a stop. This imposes a major hurdle and makes transit an unattractive mode for many origin and destination pairs.

Several studies have looked into transit in the era of ridesourcing and microtransit, both from a competition that erodes transit ridership, as well as an FMLM solution that may improve transit use. There are mixed opinions on whether these services help or erode existing transit services. [Shaheen and Chan \(2016\)](#) studied shared mobility as a potential to overcome the FMLM problem. Their comparison of several shared modes, along with the more recent microtransit option, shows that there is indeed a gap to fill in terms of improving public transit use by solving the FMLM problem. Throughout their study, each shared mode (e.g., shared vehicles, bikes, or scooters) had the potential to improve transit use, but this was not always the case as they may emerge as competing modes. [Stiglic et al. \(2018\)](#) corroborates this from a carpooling perspective, where travelers may share rides to get to and from a rail line. [Hall et al. \(2018\)](#) conducted a statistical analysis of Uber trip data, and their conclusions also aligned with [Shaheen and Chan \(2016\)](#). The three-year dataset (2013-16) showed declining transit ridership after Uber’s entry into the market in large regions and regions with small transit agencies. Even though smaller cities saw an increase in transit ridership, the ridesourcing service seemed to decrease transit use overall.

[Bian and Liu \(2019\)](#) used a static optimization approach for a train station in New Jersey to check the feasibility of a personalized pooled service for first-mile access while taking into account preferred arrival times, disutilities from sharing with strangers, and inconvenience from early arrival. Overall, the results seemed to suggest that such a service should improve revenues and mode shares for transit. Similarly, [Huang et al. \(0\)](#) used a simulation-based method to analyze the use of shared automated vehicles (SAVs) for FMLM service to rail transit connections in Austin, Texas. The study found that SAV helped to increase the percentage of users shifting from driving alone to transit, but the total travel time served as the most significant determinant in trip-makers’ mode share. Using a simulation-based approach as well, [Gurumurthy et al. \(2020\)](#) showed that SAVs are not as useful to bus transit on a regional scale. Their results suggest that providing low-cost fares may deter the use of transit and lead to a rise in the SAV mode.

A stated-preference survey analysis by [Yan et al. \(2019\)](#) revealed that transit ridership might increase when used with shared mobility services, where this boost in ridership results from reduced wait and in-vehicle travel times. However, transfer penalties were not considered, so the university-focused result may be biased. [Reck and Axhausen \(2020\)](#), on the other hand, incorporated transfer penalties and showed that even small penalties of about 5-10 minutes deprives nearly 90% of all travelers the time-cost savings that such ridesourcing services may provide.

In terms of PPPs, existing case studies agree that merging innovative shared modes with transit may be beneficial, but care must be taken to ensure the proper distribution of these benefits. [Feigon and Murphy \(2016\)](#) reported on the rise in shared modes, the corresponding benefits to the system, and the need for transit agencies to evolve from fixed-route mass

movers to mobility agencies. Travelers in regions with high transit and ridesourcing use were found to spend less on transportation, on average, and were less likely to buy a new car. Although shared mobility options were not preferred for commute trips, transit use, on average, was found to be higher. [Blodgett et al. \(2017\)](#), [Westervelt et al. \(2018\)](#) and [Lucken et al. \(2020\)](#) conducted interviews of several U.S. transit agencies that have PPP's with ridesourcing companies; their studies highlight how quickly such PPP contracts are emerging throughout the country. In general, PPPs were found to be either agency-owned or agency-subsidized partnerships.

Most agencies are continuously changing their PPPs to ensure the provision of ADA compliant and equitable service ([Lucken et al., 2020](#)). As private companies, TNC's are often concerned with maximizing profit at the expense of equitable service. TNCs also require smartphones and do not cater to travelers without a credit or debit card. In contrast, the use of microtransit allows a transit agency to offer ADA compliant vehicles and are better placed to serve all travelers. Irrespective of equity-related disadvantages, many agencies are seeing an increase in transit use after implementation of PPP programs ([Blodgett et al., 2017](#); [Westervelt et al., 2018](#); [Lucken et al., 2020](#)). Moreover, without PPPs, the inequity in obtaining affordable and accessible travel may worsen—[Jin et al. \(2019\)](#) report low pickups by Uber in areas with a larger percentage of minority groups.

While both ridesourcing and microtransit have advantages and disadvantages from a qualitative point of view, further analysis is needed to quantify the impact of PPPs on transit ridership. This paper's contribution stems from the quantitative analysis of ridesourcing and microtransit programs; specifically, the proposed study investigates the impact of shared mobility partnerships on the fixed-route transit service in Austin, TX.

### 3. Data Description

This study uses data from several sources. The public transit demand is obtained from the Automatic Passenger Count (APC) information for Austin, publicly available through the Texas Open Data Portal.<sup>1</sup> It provides public transit vehicle information such as bus boarding and alighting counts, arrival and departure times, vehicle location (latitude and longitude coordinates), among others. This data is combined with stop locations obtained from the General Transit Feed Specification (GTFS) data. The vehicle location from APC was matched with the stop location identification number from GTFS. The processing and cleaning stage included the removal of double counts per stop, counts located more than 50 meters away from the corresponding stop, and extreme values of boarding and alighting count.

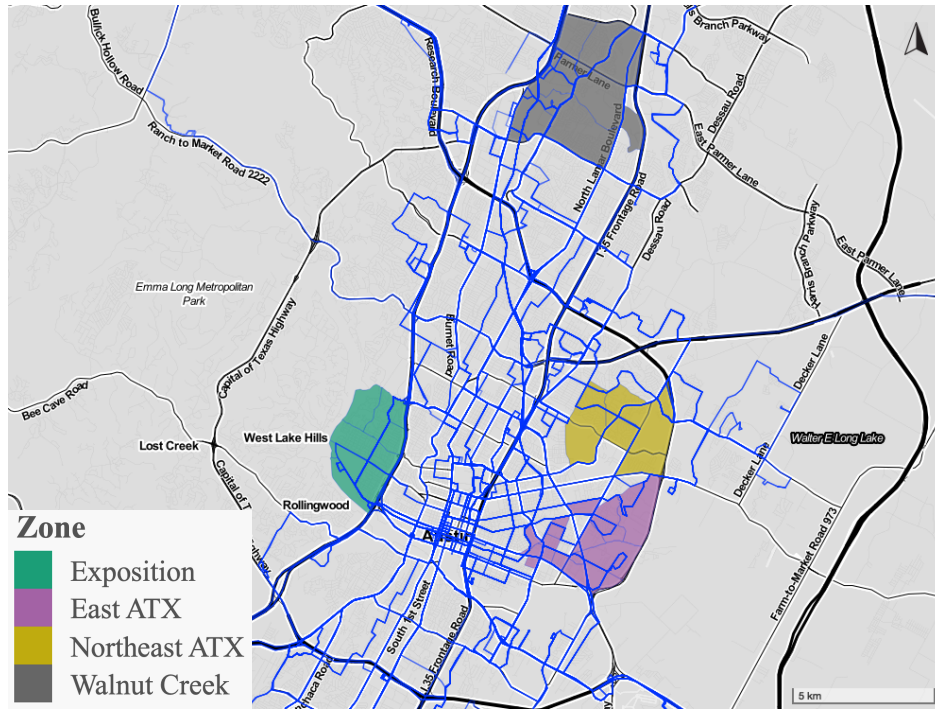
The information from the TNC trips and the microtransit service was provided by Austin's public transit agency, Capital Metropolitan Transportation Authority (CapMetro). In June 2018, CapMetro made significant changes in the bus network ([CapMetro, 2018](#)). These changes are referred to as CapRemap. After the renovations, CapMetro defined several "Mobility Innovation Zones," where they implemented alternative mobility options by using various pilot projects. This change implied the removal of some of the fixed-route

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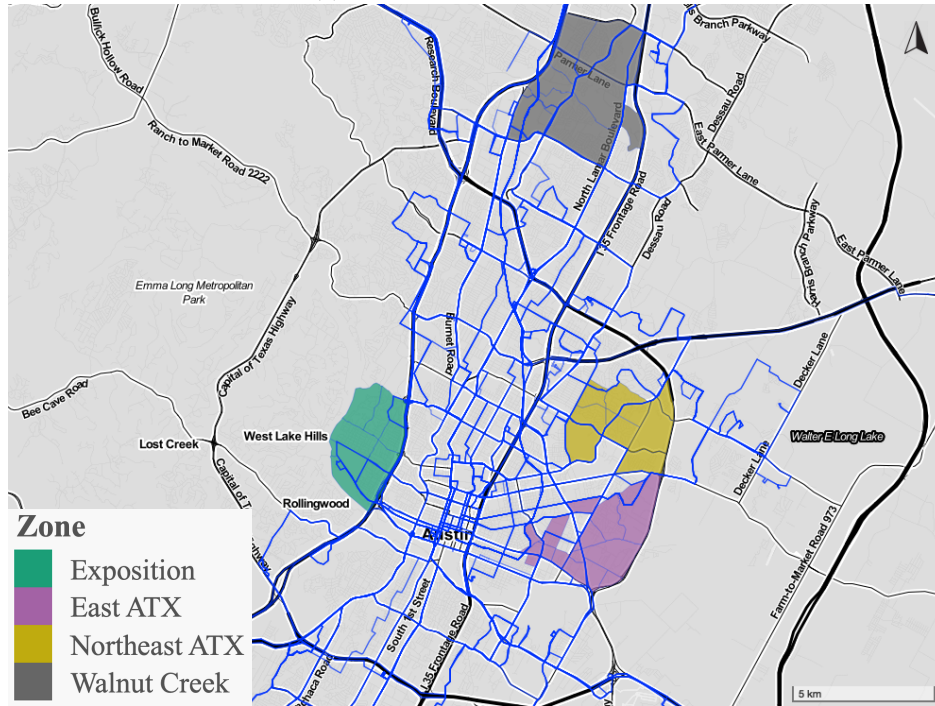
<sup>1</sup>This website can be accessed at <https://data.texas.gov/>



services and the introduction of a TNC (and eventually a microtransit) service. Figure 1 shows the location of the four areas analyzed, represented as Traffic Analysis zones (TAZs), and the bus network before and after the bus services changes.



(a) Bus routes before CapRemap



(b) Bus routes after CapRemap

Figure 1: Description of mobility innovation zone TAZs

The first pilot program implemented by CapMetro was a partnership with RideAustin, a non-profit TNC based in Austin, Texas. The program started with the Exposition area in June 2018 (right after CapRemap happened) and ended in October 2018. The other zones initiated it in October 2018 and ended in April 2019, approximately. The TNC program consisted of free TNC trips offered to public transit users from the designated areas. The service was implemented exclusively to solve FMLM accessibility, and it involved trips with origins or destinations set to a specific stop.

The second pilot program, currently in operation, consists of a geofenced microtransit service in a partnership with Via. In this case, the service has the same cost as a bus ride (USD 1.5), but it includes intrazonal door-to-door travel and also allows for FMLM trips. The service started in August 2019 in the same areas where the TNC program was functioning four months before.

In addition to TNC, microtransit, and public transit trip information, socio-demographic information was obtained, including race and ethnicity, age distribution, and household information to characterize the study area. This information is obtained using TAZ-level data from the Capital Area Metropolitan Planning Organization (CAMPO) website and using the American Community Survey (ACS) 2016. The ACS information is aggregated at Block Groups (BG) level; therefore, an additional spatial process was required to summarize at TAZ-level. The process consisted of intersecting TAZ and BG areas to estimate the proportion of BG per TAZ. The TAZ summary included the average BG values weighted by the BG area and population density. Table 2 provides a summary of description variables for each study area. The four areas show different characteristics. For example, Exposition has the highest average annual household income of \$78k, while for the East Austin zone, the average household income is \$ 31k, a difference of 40 percent.

Table 1: Description of the mobility innovation zones

Variables	Exposition	East	Northeast (Mean value)	Walnut Creek
Transit supply [Sept. 2018]				
Stop density (stops/ $km^2$ )	4.73	11.04	7.03	6.05
Bus frequency weekday peak hour (bus/hour)	10.37	7.18	11.03	8.49
Bus frequency weekend peak hour (bus/hour)	6.09	5.84	8.86	5.65
Socio-demographic information [2015]				
Population density (residents/ $km^2$ )	1,247	1,346	1,730	1,754
Employment density (employees/ $km^2$ )	778	1,122	466	1,779
Retail employment density (employees/ $km^2$ )	108	188	131	293
Race or ethnicity [2016]				
Proportion of White population	0.85	0.71	0.70	0.65
Proportion of Black/African American pop.	0.02	0.12	0.22	0.12
Proportion of Asian population	0.10	0.13	0.09	0.06
Household information [2015]				
Average household size	2.62	2.61	2.85	1.91
Median household income (USD)	78,288	31,453	43,740	45,207
Sample size (number of TAZs)	9	17	10	14

## 4. Methodology

This study aims to evaluate the impact of incorporating shared mobility services on public transit ridership. For this, a quasi-experimental difference-in-differences (DID) analysis was developed to investigate the causal relationship between mobility services and bus transit. The proposed DID approach calculates the effect of a treatment on an outcome; this effect is determined by comparing the average change of the outcome variable within a treatment group to the corresponding change in a control group. In this case, the treatments are the implementation of shared-mobility programs, and the outcome corresponds to the bus transit ridership. The treatment groups are the areas where the service was implemented. The control groups are areas with similar socio-economic, demographic, and mobility characteristics, but where the shared services were not implemented.

The causal analysis requires that the only change in the study area’s conditions is due to the treatment application. This restriction comes from the stable unit treatment value assumption (SUTVA). SUTVA requires that a particular unit’s response depends only on the assigned treatment, not the treatments of other events or other areas around it. In this case, the TNC service was implemented right after CapRemap when CapMetro made several public transportation network changes. Therefore, it is not possible to isolate the effect of TNC trips from the bus transit demand since it may also capture the impact of the CapRemap changes. The microtransit service, or Pick-Up program, started operating in August 2019, more than a year after CapRemap began, which allows for a more isolated analysis. For this reason, the DID analysis is focused only on microtransit, and TNC services will be analyzed qualitatively in the results section.

To evaluate the effect of the microtransit services on the bus transit demand, first, an intervention date is defined as the date the microtransit started operating, corresponding to August 2019. Then, the pre-intervention period is described from August 2018 to August 2019. Although this period includes months close to the CapRemap date, its effect would not significantly affect the results since there is a large sample (a year). The CapRemap effect would eventually stabilize during this period. Also, although this period includes months in which the TNC service was functioning, the low demand for the service implies that it would not have a significant impact either. The post-intervention period is defined from August 2019 until December 2019. Figure 2 shows a timeline with the most critical events in the study area and the period definitions.



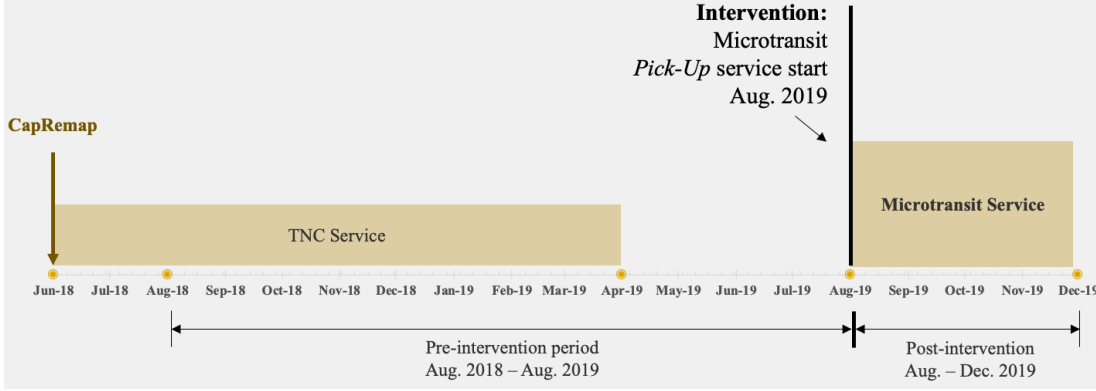


Figure 2: Timeline and period definition

Furthermore, the analysis is extended to include areas surrounding the service zones to account for trips made as FMLM with routes and stops outside the limits of the service area. The following sections further discuss the DID method and explain the methodology used to find the control zones and the buffer-area analysis.

#### 4.1. Difference-in-differences (DID) method

DID is a quasi-experimental research study design often used to study causal relationships in settings where randomized trials are infeasible. This study aims to compare the potential outcome that results from the implementation of the microtransit program (i.e., treatment) with the alternative potential outcome describing the case when the program is not implemented (control). The outcome variable considered is bus transit ridership. Since both potential outcomes can not be observed at the same time and in the same area, the potential outcomes with treatment are factual (can be observed), but the potential outcomes with no treatment are counterfactual (cannot be observed). For this, data from a control group is used to impute untreated outcomes in the treated group. This control group corresponds to areas with similar characteristics but where the Pick-Up (microtransit) service was not provided.

The DID setup uses the Pick-Up service zone as the unit of analysis. This Pick-Up zone is composed of a set of TAZs that represent the treatment group. To define the control group, the treatment group TAZs are matched to reference TAZs not in the Pick-Up service zone. Thus, there are two sets of TAZs composing the treated group and the control group. These two groups  $g = 1, 2$  (where group 1 is treatment and group 2 is control) are observed in multiple time periods summarized in monthly bus transit demand from August 2018 until December 2019. These months are assigned to the pre-intervention period and the post-intervention period dummy variable based on the description shown in Figure 2. In the first period, both groups are exposed to the control conditions. In the second period, the treatment is applied to the treated group but not to the control group. The standard DID estimate equation is described as follows:

$$Y_{gt} = \beta_0 + \beta_1 T_g + \beta_2 P_t + \beta_3 D_{gt} + \epsilon_{gt} \quad (1)$$

$$D_{gt} = T_g * P_t \quad (2)$$

Where,  $Y$  is the monthly bus transit demand,  $g$  is the group number ( $g = 1, 2$ ) observed in the two time periods  $t$  ( $t = 1, 2$ ). The dummy variable  $T_g$  identifies the time invariant observations in group  $g$ , i.e., its value is 1 for group 1 (treatment) and 0 for group 2 (control). While the dummy variable  $P_t$  indicates observations from period  $t$  and does not vary across the groups (i.e, its value is 1 for pre-intervention period and 0 for post-intervention period). The treatment variable  $D_{gt}$  is the product of these two dummy variables. The  $\beta_0$  coefficient corresponds to the baseline average,  $\beta_1$  is the time trend in the control group,  $\beta_2$  is the difference between the two groups before the intervention, and  $\beta_3$  is the difference in changes over time, also known as the average effect of treatment on the treated (ATT) – the effect of treatment on the treated group in the post-treatment period, as described in Equation 3. Figure 3 shows a graphical representation of the coefficients.

$$ATT \equiv \mathbb{E}[Y^1(2) - Y^0(2)|A = 1] \quad (3)$$

Where,  $Y^a(t)$  is the potential outcome given treatment  $a$  at time  $t$ . Here,  $t = 2$  represents the post-treatment period,  $a = 1$  represents the treatment,  $a = 0$  represents the no treatment, and  $A = 1$  refers to the treated group.

The identification of causal effects from the DID model depends on several assumptions. In addition to the SUTVA described previously, the model assumes a “parallel trend” establishing that both the treated and control units would evolve along a parallel path in the absence of treatment. A plot of the outcomes for the treated and control group in the pre-treatment period is used and discussed in the results section as evidence supporting this assumption.

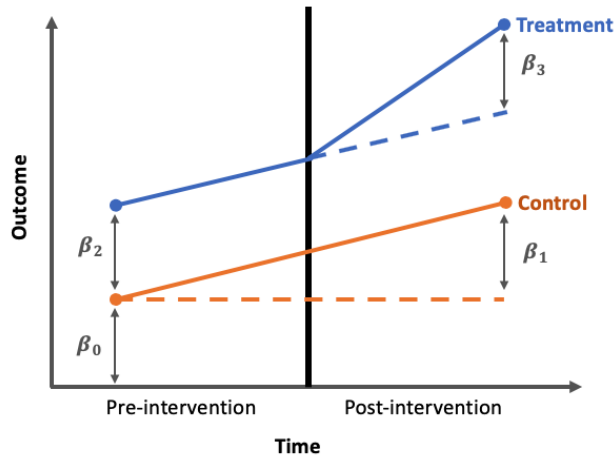


Figure 3: Difference-in-differences

#### 4.2. Matching control groups

The control groups are found using a matching technique. Rather than using the entire sample population to estimate the DID effect, units in the control group are selected based on their “closeness” to units in the treated group. Matching is attractive in DID analysis because it improves the groups’ comparability and possibly their outcome trends.

The matching is done at the TAZ-level by estimating the Mahalanobis distance between pairs of TAZs; the Mahalanobis distance is a metric of closeness used to find how similar two sets of covariates are. The covariates used include population density, retail employment density, median income, the proportion of White population, stop density, and bus frequency during weekdays and weekends. The distance corresponds to the square root of the squared difference of the set of covariates scaled using its covariance, as denoted in Equation 4. For each TAZ in the treatment group (Pick-Up service zone), the Mahalanobis distance is computed with every possible TAZ in the control group. Then, the treatment TAZ is matched to the closest control TAZ (minimal Mahalanobis distance). A TAZ in the control group is matched to at most one TAZ in the treatment group. The set of eligible TAZs for the control groups correspond to those located in the CapMetro Austin service area, where the TAZs located within the Pick-Up service zones are excluded.

$$D(X_i, X_j) = \sqrt{(X_i - X_j)^T S^{-1} (X_i - X_j)} \quad (4)$$

In Equation 4,  $D(X_i, X_j)$  is the Mahalanobis distance between TAZ pairs.  $X_i$  is the vector of covariates for TAZ  $i$  in the treated group (Pick-Up service zone).  $X_j$  is the vector of covariates for TAZ  $j$  from the set of TAZs in the control group.  $S$  is the covariance matrix of  $X$  used to scale the variables.

Table 2 shows the description of the control groups found using this method. This table can be compared to Table 3, corresponding to the treatment groups. Although the matching technique is not perfect, the pair of groups share similarities that make the DID analysis possible.

Table 2: Description of the control group TAZs

Variables	Exposition	East (Mean value)	Northeast	Walnut
Transit supply [2018]				
Stop density (stops/ $km^2$ )	5.27	6.95	15.53	4.52
Bus frequency weekday peak hour (bus/hour)	9.49	6.72	11.99	9.19
Bus frequency weekend peak hour (bus/hour)	8.88	4.88	7.30	6.75
Socio-demographic information [2015]				
Population density (residents/ $km^2$ )	1,563	1,561	2,023	1,545
Employment density (employees/ $km^2$ )	679	1,654	1,879	1,430
Retail employment density (employees/ $km^2$ )	348	323	528	354
Race or ethnicity [2016]				
Proportion of White population	0.85	0.73	0.70	0.70
Proportion of Black/African American pop.	0.06	0.09	0.10	0.13
Proportion of Asian population	0.10	0.07	0.05	0.06
Household information [2015]				
Average household size	2.47	2.37	2.64	2.20
Median household income (USD)	68,711	43,629	38,640	43,395
Sample size (number of TAZs)	9	17	10	14

#### 4.3. Buffer areas

Changes that affect the transit demand in the Pick-Up service zones may influence the proximate areas causing a spillover effect. For example, users may take the microtransit service to access bus stops outside the service area. The spillover effect would violate the DID SUTVA assumption since the transit demand changes are not isolated to the Pick-Up service areas but may include the surrounding areas. To limit this effect, the matching and DID process is repeated with a different unit of analysis; specifically, the modified treatment group consists of the Pick-Up service zones in addition to surrounding buffers. In other words, the treatment group would include an augmented area that adds adjacent TAZs to the Pick-Up service areas. Figure 4 shows the location of the buffer zones around each service area.

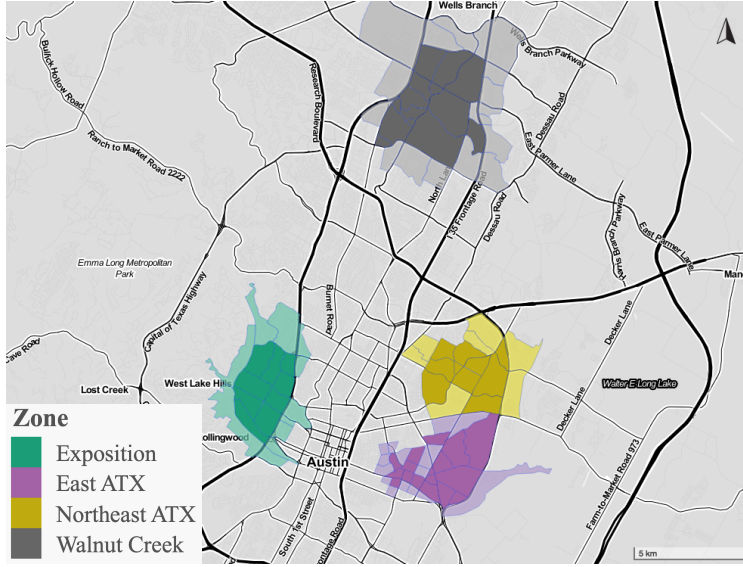


Figure 4: TAZs buffer illustration: the DID analysis is also implemented for augmented service areas that include a surrounding buffer

## 5. Results and Discussion

This section presents the results and main findings. First, public transit, TNC, and micro-transit demand and trip characteristics are described. The second part presents the DID results used to evaluate the integration of microtransit into the fixed-route services.

### 5.1. Demand analysis

The historical monthly demand for the bus service in each mobility innovation zone is obtained using information from the passenger counts. This demand is compared with the monthly demand reported for the TNC and microtransit service. Figure 5 presents the comparison of the estimates.



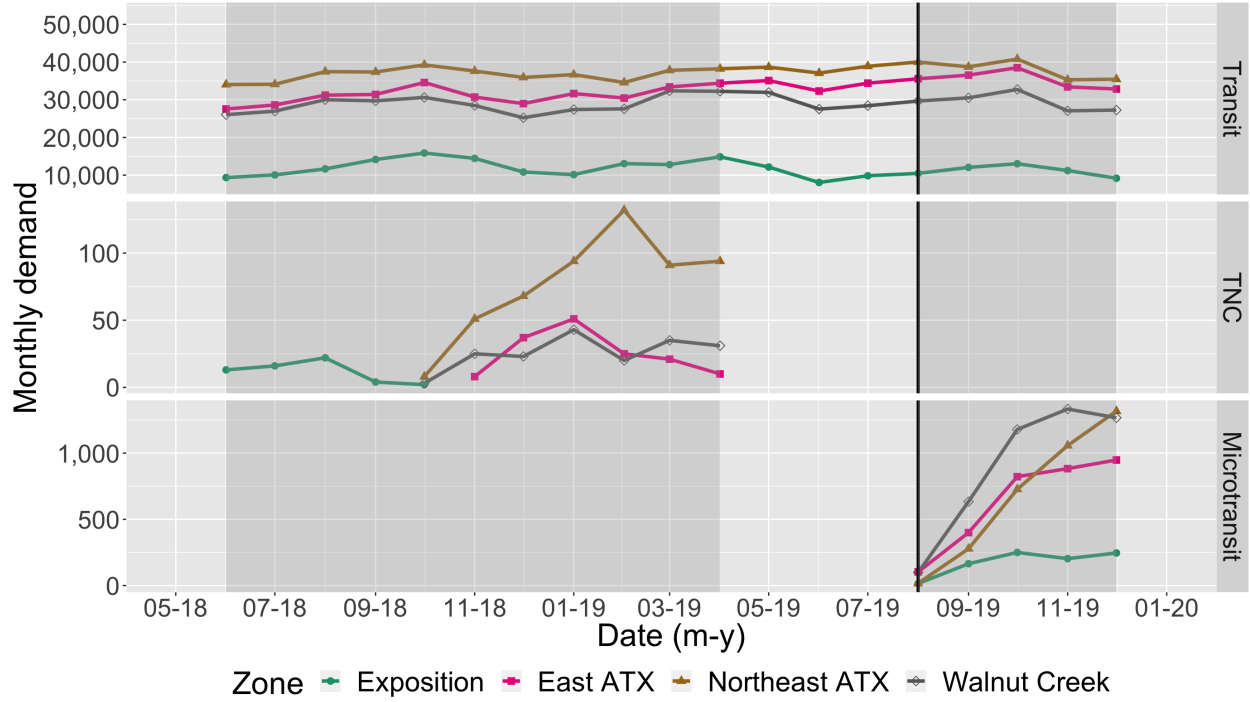


Figure 5: Monthly demand for bus transit, TNC, and microtransit by zone

The information in Figure 5 shows a marked difference in the demand for TNC FMLM trips and microtransit. On average, there were 37 TNC trips per month and 597 microtransit trips per month, a difference of approximately 1,500 percent. Furthermore, TNC demand seems to decrease with time while the microtransit demand increased. However, it is important to highlight that these two modes functioned on different service model types. TNC trips, focused exclusively on FMLM trips, were not as popular as the microtransit service that allowed for FMLM trips and intrazonal trips. This comparison of demand is particularly useful because it allows differentiating the ridership across zones even though the service model is different. The Exposition area showed the lowest demand for TNC and microtransit, while the Northeast area showed the highest TNC demand. Walnut Creek showed the highest microtransit ridership, followed by the Northeast and East zones.

The study areas present different characteristics. The household income ranges between \$31k to \$78k – where the city’s mean is \$55k (2015), and the average household size varies considerably around Austin’s mean of 2.3 (2015). Transit stop density is low in Exposition, at five stops per sq. km, whereas East Austin has more than twice as many stops per sq. km. Population composition by race indicates a prevalence of white population on Exposition (85 percent) compared to Walnut Creek (65 percent). The Northeast area presents the highest population density and household size. East Austin and Walnut Creek show the highest employment density, and Walnut Creek’s retail employment density is almost twice the other zones.

Research on shared mobility modes showed that areas with high income and a high proportion of Caucasians do not tend to generate high demand for ridesourcing trips (Lavieri et al., 2018) or micromobility services (Zuniga-Garcia et al., 2020a; Zuniga-Garcia and

Machemehl, 2020) and users are more prone to travel by car only (Giuliano, 2003; Smart, 2015). This can be related to the low demand for both TNC and microtransit in the Exposition zone. In contrast, Walnut Creek shows the highest employment and retail employment density, which can generate more intrazonal trips and, thus, more microtransit demand.

Figure 6 shows a comparison of the TNC and microtransit trips in terms of trip distance, duration, and driver reach time across the study areas. The plots describe the distribution of the trip’s characteristics summarized in box plots. The TNC trip distance average ranges between 0.6 miles (Exposition) and 1.8 miles (East Austin). In contrast, the microtransit distance of these two zones is greater for Exposition, with an average of 1.0 miles, and lower for East Austin, with 1.1 miles. Northeast and Walnut Creek areas show similar trip distances, both across modes and across sites, with an average of 1.2 miles approximately. On average, the trip duration for microtransit services is higher than for TNC trips.

The driver reaching time is the time it took the driver to pick up the user after the service was requested and is a good indicator of the level of service of the mode (Zuniga-Garcia et al., 2020b; Tec et al., 2019). The average TNC driver reaching time was higher than the microtransit services for East and Northeast Austin zones, with differences of 2.9 and 1.9 minutes, respectively. However, the Walnut Creek area showed a lower TNC time with a difference of 3.5 minutes. The information on this variable for the Exposition area was not available. Overall, these results indicated that microtransit services offered a better level of service than TNCs at East and Northeast Austin. At the same time, TNCs served better at Walnut Creek compared to microtransit service. However, Walnut Creek showed a higher microtransit demand, which indicates that the level of service difference is not influential on user demand.

The results described indicate that, among the two shared mobility modes servicing the same area, microtransit trips seem to present the highest user demand. Their trips tend to last longer, and in some cases, the level of service difference did not influence user demand. Likely, the FMLM trips within these areas are not predominant, explaining the difference in demand for TNCs services compared to microtransit.

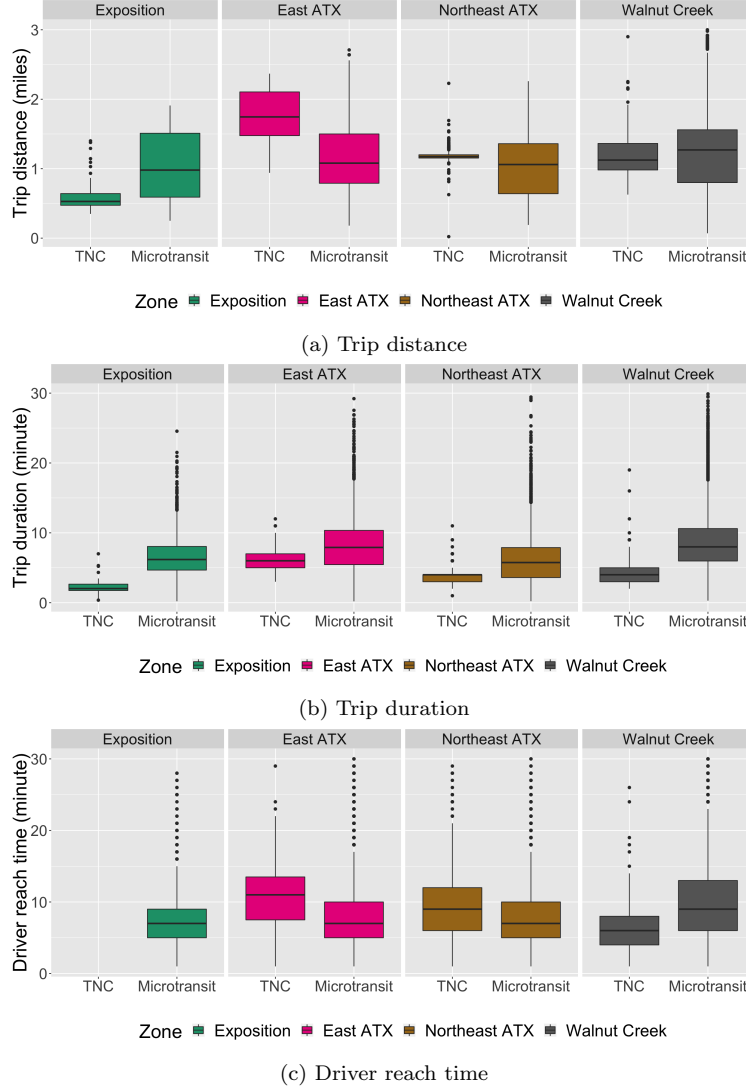


Figure 6: Description of TNC and microtransit trips

## 5.2. Difference-in-differences results

The quasi-experiment consists of a DID analysis of the integration of microtransit into the fixed-route services. A DID model was used to understand the effect of microtransit in altering bus transit demand. The case study of Austin, Texas, revealed that the mobility innovation zones envisioned by the public transit agency proved to be useful for travel within the zones, as seen from the demand for microtransit. However, the results suggest that microtransit had no significant impact on transit use in three of the four mobility zones.

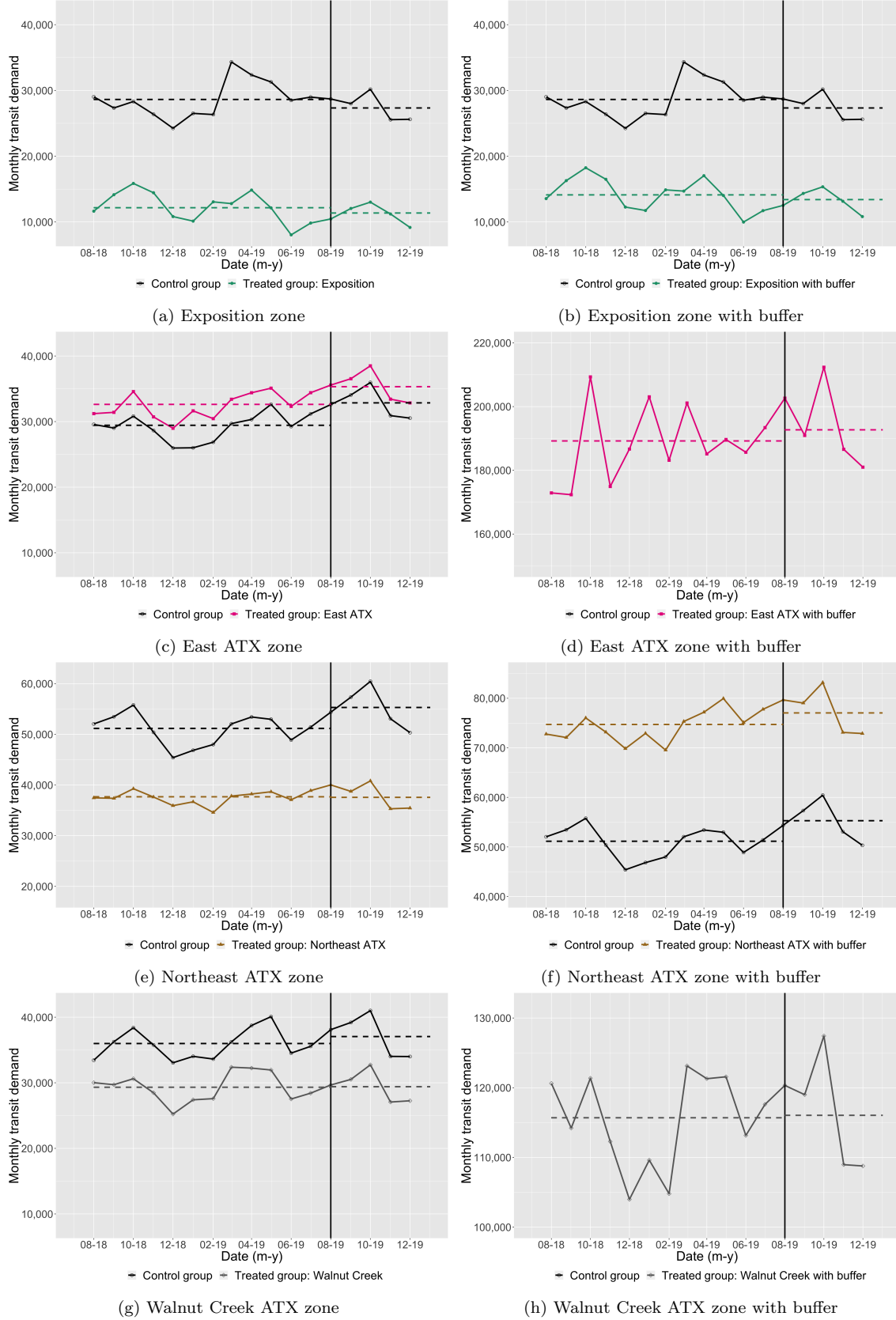


Figure 7: Average transit demand trends of the mobility innovation zones and the control groups before and after the microtransit service

Figure 7 presents the monthly bus transit demand of the treated groups compared to the control groups. The dashed lines represent the average value for the demand in the pre-intervention and post-intervention periods. The left column presents the zone analysis, while the right column shows the zone analysis when including the buffer areas. East Austin and Walnut Creek buffer areas had a significantly higher transit demand compared to the control group. Thus, the control group is not included in the plot to show the monthly changes in the demand trend. Although the control groups were selected based on similarity in resident population characteristics and bus transit service characteristics, a significant difference in transit demand was inherent between the control and treatment zones even before treatment. This finding is expected, but the trend in transit use across time for the control and treatment groups remained parallel from one month to the next, satisfying the parallel trend assumption of the DID model.

Table 3 shows the estimated coefficients for each of the four zones studied, as well as the estimates of the zones, including the buffered area around the mobility innovation zones. The coefficient  $\beta_1$  is an indicator of the time trend in the control groups and the treatment group’s expected tendency. The results indicate that the bus transit demand increased over time except for the Exposition zone, where the demand decreased. The mobility innovation zone was envisioned for neighborhoods deemed transit deserts, so this result is intuitive for the three regions (with better transit use in the buffered area). Exposition is located close to Austin’s downtown, and residents have a higher than average household income that likely translates to lower transit reliance. The clear delineation by the MoPac expressway to the east of this mobility zone also supports the continued lower trend in transit use in the buffered areas.

The difference in transit demand between the control and treatment zones is captured by the coefficient  $\beta_2$ , and is largely negative across all but one zone – East ATX, which implies that the control group in this area showed a lower transit ridership than the treatment group. The magnitude of  $\beta_2$  is higher for the buffer areas, as expected. In the buffer case, the treatment group included a higher number of TAZs, and therefore, it captured a higher transit ridership. However, it can be highlighted that the magnitude in East ATX increased significantly when the buffer area was included. This result is significant because it captures the transit demand in one of the main terminals of CapMetro, a place that includes several transit routes.

The primary objective of this paper was to test the differential impact of bus transit use with microtransit availability in these mobility zones. Prior studies have been divided on whether microtransit or TNC availability for FMLM transit access helps improve transit demand. The DID estimate is captured by the coefficient  $\beta_3$  or the ATT (refer to Equation 3), which will directly assess the microtransit treatment effect on transit trips. The DID analysis found no significant difference in transit use based on the introduction of microtransit use in Exposition, East Austin, and Walnut Creek neighborhoods, but found a statistically significant decrease in transit use in Northeast Austin.



Table 3: DID Results

<b>Coefficient</b>	<b>Estimate</b>	<b>p-value</b>	<b>Estimate</b>	<b>p-value</b>
<i>Zone:</i>	<i>Exposition</i>		<i>Exposition with buffer</i>	
$\beta_0$	28,641	0.00 *	28,641	0.00 *
$\beta_1$	-1,302	0.35	-1,302	0.37
$\beta_2$	-16,467	0.00 *	-14,527	0.00 *
$\beta_3$	495	0.80	604	0.77
$R^2$	0.93		0.90	
Adj. $R^2$	0.92		0.89	
<i>Zone:</i>	<i>East ATX</i>		<i>East ATX with buffer</i>	
$\beta_0$	29,428	0.00 *	29,428	0.00 *
$\beta_1$	3,435	0.01 *	3,435	0.51
$\beta_2$	3,200	0.00 *	159,805	0.00 *
$\beta_3$	-738	0.69	50	1.00
$R^2$	0.48		0.99	
Adj. $R^2$	0.42		0.99	
<i>Zone:</i>	<i>Northeast ATX</i>		<i>Northeast ATX with buffer</i>	
$\beta_0$	51,150	0.00 *	51,150	0.00 *
$\beta_1$	4,139	0.01 *	4,139	0.05 *
$\beta_2$	-13,490	0.00 *	23,566	0.00 *
$\beta_3$	-4,227	0.05 *	-1,805	0.54
$R^2$	0.89		0.92	
Adj. $R^2$	0.88		0.92	
<i>Zone:</i>	<i>Walnut Creek</i>		<i>Walnut Creek with buffer</i>	
$\beta_0$	35,984	0.00 *	35,984	0.00 *
$\beta_1$	1,071	0.45	1,071	0.73
$\beta_2$	-6,661	0.00 *	79,701	0.00 *
$\beta_3$	-1,000	0.62	-718	0.87
$R^2$	0.70		0.98	
Adj. $R^2$	0.67		0.98	

\*Significant at 95 percent confidence level

The three mobility zones not showing a difference in transit use are quite different in household and socio-economic characteristics. The key difference between these three zones and Northeast Austin was the ratios of population to employment density, which means that many short trips may have been possible within these mobility zones. Contrary to that, Northeast Austin had an imbalance in trip-generations and trip-attractions. This may intuitively mean that this neighborhood sees a larger share leaving the zone for work, which would also explain that this zone had the highest number of TNC trips. The high average household size may mean that a microtransit FMLM trip to a transit route may not have been more attractive than a personal vehicle available at the origin location.

These results can be inferred from two lenses. From the transit operator's perspective, the deployment of microtransit in transit deserts helps provide mobility options for travel within the demarcated zone. Travelers cannot be expected to choose to transfer from a microtransit ride to a fixed-route transit line to reach their destinations outside these zones. Suppose the transit operator's primary objective is to provide mobility options while saving

costs associated with unused fixed-route transit lines. In that case, mobility innovation zones in locations that may not be transit-dependent but have sufficient zonal trip generations and attractions can be expected to find the microtransit service useful. However, the microtransit service does not help increase fixed-route transit ridership. From a system perspective, microtransit geofenced in transit deserts may not help improve travelers' mobility and access at the system level. Personal auto ownership may continue to be essential to access destinations outside of these zones.

## 6. Summary and Conclusions

This study analyzed the integration of two shared mobility services into the public transit service using data from pilot programs offering TNC and microtransit services in the same area during different periods. Ridership data was used to compare the demand for transit, TNC, and microtransit and describe the trips' principal characteristics, including trip distance, duration, and driver reaching times. Furthermore, a DID quasi-experimental method was developed using monthly transit ridership data to analyze the causal relationships between the microtransit service and bus demand. The main results suggest that TNC services, focusing only on FMLM, were not as popular as microtransit services offering FMLM and intrazonal trips. Even though the microtransit trips were longer and, in some cases, the driver response times were higher than for TNC trips.

This case study reflects the challenges that public transit agencies face in areas with low demand, where fixed-route services are not cost-effective. Although the results indicate that there is no integration between these shared mobility options and the transit system, the benefits of the program go beyond measurable demand and costs. There is a need for performance metrics that can capture the benefits of these options for both users and providers, capable of measuring the improved mobility, increased safety, and enhanced customer experience that these users experienced.

The results and methods proposed in this study can serve multiple purposes. First, from the transit agency point of view, this study provides a methodological framework for analyzing mobility services' integration into the transit system that can be used in other areas with similar PPPs services. Second, it evaluates how these partnerships can potentially be used to help under-served areas and improve transit accessibility from the users' point of view. Finally, from a transportation research point of view, this study contributes to the scarce literature in this area providing empirical evaluations of the effects of incorporating these services into the transit system.

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