Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?

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ABSTRACT

Public transit ridership in major US cities has been flat or declining over the past few years. Several authors have attempted both to explain this trend and to offer policy recommendations for how to respond to it. Past writing on the topic is dominated by theoretical arguments that identify possible explanations, with the few empirical analyses excluding the most recent data, from 2015-2018, where the decline is steepest. This research conducts a longitudinal analysis of the determinants of public transit ridership in major North American cities for the period 2002-2018, segmenting the analysis by mode to capture differing effects on rail versus bus.

Our research finds that standard factors, such changes in service levels, gas price and auto ownership, while important, are insufficient to explain the recent ridership declines. We find that the introduction of bike share in a city is associated with increased light and heavy rail ridership, but a 1.8% decrease in bus ridership. Our results also suggest that for each year after Transportation Network Companies (TNCs) enter a market, heavy rail ridership can be expected to decrease by 1.3% and bus ridership can be expected to decrease by 1.7%. This TNC effect builds with each passing year and may be an important driver of recent ridership declines.

Key Words: Transit Ridership, Public Transportation, Ridesourcing, TNC, Uber, Bus, Rail, Longitudinal Analysis

INTRODUCTION

Following strong ridership growth during much of the previous decade (*1*), public transit ridership in major US cities has been flat or declining over the past few years (*2–4*). The changes vary by mode and by agency, but can be observed using data from the National Transit Database (NTD) (*5*), as shown in Figure 1. Figure 1 shows the percent change in transit ridership, using Fiscal Year (FY) 2002 as a base, for the largest transit agencies in seven large US cities: Boston, New York, Washington, DC, Chicago, Denver, San Francisco and Los Angeles. Three separate graphs show the ridership on heavy rail, light rail and bus, with heavy and light rail only available in a subset of cities. The graphs show that heavy rail ridership grows steadily in four of five cities until about 2014, then declines, with the decline in Washington, DC starting earlier. Light rail ridership is relatively flat in Boston and San Francisco, and grows substantially in Denver and Los Angeles, two cities that expanded their light rail systems over this period. Bus ridership is relatively flat for much of this period, with noticeable declines starting between 2013 and 2016 on each of the bus systems except San Francisco, which has embarked on a series of bus service improvement projects over this period (*6*).

A number of explanations have been offered for what might be causing this trend, including: income growth combined with cheap gas (*7*); increased car ownership (*2*, *3*); transit service cuts (*8*); reliability issues associated with deferred maintenance (*2*, *9*); increased bicycling, bike sharing, and electric scooter use (*3*, *4*); and the expansion of Transportation Network Companies (TNCs) such as Uber and Lyft (*3*, *4*). Crafting an effective policy response to this trend depends upon first understanding its cause.

Two recent studies are worth considering in further detail: an analysis of ridership trends in Southern California (*10*) and a longitudinal study of ridership in 25 North American cities (*11*).

Manville et al (*10*) considered the issue of falling transit ridership in Southern California and concluded that the trend was largely due to increased auto ownership among immigrant populations. Their recommended response is to convince people who rarely or never use transit to do so occasionally. Their conclusion is based on data covering the period from 2000-2015, and shows that much of the decrease in auto ownership occurred between 2000 and 2010. In contrast, the NTD data (Figure 1) show that the steepest decline in transit ridership occurs from 2015-2018. Given that auto ownership is a long-term decision, it would be surprising if it changed rapidly enough to explain this more recent decline.

Boisjoly et al (*11*) find that transit service cuts and auto ownership are the main determinants of transit ridership. They argue that given this evidence, transit agencies should prioritize expanding service to counteract these trends. Their method was a longitudinal analysis of the determinants of transit ridership using 2002-2015 NTD for 22 US cities, plus equivalent data for 3 Canadian cities. Specifically, they estimated panel data regression models, in this case multilevel mixed-effects models, to correlate the changes in transit ridership with changes in descriptive variables such as vehicle revenue miles (VRM), average fare, the share of zero-car households and population. This is a logical approach to studying the problem. Similar panel data methods used previously to study the determinants of transit ridership changes (*12–14*), with those methods offering an advantage over time-series models which are sometimes used as well (*15*, *16*) because the panel models can consider data from multiple cities at once.

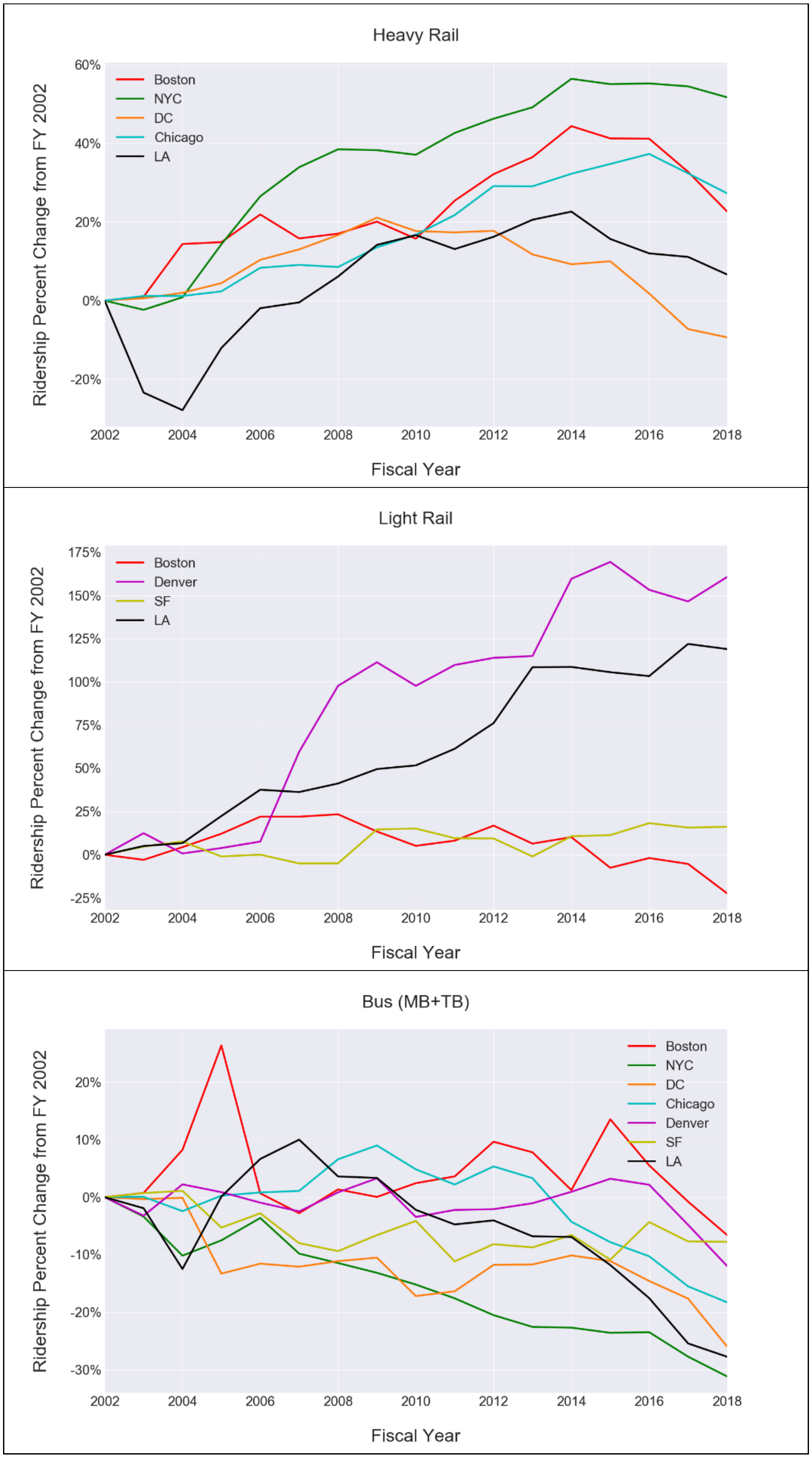


FIGURE 1. Percent Change in Transit Ridership from 2002

While Boisjoly's methodology is sound, their data ends in 2015, which is about when we observe some of the largest ridership declines begin (see Figure 1). This raises the possibility that their models miss the most important part of the trend. In addition, their models are based on the total ridership in each city, summed across modes. As can be observed by the different trends between light rail and bus in Denver and Los Angeles, there is a possibility that this aggregation washes out the change we are trying to detect. This paper updates Boisjoly's analysis using the most recently available data, segmented by mode. In doing so, we consider whether their conclusions still hold, as well as possible implications for effective policy responses by transit agencies.

BACKGROUND AND LITERATURE REVIEW

A number of studies have examined the factors that influence transit ridership (*1*, *12–20*). These studies point to a core set of variables that are included across multiple studies, and can be considered as well established determinants. These include: population, employment, VRM, fare, car ownership and gas price.

Evaluation of the recent declines is dominated by theoretical arguments of what may have changed over the past few years, often appearing in blog posts and media articles (*2–4*, *7–9*). These articles are useful in identifying potential causes, which include:

- Income growth combined with cheap gas (*7*),
- Increased car ownership (*2*, *3*),
- Service cuts (*8*),
- Reliability issues associated with deferred maintenance (*2*, *9*),
- Increased bicycling, bike sharing, and more recently electric scooters (*3*, *4*), and
- The expansion of Transportation Network Companies (TNCs) such as Uber and Lyft (*3*, *4*).

It is worth considering each of these factors, first by noting that the first three overlap with the core variables noted above. The economy has been strong over the past few years, with employment growth outpacing income growth. Income growth could lead to increased car ownership and decreased transit ridership. However, it is also associated with strong employment growth, and transit ridership tends to increase with employment growth because more people commute to work. Gas prices have declined, hitting an average of $2.83 per gallon in April 2018 compared to $3.63 per gallon five years earlier (*21*), so this may be a contributing factor.

Car ownership is another logical determinant of transit ridership, with 0-car households especially dependent upon transit. As discussed previously, Manville et al (*10*) attributed falling transit ridership in Southern California largely to increased auto ownership among immigrant populations. It is not clear whether car ownership is changing quickly enough to explain the rapid transit ridership decline since 2015, but it is clearly a factor that must be considered.

Service cuts were identified by Boisjoly (*11*) as the driving factor, and it is logical that they would affect ridership. The question is: how much? To better understand this, we can examine the change in ridership versus the change in VRM. Figure 2 shows the percent change in ridership per VRM for the same cities and modes shown in Figure 1. The light rail trend is the most obviously different, with the large growth in total light rail ridership in Denver and Los Angeles apparently driven by expanded service on those systems. However, Figure 2 also shows that ridership per VRM is decreasing on most systems. In particular, we observe that the recent bus service expansion in San Francisco seems to have counteracted a background trend of declining ridership per VRM. These data suggest that something else has changed over the past few years, beyond service provision, that is contributing to the decline in an important way.

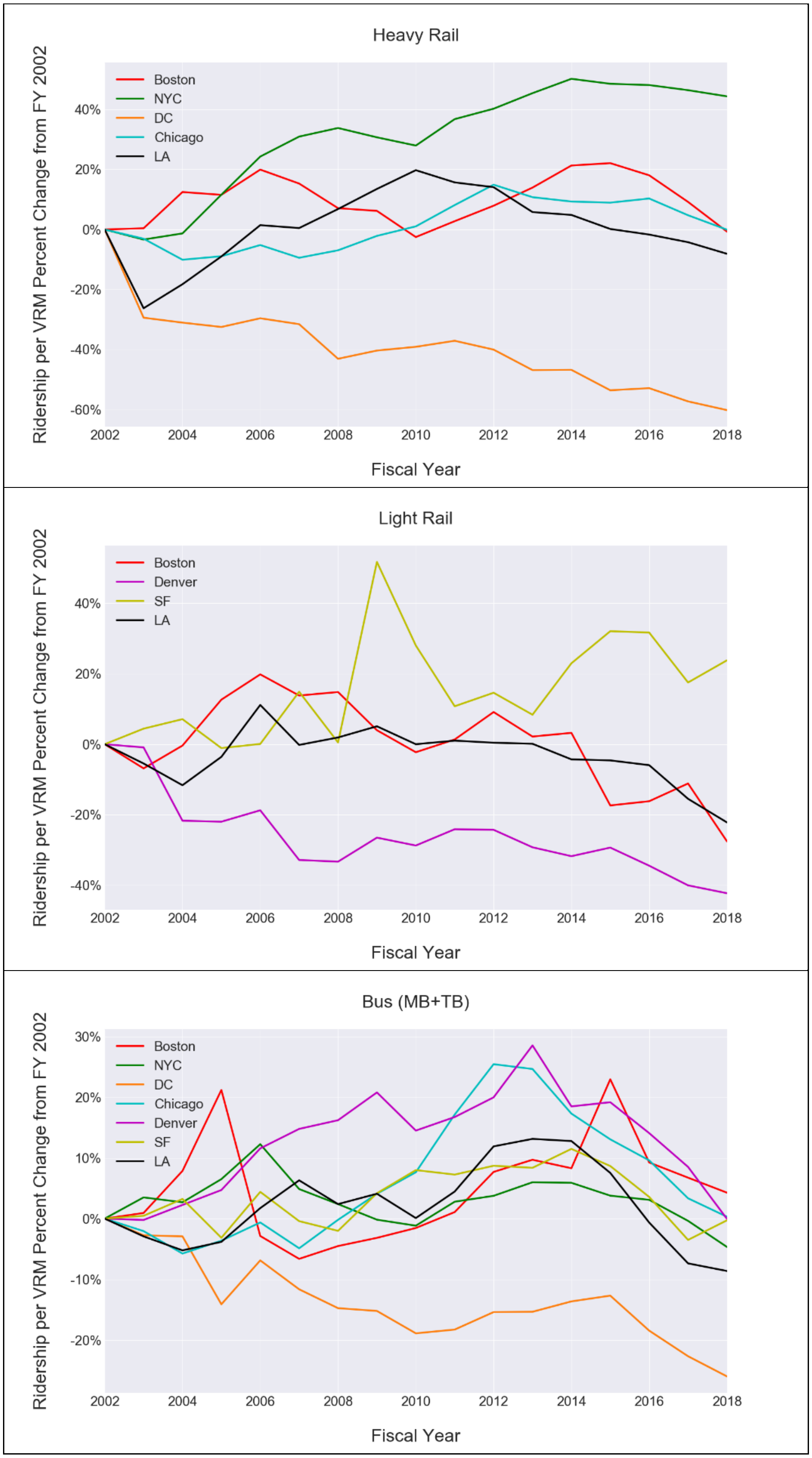
Reliability and maintenance issues are a potential contributing factor, although their influence may be limited to specific systems, such as New York and Washington heavy rail.

Bike sharing is new in many cities over this period, while bicycling broadly is experiencing a "renaissance" with expanded bike lanes in many cities and increased use (*22*, *23*). Bike share, and bicycling in general, could compete with transit if transit users switch to bike, or it could complement transit by providing first- and last-mile connectivity. Boijoly et al (*11*) include in their models a flag for the presence of bike sharing, and find that it is correlated with higher transit ridership, although not at a statistically significant level. Conversely, Campbell and Brakewood conducted a more detailed study of the effect of bike sharing on bus ridership in New York, and found that each additional 1000 bike share docks proximate to a bus route are associated with a 1.7% to 2.4% decrease in bus ridership (*24*). It would be reasonable to expect a similar effect from the introduction of electric scooters or similar new modes.

There is disagreement over the effect of TNCs on transit ridership. Some authors argue that TNCs are likely to increase transit ridership by providing first- and last-mile connectivity, providing service at locations and times (such as late at night) when there is less transit service provided, or by reducing car ownership (*25*, *26*), while other studies show that TNC users are likely to switch from transit, reducing ridership (*27–29*). Both may be true to varying degrees. A survey of TNC users in seven US cities finds that TNCs are associated with a 6% derease in bus trips, a 3% decrease in light rail trips, and a 3% increase in commuter rail trips (*30*).

As a proxy for TNC use, Boijoly et al (*11*) test the presence of Uber in their longitudinal model, and find that it is associated with higher transit ridership, but that the effect is not significant. They conclude from this that TNCs are not a major determinant of the recent decline in transit ridership, although they do also note that there is a general lack of TNC use data. Similarly, Manville et al (*10*) note that they have very little data to measure the effect of TNCs on transit ridership, but go on to dismiss the importance of TNCs effect on transit using theoretical arguments similar to those in (*25*, *26*).

It is important here that we not confuse the lack of data with the lack of importance, and that we consider what we can learn from locations where we do have data. One such location is San Francisco, where there were 170,000 daily TNC trips in 2016, representing 15% of intra-San Francisco vehicle trips (*31*). An analysis of these data in combination with automated passenger count (APC) data found that TNCs decrease bus ridership, but not rail (*32*). Another location where reasonably good TNC data exist is New York, where TNC trips must be reported to the city's Taxi and Limousine Commission, and a recent study found that TNC use appears to be associated with decreasing transit ridership (*33*).



1 **FIGURE 2. Percent Change in Transit Ridership per Vehicle Revenue Mile from 2002**

The New York data are particularly useful because they are available by month. Figure 3 shows the total daily Uber and Lyft trips in New York (*34*), which grow from about 60,000 to nearly 600,000 between 2015 and 2018. This rapid TNC growth corresponds to a period of declining transit ridership (daily subway and bus ridership in New York decrease by 580,000 boardings between April 2015 and April 2018 according to the NTD), as well as to a period beyond the bounds other recent studies. It further demonstrates that the presence of Uber is not a binary variable, and given the dramatic change in magnitude, we would expect the quantity of trips to matter.

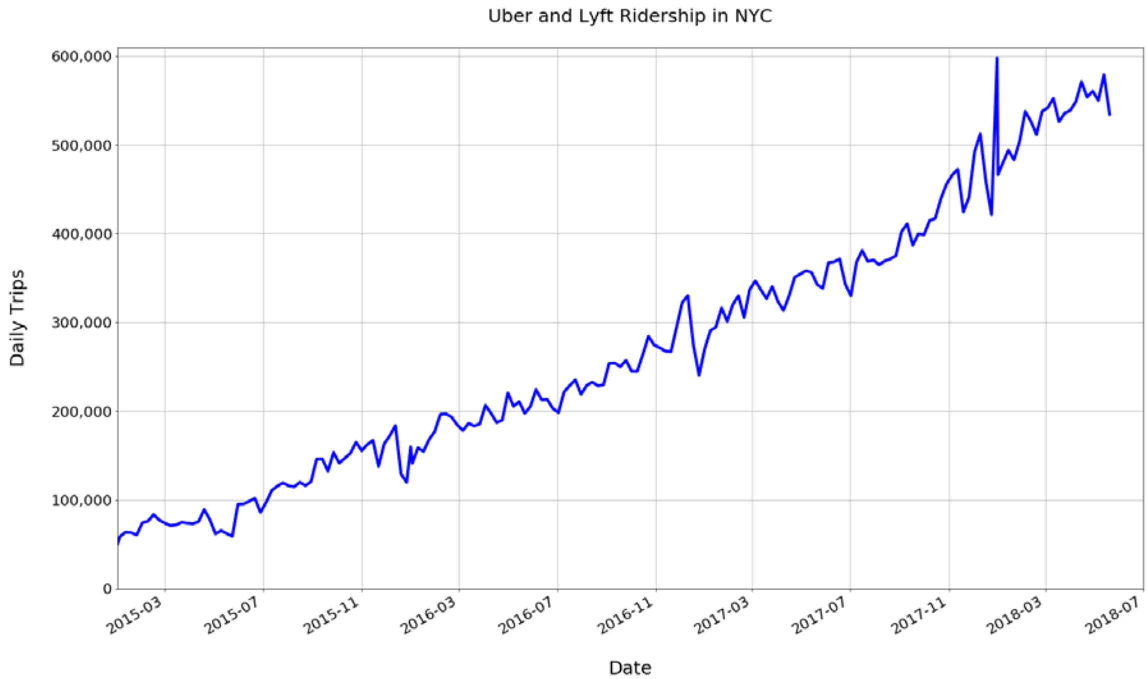


FIGURE 3. Daily TNC Trips in New York

This research aims to consider each of these factors, using the most recently available data. It follows the methodology employed by Boijoly et al's (*11*), with the following extensions:

- It considers data from 2002 through April 2018, the most recently available in the NTD,
- It segments the analysis by mode, to capture the possibility that the effects are different for different transit modes,
- It uses monthly data rather than annual data, which is the native resolution of the NTD,
- It includes employment in the model in order to capture the effect of economic growth over the past few years, and
- It considers that the TNC effect is not binary, but instead increases with the growth of TNCs. Because we still lack data on TNC use beyond a few specific cities, we make an assumption that TNC use grows linearly starting from the date it is introduced to a new market. To capture this, we use a variable that is defined as the number of years since Uber entered the market to take the place of the binary Uber presence variables.

A few other differences from the previous study should be noted. First, the study is limited to 22 US cities, excluding the three Canadian cities for which data are not publicly available. Second, it uses a different econometric model: a random-effects model instead of a mixed-effects model. Incorporating both would be a useful future improvement.

DATA AND METHODS

For this study, we conducted a longitudinal analysis using monthly transit ridership data from the National Transit Database for the 22 transit agencies and four modes (commuter rail, heavy rail, light rail and motor bus) shown in Table 1. Unlinked passenger trips are available for each mode allowing a total of 51 agency-mode combinations. All NTD data were collected from January 2002 to April 2018.

In addition to the ridership data, this study considers the possible determinants listed as variables in Table 2. NTD is also the source for vehicle revenue miles and fares, with VRM broken out by mode. The average fare is calculated as the fare revenue divided by the unlinked passenger trips. It is adjusted for inflation, with 2016 USD as the base rate. All dollar-based data were adjusted for inflation using 2016 as the base year.

We gathered data for the metropolitan population from the American Community Survey (ACS) 1-year estimates, and from the 2000 Census. The ACS data were collected from 2005 to 2017. We linearly interpolated the years 2000 to 2005 to come up with data for years 2002 to 2004. We extrapolated the data to 2018 to extend the usefulness of the data. We also linearly interpolated between years to get the data in monthly terms. The percent of households with zero vehicles is from the same sources and processed in the same way.

Metropolitan land area for the 22 metropolitan areas was also sourced from the United States Census Bureau's numbers for the urban area in 2010. We assumed that the metro land area remained constant throughout the time period of our research. Employment data also came from the Bureau of Labor Statistics. Monthly data was given for the full array of dates in our research.

Gasoline price data were sourced from the US Energy Information Administration. The data came in as a weekly figure. We took the weekly data, calculated monthly averages and adjusted for inflation to 2016 US dollars.

Data for Uber's start date in each city was found primarily from Uber's press releases. Other confirming sources include local newspaper articles. Bike share start-up dates were found from local newspaper articles and from Oliver O'Brien's bike share map (*35*). We split the years since Uber and bike share presence variables into the four different modes used in this model to account for any differences between the modes.

TABLE 1: Metropolitan Areas, Transit Agencies, and Modes Analyzed

Metropolitan Area	Core City	Transit Agency	Modes
Atlanta - Sandy Springs - Marietta, GA	Atlanta	Metropolitan Atlanta Rapid Transit Authority (MARTA)	Heavy rail, motor bus
Baltimore - Towson, MD	Baltimore	Maryland Transit Administration	Heavy rail, light rail, motor bus
Boston - Cambridge - Quincy, MA-NH-RI	Boston	Massachusetts Bay Transportation Authority (MBTA)	Commuter rail, heavy rail, light rail, motor bus
Chicago - Joliet - Naperville, IL-IN-WI	Chicago	Chicago Transit Authority (CTA)	Heavy rail, motor bus
Cleveland - Elyria - Mentor, OH	Cleveland	The Greater Cleveland Regional Transit Authority	Heavy rail, light rail, motor bus
Dallas - Fort Worth - Arlington, TX	Dallas	Dallas Area Rapid Transit (DART)	Light rail, motor bus
Denver - Aurora - Broomfield, CO	Denver	Denver Regional Transportation District	Light rail, motor bus
Houston - Sugar Land - Baytown, TX	Houston	Metropolitan Transit Authority of Harris County (Metro)	Light rail, motor bus
Los Angeles - Long Beach - Santa Ana, CA	Los Angeles	Los Angeles County Metropolitan Transportation Authority (LACMTA)	Heavy rail, light rail, motor bus
Miami - Ft. Lauderdale - Pompano Beach, FL	Miami	Miami - Dade Transit (MDT)	Heavy rail, motor bus
Minneapolis - St. Paul - Bloomington, MN-WI	Minneapolis	Metro Transit	Light rail, motor bus
New York - Northern New Jersey - Long Island, NY-NJ-PA	New York	MTA New York City Transit (NYCT)	Heavy rail, motor bus
Philadelphia - Camden - Wilmington, PA-NJ-DE-MD	Philadelphia	Southeastern Pennsylvania Transportation Authority (SEPTA)	Commuter rail, heavy rail, light rail, motor bus
Pittsburgh, PA	Pittsburgh	Port Authority of Allegheny County	Light rail, motor bus
Portland - Vancouver - Hillsboro, OR-WA	Portland	Tri-County Metropolitan Transportation District of Oregon	Light rail, motor bus
Sacramento - Arden - Arcade - Roseville, CA	Sacramento	Sacramento Regional Transit District	Light rail, motor bus
San Diego - Carlsbad - San Marcos, CA	San Diego	San Diego Metropolitan Transit System	Light rail, motor bus
San Francisco - Oakland - Fremont, CA	San Francisco	San Francisco Municipal Railway (SFMTA)	Light rail, motor bus
San Jose - Sunnyvale - Santa Clara, CA	San Jose	Santa Clara Valley Transportation Authority	Light rail, motor bus
Seattle - Tacoma - Bellevue, WA	Seattle	King County Department of Transportation (King County Metro - KCM)	Light rail, motor bus
St. Louis, MO-IL	St. Louis	Bi-State Development (BSD)	Light rail, motor bus
Washington - Arlington - Alexandria, DC-VA-MD-WV	Washington	Washington Metropolitan Area Transit Authority (WMATA)	Heavy rail, motor bus

TABLE 2: Description of Available Variables

Variable	Source	Description	Date Range Available	Unit	Notes
Ridership (UPT)	NTD	Number of unlinked passenger trips	2002-2018	Trips	
Vehicle Revenue Miles (VRM)	NTD	Miles that vehicles travel while in revenue service	2002-2018	Miles	
Fare	NTD	Fare revenue per UPT	2002-2018	2016 USD / trip	Adjusted for inflation. Base rate 2016 USD.
Population	American Community Survey	Metro population	2005-2017	Persons	Interpolated data between 2000-2005 to capture years 2002-2004. Extrapolated to 2018. July data given - linearly interpolated to make data monthly.
Percent of household without a car	American Community Survey	Percent of households without a car	2005-2017	Percent	2005 data used for years 2002-2004. 2017 data used for 2018. July data given - linearly interpolated to make data monthly.
Metro Land Area	US Census Bureau	Land area of the metropolitan area	2010	Squared miles	
Employment	Bureau of Labor Statistics	Employed persons in metropolitan area	2002-2018	Persons	
Gas price	US Energy Information Administration	Average price of gas	2002-2018	2016 USD	Weekly data given. Averaged weeks in each month to come up with monthly data. Adjusted for inflation. Base rate 2016 USD.
Years Since Uber	Uber press releases and other news outlets	Years since Uber first appeared in metro area		Years	
Bike Share Presence	Bike Share Map and other news outlets	Whether or not a city has a bike sharing system		1 = Present 0 = Not Present	

We analyze these data using a random-effects panel data model (*36*). A random-effects model is a form of a regression model that estimates the correlation between the dependent variable (unlinked passenger trips) and a set of descriptive variables based on differences both across the 51 entities and through time. Such models have been applied successfully in other studies transportation studies (*37*). We also tested a fixed-effects model, but found that it resulted in an employment coefficient with an illogical sign. We specify the model using a log transformation on the dependent variable, and on all descriptive variables except the Uber and bike share terms. For a log-log model, the coefficients can be interpreted directly as elasticities.

RESULTS

Table 3 shows the model estimation results. The first set of variables is a set of constants, one for each month,that serve to control for seasonality.

The core variables are each significant and have a logical sign. Ridership increases with an increase in VRM, and decreases with fare increases, as we would expect. The coefficients show that higher metropolitan area population is correlated with higher ridership. This is intuitive because if more people live in the metropolitan area, then more people are bound to opt for transit as a transportation option. The model indicates that increasing the percentage of households that do not own a car will have a positive effect on transit ridership. The metro land area has a positive coefficient, although this is not thought to be especially important. Increased employment is also correlated with increased transit ridership. Similar to increasing population, it is apparent that more employment in an area will mean that more people commuting to and from work, thus increasing transit ridership. Higher gas prices are correlated with higher ridership, as travelers look to save money by switching to transit when gas prices are high.

The effect of bike sharing varies by mode. The commuter rail coefficient is negative, but insignificant, so we ignore it. Of more interest are the heavy rail, light rail and bus coefficients, each of which is significant, but with different signs. The positive coefficients for rail suggest that bike share is a complement to rail, perhaps because it can be linked with rail trips serving a first- and last-mile role. In contrast, the bus coefficient is negative and significant, suggesting that bike share reduces bus ridership. This is also logical because bus trips are on average shorter than rail trips, and thus users may be more likely to switch to bike share due to the similar distances served by both modes.

The TNC coefficients also vary by mode. The commuter rail coefficient is positive, suggesting complementarity, but insignificant. The heavy rail and bus coefficients are negative and significant. This suggests that TNCs reduce transit ridership. The effect is greater for each year after TNCs enter a market, with the coefficient interpreted as a growth rate. After TNCs enter a market, heavy rail ridership decreases by 1.29% per year, and bus ridership decreases by 1.70% percent per year. This is reasonable to expect as TNC use grows after entering a market. The light rail coefficient is also negative, but is insignificant.

TABLE 3: Model Estimation Results

Variable	Coefficient	T-Statistic*
Constants		
Month - January	3.3671	3.6802
Month - February	3.3682	3.6813
Month – March	3.4315	3.7509
Month – April	3.4169	3.7351
Month – May	3.4286	3.7479
Month – June	3.4070	3.7243
Month – July	3.3982	3.7147
Month - August	3.4198	3.7384
Month – September	3.4435	3.7642
Month – October	3.4666	3.7894
Month – November	3.3965	3.7125
Month – December	3.3537	3.6655
Core Variables		
Vehicle Revenue Miles (ln)	0.4620	64.184
Fare Revenue per UPT (ln)	-0.1253	-12.682
Metro Population (ln)	0.1366	2.3461
Percent Households with No Vehicle (ln)	0.2451	6.7622
Metro Land Area (ln)	0.2131	2.1882
Employment (ln)	0.1305	2.1105
Gas Price (ln)	0.1062	15.092
Bike Share Effect		
Presence of Bike Sharing - Commuter Rail	*-0.0764*	*-1.2675*
Presence of Bike Sharing - Heavy Rail	0.0670	5.5149
Presence of Bike Sharing - Light Rail	0.0407	3.9642
Presence of Bike Sharing - Motor Bus	-0.0184	-2.1920
TNC Effect		
Years Since Uber - Commuter Rail	*0.0195*	*1.4235*
Years Since Uber - Heavy Rail	-0.0129	-4.1420
Years Since Uber - Light Rail	*-0.0038*	*-1.3908*
Years Since Uber - Motor Bus	-0.0170	-7.7084
R-squared (between groups)	0.7771	
R-squared (within groups)	0.4387	
R-squared (overall)	0.7671	
Log-likelihood	5415.6	
Entities	51	
Time Periods	196	
Observations	9467	

* Insignificant variables are in gray *italics*.

Table 4 illustrates the effect of the bike share and TNC variables, relative to the effect of changes in VRM. The values show that bike share is associated with a 6.9% increase in heavy rail ridership, a 4.2% increase in light rail ridership, and a 1.8% decrease in bus ridership, corresponding directly to the estimated coefficients. The TNC effect is a 1.3% decrease in heavy rail ridership and a 1.7% decrease in bus ridership per year. In a market like San Francisco, where Uber started operations in 2010, the model implies that we would expect a 12.7% decrease in bus ridership, all else being equal. The estimated coefficient on VRM is 0.462, which means that a 1% increase in VRM corresponds to a 0.42% increase in VRM. This is specific to the mode, but the coefficient is not segmented by mode. Extending this further, Table 4 shows the effect of different percent increases in VRM. Continuing with San Francisco as an example, this result suggests that SFMTA would need to increase bus service by slightly more than 25% in order to offset the loss of bus ridership to TNCs.

TABLE 4: Effect of Changes in Select Variables

	Mode*			
Change	**Commuter Rail**	**Heavy Rail**	**Light Rail**	**Bus**
Bike Share Enters Market				
Binary Effect	*-7.4%*	6.9%	4.2%	-1.8%
TNCs Enter Market				
Year 1	*2.0%*	-1.3%	*-0.4%*	-1.7%
Year 2	*4.0%*	-2.5%	*-0.8%*	-3.3%
Year 3	*6.0%*	-3.8%	*-1.1%*	-5.0%
Year 4	*8.1%*	-5.0%	*-1.5%*	-6.6%
Year 5	*10.2%*	-6.2%	*-1.9%*	-8.1%
Year 6	*12.4%*	-7.4%	*-2.3%*	-9.7%
Year 7	*14.6%*	-8.6%	*-2.6%*	-11.2%
Year 8	*16.9%*	-9.8%	*-3.0%*	-12.7%
Increase VRM				
5%	2.3%			
10%	4.6%			
15%	6.9%			
20%	9.2%			
25%	11.6%			

* Statistically insignificant effects are in gray *italics*.

DISCUSSION

The results presented above represent provide insight into the determinants of public transit ridership in 22 US cities. The core variables included in the model include service provision, fares, population, employment, auto ownership, land area and gas price. The estimated coefficients on these core variables are logical, and consistent with previously published research (*1*, *12–19*). Most variables are consistent in sign, and often in magnitude, with the study being replicated (*11*), with notable differences in the statistical method used and in the fact that our models include employment. The inclusion of an employment term is especially important given the strong economic growth over the past few years. Employment growth should result in a net increase in transit ridership, making the declines observed since 2015 more stark.

The bike share term estimated in our model suggests that bike share increases heavy rail and light rail ridership, but decreases bus ridership. Boisjoly et al (*11*) find that bike sharing has a positive but insignificant effect on transit ridership. The difference between the two findings may be due to averaging across modes. Our result is also consistent with Campbell and Brakewood's finding that bike share has decreased New York bus ridership (*24*).

Our finding suggests that TNCs reduce transit ridership, specifically on heavy rail and bus. Further, we find that the effect increases as TNCs become more established in a market. This finding differs from that of Boisjoly et al (*11*), with the difference potentially attributable to our inclusion of more recent data, or specification of the variable such that it is an effect that grows with time. Our finding supports related research on the effect of TNCs on transit ridership (*30*, *32*, *33*), and contradicts the arguments made by some shared mobility advocates (*25*, *26*). It should be noted, however, that the estimated effect of TNCs on heavy rail is likely to be heavily influenced by New York subway ridership, and may differ if the study were expanded to more cities.

This raises another limitation of the study—it is focused on 22 large US cities, and these effects may be different for smaller and medium cities with a different composition and character. In addition, certain cities may be influenced by specific conditions, such as service changes or maintenance issues that are not captured here. It would be useful for future studies to both expand the analysis to more cities, and to examine specific cities in further detail.

A second limitation of this study is the aggregate treatment of both bike share and TNCs. The former is treated as a binary variable, and the latter as a trend starting from the date of Uber's entry into the market. Actual ridership data for both would improve the analysis, although the prospects of obtaining the first without regulatory intervention may be stronger.

CONCLUSIONS

This study aimed to extend recently published research that conducted a longitudinal analysis of the determinants of public transit ridership in major North American cities (*11*). In doing so, it extended the longitudinal analysis to cover the period from 2015-2018 when notable declines in public transit ridership are observed. It also segments the models by mode to capture differing effects on rail versus bus.

Our results suggest that previous conclusions that reductions in bus VRM explain the reduction in transit ridership in many North American cities (*11*) may be flawed. While we do find that VRM is an important determinant of transit ridership, we also find it to be insufficient to explain the recent ridership declines, particularly the decline in ridership per VRM observed since 2015 for both bus and rail modes.

Our research also suggests that past research findings that TNCs and other emerging modes either increase or do not affect transit ridership (*11*, *25*, *26*, *38*) are likely incorrect. Our results show that the introduction of bike share in a city is associated with light and heavy rail ridership, but a 1.8% decrease in bus ridership. Our results also suggest that for each year after TNCs enter a market, heavy rail ridership can be expected to decrease by 1.3% and bus ridership can be expected to decrease by 1.7%. This effect increases with time as TNCs increase in use. The effect of TNCs is substantial—after 8 years this would be associated with a 12.7% decrease in bus ridership.

While bike share is a sustainable mode of transport, the consequences of a shift from public transit to TNCs go beyond the effect on transit agencies. Recent research suggests that this shift results in a large increase in traffic congestion (*33*, *39–42*), which may result in most travelers being worse off.

The implication of misdiagnosing the causes of recent ridership declines is that it may lead to ineffective policy responses. Boisjoly et al (*11*) recommend that transit agencies should focus their efforts on expanding service to attract ridership. While expanding service does result in a net increase ridership, as can be observed from the recent bus service expansion in San Francisco, the amount of service expansion required to offset the TNC effect is substantial. To offset the expected 1.7% annual loss of bus riders to TNCs, transit agencies would need to increase bus VRM by 3.7% per year. After eight years, this would result in more than a 25% service expansion just to maintain existing ridership. While service expansions are clearly valuable, transit agencies are fighting an uphill battle. In order to implement effective policies, it may be necessary to reach beyond the bounds of the transit agencies themselves and partner with cities to consider strategies such as congestion pricing, or reallocating right-of-way on urban streets away from cars and to transit.

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