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# Invest in the ride: A 14 year longitudinal analysis of the determinants of public transport ridership in 25 North American cities

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A B S T R A C T

Public transport ridership has been steadily increasing since the early 2000s in many urban areas in North America. However, many cities have more recently seen their transit ridership plateaued, if not decreased. This trend in transit ridership has produced a lot of discussion on which factors contributed the most to this new trend. While no recent study has been conducted on this matter, understanding the levers that can be used to sustain and/or increase transit ridership is essential. The aim of this study is, therefore, to explore the determinants of public transport ridership from 2002 to 2015 for 25 transit authorities in Canada and the United States using a longitudinal multilevel mixed-effect regression approach. Our analysis demonstrates that vehicle revenue kilometers (VRK) and car ownership are the main determinants of transit ridership. More specifically, the results suggest that the reduction in bus VRK likely explains the reduction in ridership observed in recent years in many North American cities. Furthermore, external factors such as the presence of ridesourcing services (Uber) and bicycle sharing, although not statistically significant in our models, are associated with higher levels of transit ridership, which contradicts some of the experts' hypotheses. From a policy perspective, this research suggests that investments in public transport operations, especially bus services, can be a key factor to mitigate the decline in transit ridership or sustain and increase it. While the results of this study emphasize that fare revenues cannot support such investments without deterring ridership, additional sources of revenues are required. This study is of relevance to public transport engineers, planners, researchers, and policy-makers wishing to understand the factors leading to an increase in transit ridership.

## 1. Introduction

Most major cities in North America aim to increase transit ridership in order to achieve multiple societal goals, such as reduction in congestion and greenhouse gas emissions (Adler and van Ommeren, 2016; Beaudoin and Farzin, 2015; LaBelle and Stuart, 1996). Throughout the 1990s and 2000s, transit ridership has steadily increased in most cities (American Public Transportation Association, 2010; El-Geneidy et al., 2009; U.S. Department of Transportation, 2000), although many have seen their transit ridership plateaued, if not decreased in the most recent years (Curry, 2016; Fitzsimmons, 2017; Levinson, 2017; Linton, 2016; Nelson and Weikel, 2016).

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Previous research has explored whether transit ridership is primarily driven by external factors such as gas price, wider economic conditions and mode competition or a result of internal agency factors such as fares and the amount invested in the network through capital and operation costs (Abdel-Aty, 2001; Pasha et al., 2016; Taylor et al., 2009; Thompson et al., 2012). While many hypotheses have been undertaken to explain the recent trend in ridership, including emerging shared economy services such as Uber as well as falling gas prices and fare increases, (CISION, 2017; Levinson, 2017; Nelson and Weikel, 2016), no recent study has, to our knowledge, been conducted to assess the determinants of public transport for multiple transit authorities in North America.

The aim of this study is, therefore, to explore the determinants of public transport ridership from 2002 to 2015 for 25 transit authorities in Canada and the United States. From a policy perspective, we specifically investigate the relationship between operations, measured through vehicle revenue kilometers (VRK), fares and transit ridership, while controlling for other internal and external variables. Using data from the National Transit Database (NTD) for US agencies and the Canadian Urban Transit Association (CUTA) for Canadian agencies, we undertake a longitudinal multilevel regression analysis approach. A first analysis models the total VRK of all modes, while the second one distinguishes between bus and rail VRK. A conceptual model is then presented to shed light on the interrelationship between operations, fare policy, external factors and ridership. This study is of relevance to public transport engineers, planners, researchers, and policy-makers wishing to understand the factors that can lead to an increase in transit ridership.

## 2. Literature review

### 2.1. Determinants of public transport ridership

#### 2.1.1. Micro vs macro level

Many studies have sought to identify the determinants of transit ridership, although these can be dependent on whether the question is asked at the macro or the micro level (Chen et al., 2011). Several studies at the micro-level have focused on 'the individual', specifically how aspects of the individual, such as socio-demographics and personal preferences, can affect transit usage or how individuals respond to changes in parameters such as income or the built environment (Abdel-Aty, 2001; Chen and McKnight, 2007; Pasha et al., 2016). Such studies have been on occasion developed further within market segmentation approaches, thus determining key sectors of the population where transit uptake may be more responsive, such as students, recent immigrants, larger family sizes and the unemployed (Farber et al., 2014; Grimsrud and El-Geneidy, 2013; Jacques et al., 2013; Krizek and El-Geneidy, 2007).

Other studies have examined this question at the macro level, to understand how larger regions as a whole respond to changes in internal factors such as agency expenditures and provisions or external factors, such as unemployment rates, gas prices or Gross Domestic Product (GDP) per capita (Chen et al., 2011; Currie and Phung, 2007, 2008; Iacono, 2006; Kain and Liu, 1999; Liu, 1993), while some others tried to do a mix between the micro and macro levels (Guerra and Cervero, 2011). Our own study of transit ridership determinants lies within the macro-level line of enquiry, and it is therefore important to acknowledge the work that has already been undertaken in this area.

#### 2.1.2. Internal vs external factors

The determinants of transit ridership within macro-level analyses are typically categorized as either internal or external factors, where internal factors relate entirely to decisions, policies and conditions determined by the transit agency or the municipalities providing subsidies. Whilst external factors typically equate to wider economic influences affecting society at large, such as unemployment rates and gas prices, which subsequently impact gas prices in the region (Taylor and Fink, 2009). There is some debate within the literature as to whether internal or external factors have more influence over transit ridership. Kain and Liu (1999) observed that within two transit agencies in the US, Houston and San Diego, internal factors such as service increases and fare reductions had the ability to increase ridership, even during times when ridership was falling within other agencies due to suspected external factors. Taylor et al. (2009), by contrast, found that external factors such as metropolitan population and area, economic vitality and low levels of car access were responsible for the majority of variation in transit ridership, although fares and service levels did have some (albeit lesser) impacts.

Focusing specifically on external factors, the literature has found some factors to be more significant than others. Population size and employment rate are both examples of variables that have demonstrated statistically significant positive relationships with ridership in previous studies (Gómez-Ibáñez, 1996; McLeod et al., 1991; Taylor et al., 2009). Gas price, by contrast, has produced mixed results, namely in the US, with McLeod et al. (1991) finding no statistically significant association, Taylor et al. (2009) finding positive, yet only marginally significant associations and Chen et al. (2011) finding statistically significant relationships when short term and long term elasticities are considered. In Germany, Frondel and Vance (2011) observed at the individual level that gas prices have a positive and significant influence on transit ridership. Holmgren (2007) also found a positive association between ridership and fuel prices in both Europe and USA, Canada and Australia, although more pronounced in Europe in both the short and long term.

For internal factors, it is evident within the literature that fares are found to hold a negative, statistically significant relationship with transit ridership (Balcombe et al., 2004; Chen et al., 2011; Kain and Liu, 1999; McLeod et al., 1991; Taylor et al., 2009). The service levels provided by the agency demonstrate a positive, statistically significant relationship with ridership, although studies differ considerably in how service levels are measured. Vehicle revenue miles (VRM) or vehicle revenue hours (VRH) were adopted by Gómez-Ibáñez (1996), Kain and Liu (1999) and Taylor et al. (2009), while the fleet size or the number of vehicles operated in maximum service (VOMS) was adopted by McLeod et al. (1991). Guerra and Cervero (2011) used two calculated variables, VRM and additionally VRM/directional route miles. These approaches are recognized within the respective studies as being representative of the scale or quantity of the service levels, as opposed to the quality. The general consensus within these studies is that increased service levels, however they are measured, have positive impacts on overall transit ridership, with ridership typically measured using the total unlinked passenger trips given that linking trips to a defined number of riders is difficult to achieve (Chen et al., 2011; Gómez-Ibáñez, 1996; Kain and Liu, 1999; McLeod et al., 1991; Taylor et al., 2009). Currie and Wallis (2008) draw similar conclusions after interviewing international bus planning experts regarding best practices for increasing bus ridership: the major factors influencing substantial patronage growth included increased service frequency, increased amount of service generally and increases in the network coverage (Currie and Wallis, 2008). Additionally, service quality improvements, specifically reliability and dependability of the transit system, can increase transit ridership, while a decline in service reliability can result in a loss of ridership (Bates et al., 2001; Currie and Wallis, 2008; Noland and Polak, 2002). While most transit agencies monitor performance, transit agencies do not use a uniform measure of reliability, thus including such data on service quality is not presently possible.

Previous studies have used NTD data to assess the determinants of transit ridership, and in these instances the adopted modeling approach is worth considering. Guerra and Cervero (2011) used a standard ordinary least squares (OLS) technique, whilst Lee and Lee (2013) and Taylor et al. (2009) adopt a two-stage least squares regression analysis, contending that a standard OLS model results in biased and inconsistent estimates, which inherently occur because the relationship between transit service supply and consumption is causal and two-directional. Lee and Lee (2013) incorporated a range of scales within their study, using some variables such as ridership in monthly observations, whilst combining these with annual records for others.

The objective of this study is, therefore, to build on previous work to incorporate recent observations and to propose several enhancements. The first relates to the lack of longitudinal studies in this area, whereby we aim to demonstrate the relationship between operations in a transit network and the observed ridership over a fourteen-year period, using all data aggregated at the annual level. Very few studies have used longitudinal and cross-sectional data to assess the determinants of ridership. While Lee and Lee (2013) used a longitudinal approach for 67 urbanized areas in the US, their observations range from 2000 to 2009. Given the new ridership trend that has been observed in most recent years, the present study includes observations from 2002 to 2015. Accordingly, our study is, to our knowledge, the first one to examine transit ridership using longitudinal and cross-sectional data for recent years. The second major enhancement consists in assessing the mix of modes (bus VRK and rail VRK) and how it relates to ridership. We also include new variables associated with the mobility transformation that many cities are currently undergoing, namely the presence of ridesourcing and bicycle-sharing systems. The third contribution is a methodological one, which consists in using a multilevel approach to control for clustering of the data within agencies. The last relates to the incorporation of major Canadian cities within the study as Canadian cities have been excluded from previous work.

## 3. Data and methodology

To achieve our research goal, we conducted a longitudinal analysis of ridership for 25 transit agencies in Canada and the United States between 2002 and 2015. The longitudinal analysis was conducted from 2002 to 2015, given the availability and consistency of data obtained for US and Canadian transit agencies. Our methodology for selecting the transit authorities is inspired from a previous study assessing the quality and affordability of service among transit agencies in North American cities (Verbich et al., 2017). To obtain a relatively homogenous sample, we only selected transit agencies located in metropolitan areas with a population over 1.5 million in 2015 that operate at least two modes (bus, streetcar, light rail and/or heavy rail). When multiple transit agencies were serving the same metropolitan area, we selected the one with the larger fleet size. As a result, this study includes 25 transit agencies, which typically provide bus as well as streetcar and/or heavy and light rail (Table 1). It is important to note that the transit agency might not serve the entire metropolitan area.

### 3.1. Data

The data used in this research comes from a variety of sources (Table 2). The operating data of the transit authorities in the United States and Canada was respectively collected from the NTD and the CUTA (Canadian Urban Transit Association, 2017; Federal Transit Administration, 2017). The NTD data was provided by mode, while the CUTA data was provided at an aggregated level across modes. The modes selected from the NTD data for this study are bus, streetcar, heavy rail and light rail. Only directly operated services were included in the study. While we found that a few transit agencies had data for privately purchased or subcontracted bus services, we did not include these observations when aggregating the data, since the data was not consistently available across all years. Nonetheless, we did control for the presence of such services within an agency by using a dummy variable. Ridership and fare revenues were summed across modes to obtain the aggregated value. Monetary variables such as fare revenues, GDP per capita and gas price were collected in Canadian dollars for Canadian agencies. They were then converted to US dollars as per the annual average exchange rate for each corresponding year, as stipulated by the United States Federal Reserve System (2017). All monetary values were then expressed in 2015 constant US dollars.[1] VRK was collected for bus and rail (streetcar, heavy rail and light rail) for cities in the US, however only an annual VRK aggregated across modes was available for the three Canadian cities.

The data was cleaned to ensure consistency for each agency, whilst identifying outliers at an early stage. The King County Metro

[1] Note that the magnitude, direction and significant of all non-monetary variable coefficients were consistent when using real values instead of nominal values. The significance and direction of monetary variables also remained stable, while the magnitude of the coefficient varied, given the conversion in constant dollars.

**Table 1**
Transit agencies included in the study.

| Metropolitan area | Core city | Metropolitan population | Transit agency | Modes |
|---|---|---|---|---|
| New York-Northern New Jersey-Long Island, NY-NJ-PA, US | New York | 20,182,305 | MTA New York City Transit (NYCT) | Heavy rail, bus |
| Boston-Cambridge-Quincy, MA-NH-RI, US | Boston | 4,774,321 | Massachusetts Bay Transportation Authority (MBTA) | Heavy rail, light rail, bus |
| Washington-Arlington Alexandria, DC-VA-MD-WV, US | Washington | 6,098,283 | Washington Metropolitan Area Transit Authority (WMATA) | Heavy rail, bus |
| Baltimore-Towson, MD, US | Baltimore | 2,797,407 | Maryland Transit Administration | Heavy rail, light rail, bus |
| Philadelphia-Camden Wilmington, PA-NJ-DE-MD, US | Philadelphia | 6,069,875 | Southeastern Pennsylvania Transportation Authority (SEPTA) | Heavy rail, light rail, streetcar, bus |
| Pittsburgh, PA, US | Pittsburgh | 2,353,045 | Port Authority of Allegheny County | Light rail, bus |
| Chicago-Joliet-Naperville, ILIN-WI, US | Chicago | 9,550,108 | Chicago Transit Authority (CTA) | Heavy rail, bus |
| Miami-Ft. Lauderdale Pompano Beach, FL, US | Miami | 6,012,331 | Miami-Dade Transit (MDT) | Heavy rail, bus |
| Atlanta-Sandy Springs Marietta, GA, US | Atlanta | 5,709,731 | Metropolitan Atlanta Rapid Transit Authority (MARTA) | Heavy rail, bus |
| Houston-Sugar Land-Baytown, TX, US | Houston | 6,656,946 | Metropolitan Transit Authority of Harris County (Metro) | Light rail bus |
| Dallas-Fort Worth-Arlington, TX, US | Dallas | 7,102,165 | Dallas Area Rapid Transit (DART) | Light rail bus |
| Cleveland-Elyria-Mentor, OH, US | Cleveland | 2,060,810 | The Greater Cleveland Regional Transit Authority | Heavy rail, light rail, bus |
| Minneapolis-St. Paul-Bloomington, MN-WI, US | Minneapolis | 3,524,583 | Metro Transit | Light rail, bus |
| St. Louis, MO-IL, US | Saint Louis | 2,812,313 | Bi-State Development (BSD) | Light rail, bus |
| Seattle-Tacoma-Bellevue, WA, US | Seattle | 3,733,580 | King County Department of Transportation (King County Metro-KCM) | Light rail, streetcar, bus |
| Los Angeles-Long Beach-Santa Ana, CA, US | Los Angeles | 13,340,068 | Los Angeles County Metropolitan Transportation Authority (LACMTA) | Heavy rail, light rail, bus |
| Portland-Vancouver-Hillsboro, OR-WA, US | Portland | 2,390,244 | Tri-County Metropolitan Transportation District of Oregon | Light rail, bus |
| Sacramento-Arden-Arcade-Roseville, CA, US | Sacramento | 2,274,194 | Sacramento Regional Transit District | Light rail, bus |
| San Diego-Carlsbad-San Marcos, CA, US | San Diego | 3,299,521 | San Diego Metropolitan Transit System | Light rail, bus |
| San Jose-Sunnyvale-Santa Clara, CA, US | San Jose | 1,976,836 | Santa Clara Valley Transportation Authority | Light rail, bus |
| San Francisco-Oakland Fremont, CA, US | San Francisco | 4,656,132 | San Francisco Municipal Railway (SFMTA) | Light rail, streetcar, bus |
| Denver-Aurora-Broomfield, CO, US | Denver | 2,814,330 | Denver Regional Transportation District | Light rail, bus |
| Montreal, QC, Canada | Montreal | 4,049,632 | Société de transport de Montreal (STM) | Heavy rail, bus |
| Toronto, ON, Canada | Toronto | 6,123,930 | Toronto Transit Commission (TTC) | Heavy rail, light rail, streetcar, bus |
| Vancouver, BC, Canada | Vancouver | 2,507,420 | Translink | Heavy rail, light rail, bus |

**Table 2**
Description of variables and summary statistics.

| | Source | Variable definition and construction | Unit | | | | |
|---|---|---|---|---|---|---|---|
| Continuous variables | | | | Mean | Std dev. | Min. | Max. |
| Ridership | NTD<br>CUTA | Number of unlinked passenger trips* | Trips (million) | 325 | 611 | 24 | 3510 |
| Vehicle Revenue Kilometers (VRK) | NTD<br>CUTA | Number of kilometers travelled by vehicles in revenue service* | Kilometers (million) | 102 | 135 | 12 | 728 |
| Rail Vehicle Revenue Kilometers (VRK) | NTD | Number of kilometers travelled by vehicles in revenue service (rail) | Kilometers (million) | 47 | 115 | 0.06 | 564 |
| Bus Vehicle Revenue Kilometers (VRK) | NTD | Number of kilometers travelled by vehicles in revenue service (bus) | Kilometers (million) | 50 | 35 | 9 | 166 |
| Fare | NTD<br>CUTA | Total fare revenue*,†/Number of unlinked passenger trips* | 2015 USD/trip | 0.98 | 0.24 | 0.40 | 1.92 |
| Population | American Community Survey, US Census Bureau<br>Statistics Canada | CMA population‡ | Person (million) | 4.96 | 3.82 | 1.73 | 20.2 |
| Area | American Community Survey, US Census Bureau<br>Statistics Canada | CMA geographic area‡ | Squared kilometers | 13,169 | 6080 | 2883 | 22,854 |
| Percent of household without a car | American Community Survey<br>Statistics Canada | Number of household without a car/total number of households | % of households | 0.11 | 0.06 | 0.05 | 0.32 |
| Unemployment Rate | Bureau of Labour Statistics<br>Statistics Canada | Number of unemployed/Total labour force (seasonally adjusted) | % of labour force | 6.5 | 1.9 | 2.9 | 12.3 |
| GDP per capita | Bureau of Economic Analysis, US Department of Commerce<br>Statistics Canada | Per capita real GDP by metropolitan area† | 2015 USD/capita | 65,456 | 14,161 | 27,119 | 112,851 |
| Gas Price | US Energy Information Administration<br>Statistics Canada | Average retail prices for gasoline† | 2015 USD/liter | 0.84 | 0.20 | 0.46 | 1.42 |
| Highway Mileage | Open Street Maps | Measured total length of highways within CMA through GIS | Kilometers | 2455 | 1506 | 221 | 6997 |
| Dummy variables | | | | Proportion | | | |
| Presence of private bus operator | NTD | Presence of purchased transportation for bus services, only for US agencies | 1 = present, 0 = not present | 0.33 | | | |
| Presence of Uber | Various newspapers and websites | Presence of Uber in the metropolitan area | 1 = present, 0 = not present | 0.24 | | | |
| Presence of bicycle-sharing system | Bicycle-sharing system websites | Presence of a bicycle sharing system in the metropolitan area | 1 = present, 0 = not present | 0.17 | | | |

* Data collected by mode from the US National Transit Agency data.
† All monetary variables were collected in CAD for Canadian agencies and converted to USD as per the conversion rate of the US Federal Reserve Bank.
‡ CMA is census metropolitan area in Canadian cities which is equivalent to MSA metropolitan statistical area in the United States.

agency was found to contain incomplete records for two years (2006 and 2007), therefore we excluded these two years from King County Metro from our sample.

Some specific variables were missing for certain years within the US and Canadian sources, and these were derived in different ways. The Metropolitan Statistical Area (MSA, equivalent to the Canadian Census Metropolitan Area, CMA) population for US cities was not available for the years 2002–2004, and as such these missing values were estimated by linear interpolation between 2000 and 2005. The data concerning the proportion of households without a car in the US was not available for these same years; this was rectified by using the value of 2005 for the three missing years. We decided not to interpolate these values, since the trend was not linear. In Canada, the proportion of households without a car was only available for 2006. As such, this value is used for every year of this study.

### 3.2. Statistical analysis

To explore the determinants of ridership over time, we developed two multilevel longitudinal mixed-effect models, using ridership (number of unlinked passenger trips) as the dependent variable. We nested each observation in its respective transit agency, to account for the differences imposed by the agency. The multilevel approach is increasingly used in transport geography (Wasfi et al., 2013; Witten et al., 2012), to capture the clustering of data resulting from variables that are not being controlled for in the models. For example, in this study, the structure of the transport network, perceived safety and walkability are variables that vary across agencies, and that might influence ridership. Since these variables are not directly controlled for in our study, the use of a multilevel approach reduces the estimation biases associated with the absence of such variables. We also tried nesting the transit agencies in their respective region (Canada, West Coast US, East Coast US, Midwest US, South US, Central US) to account for cultural differences. The region did not explain any of the variation in ridership, and was thus removed from the analysis. A dummy variable for Canadian agencies was also tested, but was not significant and thus removed from the models.

The models use total ridership (number of unlinked passenger trips) as their dependent variable, and ridership was transformed through the natural logarithm function to obtain a normally distributed dependent variable. The first model includes all 25 transit agencies and assesses the relationship between total ridership (across all modes), total VRK (across all modes) and fare, while controlling for external variables. The second model differs from the first model in that it separately accounts for bus VRK and rail VRK (streetcar, heavy rail and light rail). The correlation between these two variables is 0.45, which does not pose collinearity issues. This model only includes the 22 US transit agencies, as mode specific data was not consistently available through CUTA for Canadian agencies. In both models, all independent numerical variables were also transformed with the natural logarithm function in both models, to ensure ease of interpretation and comparison across coefficients. The results were nonetheless consistent in terms of statistical significance, direction and magnitude using semi-log models, where only the ridership variable was transformed.

All independent variables explored within this study are presented in Table 2. The average fare was included to account for the impact of fares on individuals' travel choice. Since fare components were not available within the NTD data, we derived the average fare by dividing total fare revenues by total unlinked passenger trips. It thus reflects the average fare paid per unlinked trip.

External factors such as gas price, unemployment rate, proportion of households without a car and GDP per capita were tested through a step-wise process in the statistical models. GDP per capita and unemployment rate were not significant as was found by Guerra and Cervero (2011) and Taylor et al. (2009), and were accordingly removed from the models. Note that the models remained stable after removing these variables or adding others. The length of highways in a metropolitan area was also tested to capture car dependency, but was found to be statistically insignificant. To account for the presence of competitors or complementors, three dummies were included in the models. The first is the presence of private bus services purchased by the transit agency. The second and third are the presence of Uber and a bicycle-sharing system respectively. Uber was selected to capture the presence of a ride-sourcing system, as it is the first major company that operated in North America, with by far the largest number of rides booked every year.

Finally, the population and geographic size of the metropolitan area were included to account for the size of the region and the number of potential riders, indirectly addressing density of population and density of operations. Note that a population density variable was also tested in the models, instead of two separate variables, and the results were consistent. Although it would have been preferable to obtain the population and area served by the transit agency, such data was not reliable in the NTD database due to sharp yet unexplained fluctuations, which appeared suspicious, given that similar fluctuations were not present for many other variables. While previous research has predicted ridership per capita (Taylor et al., 2009), it was not possible to do so given the lack of reliability of the population data across the years. In this study, the use of the multilevel approach captures the difference in the size of the metropolitan areas served by each transit agencies and the population of the metropolitan region is included in the models to control for the population growth within each transit agency.

To account for effects that occur in the medium or long term, temporal lags were tested for various variables, namely VRK, fare, gas price, GDP per capita and unemployment rate. These were all found to be insignificant, and accordingly not included in our final models. While Chen et al. (2011) found several variables to be significant with temporal lags using a monthly unit (gas price, transit fare, service level and labour force), our larger time unit (year) might explain the lack of significance found in our study.

### 3.3. Limitations

There are some limitations to the data used in the study. Firstly, one variable we would have liked to incorporate in this study concerns the physical assets of the transit agency, to capture the quality and maturity of the network. However, this data was

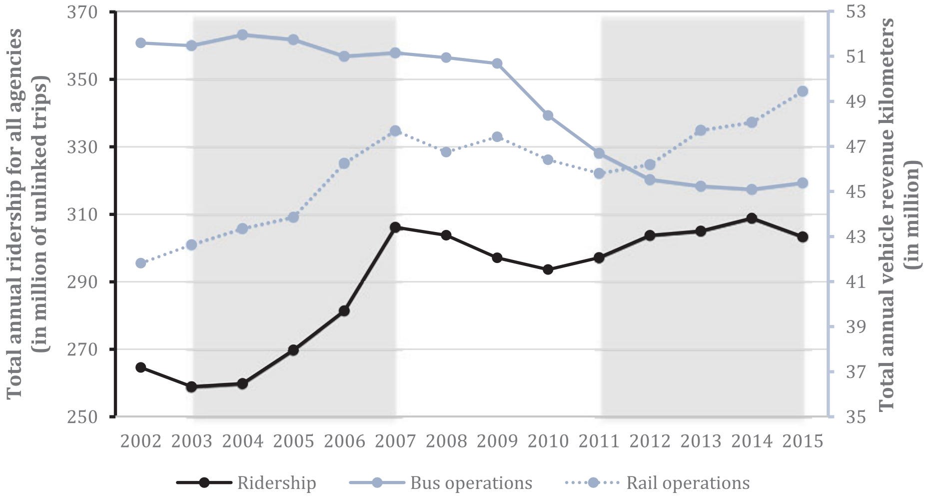


**Fig. 1.** Ridership and operations per year (total for all US transit agencies).

unavailable. We tested the capital costs, but found this to be insignificant, largely because the year that investments are made does not necessarily reflect the year when the users benefit from them. While the fleet size was available, it was not possible to include this variable due to collinearity with our VRK variable.

Secondly, some data were not available throughout all years, and thus we had to fill some gaps by generating interpolations. For example, the population of US metropolitan areas was obtained by interpolation for the years 2002–2004. Given the linearity of such a relationship, it is not expected that this is adding any substantial interference. We confirmed this by testing the models without these years, where the models remain stable. The percentage of households without access to a car was not available annually within Canada, and instead existed for only 2006. We therefore used the 2006 car ownership value for all Canadian years. Given that this variable does not fluctuate to any strong degree, and that the results are consistent when using only American cities, we are confident in our results. However, the magnitude of the coefficient could potentially change if we had more detailed data per year. In addition, population and area are obtained for the entire metropolitan area, rather than the service area due to previously mentioned unreliable observations found within the NTD. It is also important to note also that the lack of mode specific data for the CUTA agencies is an important limitation to assessing how bus and rail operations separately affect ridership in Canadian cities.

Nevertheless, the stability of the models and the consistency in our findings when testing various independent variables and excluding and including interpolated data increases our confidence in the findings of this study. Using a robust statistical technique and recent data, this study longitudinally evaluates the determinants of ridership for multiple North American agencies.

## 4. Results

### *4.1. Ridership and operations trends*

Fig. 1 shows how ridership and operations have evolved over the years.[2] The graph shows that ridership has increased over time, although pronounced drops are present in some years. It is important to note that the economic crisis that started in 2007 likely explains the pronounced increase of ridership in 2007 and the subsequent decrease resulting from the economic recovery in the following years. Putting aside the effect of the crisis, we observe the following trends: an important increase in ridership between the years 2002 and 2007 and relatively stable ridership in more recent years, from 2011 to 2015. This suggests that additional efforts are needed to increase ridership levels in the future.

Looking at the operations trends, we observe that, from 2002 to 2007, increase in rail operations, together with relatively stable bus operations, is associated with increased ridership. A similar increase in rail operations is present from 2011 to 2015, yet together with an important decrease in bus operations. Such trends in operations are this time associated with a stabilization and later decline of ridership levels. Taken together, these observations suggest that the decline in bus operations in recent years might have contributed to the decline of ridership.

Since many internal and external factors influence ridership, it is not possible to conclude from this graph on the effect of the relationship between ridership and operations. The next section investigates this relationship while controlling for other internal and external factors through multilevel longitudinal regression modeling.

[2] Note that the data from the Canadian agencies is not included in this graph, as the mode specific data was not available consistently across the years.

**Table 3**
Results of the longitudinal multilevel mixed-effect regression modeling public transport ridership (number of unlinked passenger trips) (log-transformed).

| Variable | Coeff. | Sig. | Conf. interval† | |
|---|---|---|---|---|
| *Internal variables* | | | | |
| Revenue vehicle kilometers. (ln) | 0.827 | *** | 0.744 | 0.909 |
| Average fare (ln) | −0.219 | *** | −0.290 | −0.149 |
| *External transport-related variables* | | | | |
| Presence of private bus operator | 0.116 | *** | 0.082 | 0.149 |
| Presence of Uber | 0.024 | | −0.002 | 0.051 |
| Presence of bicycle sharing system | 0.004 | | −0.028 | 0.036 |
| Proportion of carless households (ln) | 0.447 | *** | 0.279 | 0.616 |
| Gas price (ln) | 0.078 | *** | 0.034 | 0.122 |
| *Other external variables* | | | | |
| Population (ln) | 0.339 | *** | 0.173 | 0.504 |
| Area (ln) | −0.280 | ** | −0.471 | −0.088 |
| Constant | 2.491 | * | 0.096 | 4.886 |
| AIC | −665 | | | |
| BIC | −598 | | | |
| ICC | 0.90 | | | |
| Log-likelihood | 334 | | | |
| Observations | 348 | | | |
| Number of groups | 25 | | | |

* 95% significance level.
** 99% significance level.
*** 99.9% significance level.
† 95% confidence interval.

## *4.2. Results of the statistical models*

The results of the regression model are presented in Table 3. The model shows that, as hypothesized in this study, VRK is positively and significantly associated with ridership. More specifically, a 10% increase in VRK is associated with an 8.27% increase in ridership, while keeping all other variables constant at their mean. This is by far the largest contributor to ridership. Conversely, higher average fares are significantly associated with a decrease in ridership, where a 10% increase in fare is linked with a 2.19% decrease in ridership.

Interestingly, the presence of a privately operated bus service leads to increased ridership for transit agencies, suggesting that those services are complementary to the services directly operated by the transit agency. Similarly, the presence of Uber and bicycle-sharing systems in a metropolitan area, although not statistically significant, are positively associated with the ridership of a transit agency. As the literature on the impact of these mobility services is growing, there does not appear to be a clear and generalizable understanding of how these services impact travel behaviour due to a lack of available data on ridership (Henao and Marshall, 2017; Shaheen et al., 2018). Rayle et al. (2016) found mixed results regarding the impact of ridesourcing on transit use in San Francisco. A potentially competitive relationship was evident as individuals' reported choosing ridesourcing over transit for the travel time savings. Whereas, a complementary relationship was observed as individuals reported using ridesourcing interchangeably with public transport, for example using transit to reach their destination and ridesourcing for the return trip, similar to findings on the use of taxicabs and public transport (King et al., 2012). Bicycle-sharing systems are commonly designed to be well integrated with public transit service, with features such as docking stations nearby transit stations, and the integration of a transit pass with the bicycle-sharing pass (Shaheen et al., 2011). However, this design might have differential impacts on public transport modes, such as replacing a trip on the bus with a shared bicycle and should be explored further in future research. Our results seem to suggest that Uber and bicycle-sharing provides a complement to public transport service and might overall contribute to an increased number of trips when aggregating the changes in behaviour of all individuals. However, since these aspects are considered with dummy variables in this study (which might explain the non-significance of the coefficients), further studies using detailed variables (e.g.: number of trips made with Uber and bicycle-sharing systems) are needed to confirm this relationship.

As noted in the literature (Taylor et al., 2009), a greater number of households without a car is associated with more transit trips. This is the second largest contributor to ridership in our study. Conversely, the coefficient for gas price is positive and statistically significant in our model. The direction of the relationships is consistent with the literature (McLeod et al., 1991; Taylor and Fink, 2009), suggesting that higher gas prices result in higher ridership, as the private vehicle becomes less competitive financially. The magnitude of the relationship is, however, relatively small, the coefficient of gas price (0.078) being the smallest after the coefficients of Uber and bicycle-sharing systems.

With respect to other external variables, the CMA population is positively and significantly associated with ridership. When holding all other variables at their mean (including the geographic size of the CMA), a 10% increase in population is associated with a 3.39% increase in ridership. In other words, increasing the number of individuals residing in an area (and therefore population

**Table 4**
Results of the longitudinal multilevel mixed-effect regression modeling public transport ridership (number of unlinked passenger trips) (log-transformed) – mode specific operations.

| Variable | Coeff. | Sig. | Conf. interval[†] | |
|---|---|---|---|---|
| *Internal variables* | | | | |
| Revenue vehicle kilometers – rail (ln) | 0.093 | *** | 0.046 | 0.141 |
| Revenue vehicle kilometers – bus (ln) | 0.465 | *** | 0.370 | 0.559 |
| Average fare (ln) | −0.207 | *** | −0.282 | −0.132 |
| *External transport-related variables* | | | | |
| Presence of private bus operator | 0.086 | *** | 0.051 | 0.121 |
| Presence of Uber | 0.018 | | −0.009 | 0.044 |
| Presence of bicycle sharing system | 0.039 | * | 0.007 | 0.072 |
| Proportion of carless households (ln) | 0.253 | ** | 0.060 | 0.447 |
| Gas price (ln) | 0.081 | *** | 0.035 | 0.127 |
| *Other external variables* | | | | |
| Population (ln) | 0.215 | | −0.029 | 0.460 |
| Area (ln) | −0.035 | | −0.581 | 0.511 |
| Constant | 6.593 | * | 1.346 | 11.840 |
| AIC | −563 | | | |
| BIC | −515 | | | |
| ICC | 0.98 | | | |
| Log-likelihood | 327 | | | |
| Observations | 297[a] | | | |
| Number of groups | 22 | | | |

* 95% significance level.
** 99% significance level.
*** 99.9% significance level.
† 95% confidence interval.
[a] To be consistent, only observations with bus and rail were included.

density) is associated with more trips. Inversely, a 10% increase in the geographic size of the CMA is associated with a 2.80% decrease in ridership. This is likely due to a decrease in population and service density. This is consistent with the literature, where population density has been found to positively correlate with ridership (Taylor et al., 2009).

As noted in the descriptive statistics above (Fig. 1), bus operations have gone down in recent years, while rail operations have gone up. The second regression model, distinguishing between rail VRK and bus VRK, is presented below to capture these differentiated trends (Table 4). The overall results are consistent with the first model, suggesting that operations, fares and car ownership are the most important predictors of ridership, while gas price is a less important contributor. We note, however, that bicycle-sharing is significant in the second model. As mentioned above, the lack of detailed data on the presence of bicycle-sharing systems in each region might explain the inconsistency in the results. Another discrepancy with the first model is that the population and area coefficients are not significant at the 95% level. This is likely due to the nature of the data. Since the service population and area data were not reliable, the metropolitan statistical area data were used in our study. While the service area and population size roughly corresponds to the CMA population in Canadian agencies, important differences between service area and metropolitan area can be observed in several US agencies.

Most importantly, this regression model shows the differentiated association between ridership and mode specific operations. The magnitude of the bus VRK coefficient is around 5 times greater than the one from the rail VRK, suggesting a greater association between bus operations and ridership. In other words, it suggests that bus operations are more closely associated with the changes observed in ridership, which seems to confirm the trend observed in Fig. 1: increase in rail operations alone is not sufficient to sustain increase in ridership.

Accordingly, the results suggest that the decrease in bus operations in recent years is associated with the decline in ridership. Building on this, our study demonstrates the importance of bus operations to sustain ridership in the US. While further research is essential to explain this effect, some hypotheses are discussed here. First, unlike several cities in Europe, rail service is typically very focused to specific areas or needs in the US, serving mainly central areas, and suburban commuting trips. Accordingly, a large share of the population depends on busses for their daily trips, and only so many trips can be made using rail only. In most cases, the bus network was partially designed to complement the rail network. Accordingly, the decrease in bus operations might be associated with a decline in service frequency and coverage of bus feeder services, which reduces the quality of the integrated network. Another possible explanation is that it is easier to increase service coverage with bus services, and thereby attract new users. In contrast, increase in rail service is more easily achieved with increased frequency, which might not yield the same results in terms of new riders. While it was not possible to conduct a detailed assessment of bus and rail services in terms of service coverage and frequency in this study, our results highlight the need for further studies to look more specifically into this.

In line with our research, there is a common assertion that rail systems are inherently more attractive than bus systems. However, Ben-Akiva and Morikawa (2002) explored this theory and found that high performance bus service with similar frequency and service attributes as rail service (i.e. exclusive right-of-way) have similar ridership attraction. With adequate investments in both the

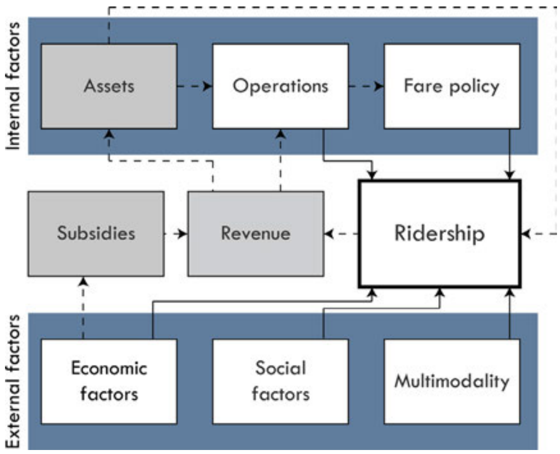


**Fig. 2.** Determinants of ridership.

operations of bus service (i.e. increasing service frequency) and improving the efficiency of bus operations, for example transit priority and dedicated bus right-of-ways, bus service can effectively contribute to transit ridership. However, the type of bus service delivered by public transit agencies and resulting ridership levels should be explored in future research.

Although the mode specific findings were derived from the US agencies only, it is possible to assume that similar conclusions could be drawn for Canadian cities, as similar urban structure and network design are present. Nonetheless, access to mode specific data in Canada would be of great value to further explore these trends. With respect to bus patronage in other parts of the world, results of this study reemphasize the findings of meta-analyses such as Currie and Wallis (2008), identifying the importance of bus service improvements, namely frequency, as a lever for increased ridership.

## 5. Discussion and policy implications

The results of this paper shed light on the internal and external determinants of transit ridership in North America, between 2002 and 2015. Overall, the results suggest that, in addition to the characteristics of the metropolitan area (size and population), internal factors (VRK and average fares) as well as car ownership are the main contributors of ridership. This suggests that transit agencies and municipalities can act locally to support transit ridership through investments in operations, fare reductions as well as policies aiming to increase density and reduce car ownership. Furthermore, our study demonstrates the importance of bus services to support high levels of ridership in US cities, and most likely Canadian cities as well.

Fig. 2 conceptualizes the relationship between internal factors, external factors, ridership and the transit agency's revenues and subsidies as was observed in our models and in our review of the literature. The white boxes represent the variables that we modelled in our analysis, while the grey boxes represent other aspects that were not included in our models. In summary, both internal and external factors influence, directly or indirectly, ridership. The internal factors include the assets of an agency, its operations and its fare policy. The external factors include multimodality, economic and social factors. Multimodality refers to the presence of alternative modes of transport such as Uber and bicycle-sharing systems. Economic factors broadly refer to gas price, economic vitality and unemployment, whereas social factors refer to cultural aspects and habits, and are reflected by car ownership in our study. Central to Fig. 2 is the revenue of the transit agency which influences the amounts that can be invested in assets and operations. Transit revenue, in turn, largely depends on subsidies and on ridership, through the fare policy.

Based on our models, transit agencies and municipalities wishing to increase their ridership should consider improving their bus service through investments in their operations, while limiting increases in fares. Operations and fare policy are closely linked, as fares provide an important source of revenue for the operating budgets. Fare revenues typically contribute 25–50% of the operating budget in large US metropolitan regions, and to up to 71% of the operating budget in Canadian cities (Verbich et al., 2017). Accordingly, investments in operations typically require fare increases, which can deter ridership. Our study shows that greater VRK with limited fare increases is key to increasing ridership. Doing so, however, inevitably requires additional sources of revenues. Improving the cost-efficiency of operations can also contribute to higher ridership with limited fare increases. While this falls outside the scope of this study, future studies could further investigate the relationship between operating costs, VRK and ridership to assess efficiency of operations. However, since the results of this study are based on multiple transit agencies, it is unlikely that improving efficiency of operations without investing more can by itself yield large gains in ridership.

While this study focused on operation costs, the assets of the agency inevitably play a role on the level of service provided to riders. Namely, improvements in operations often require investments in the assets of an agency, through the purchase of additional vehicles or the expansion of the rail network for example. While the variation in assets is not captured in our study as this information was not available, further agency-specific studies could address the relationship between assets, operations and ridership.

With respect to the external factors, policies that support multimodality and reduce car ownership can be implemented to support transit ridership. While some have suggested that Uber might deter transit ridership because transit riders that use Uber reduce their number of trips by public transport (CISION, 2017), our study seems to suggest that such a program might overall contribute to higher levels of ridership, although further studies are needed to confirm this relationship. Furthermore, bicycle-sharing systems can also contribute to higher transit use, by providing an option for the first/last mile connection to the transit network (DeMaio, 2009). Overall, ridesourcing and bicycle-sharing systems can provide options that complement the use of public transport. Similarly, recent research has found that car-sharing is strongly associated with a reduction in car ownership (Martin and Shaheen, 2011; Martin et al., 2010; Ter Schure et al., 2012). Accordingly, multimodality and strategies aiming to reduce car ownership can be implemented complementarily to increase levels of public transport ridership. Although it was not present at the time of conducting our analysis, the number of trips made by a ridesourcing and bicycle-sharing systems can be used in future studies to generate more sensitive results of the impacts of these systems.

Furthermore, our study shows that increasing gas price (through taxes for example) can positively impact ridership, whilst it can contribute to financing transit agencies. However, given the improvements in fuel efficiency, revenues from gas taxes have been declining in the last ten years in many regions in North America, therefore select regions have increased their gas taxes to counter the decrease in fuel consumption (Governing, 2017). In order to sustain a stable source of revenue, the amount of gas taxes dedicated to public transport should increase over the years, or be replaced by other sources as fuel consumption from vehicles is decreasing.

## 6. Conclusion

This paper has explored the determinants of transit ridership over time for 25 transit agencies in North America. Between 2014 and 2015, ridership declined among various transit agencies in North America, which many experts and media outlets have associated with ridesourcing services and gas prices (Bliss, 2017; CISION, 2017; Levinson, 2017). However, the findings of this study reveal that internal factors, rather than ridesourcing and gas price, are key determinants of ridership. Whilst ridership is not independent of external factors, the reduction in bus VRK is likely to have contributed to the decrease in the number of unlinked passenger trips over the years in North American cities.

The results of this study emphasize the need to invest in public transport, especially bus operations, to support higher levels of ridership. To do so, transit agencies and municipalities need to find additional sources of revenues. Our study has shown that increasing fares to support investments in operations cannot result in large increases in ridership. Gas taxes, although relevant, presents an unstable, likely diminishing, source of revenue. Other sources of revenue are thus required to finance transit. These include congestion and parking pricing, public-private partnerships and land value capture (Drzymala et al., 2012; Enoch et al., 2005). While transit agency funding falls outside the scope of this research, further studies could explore the relationship between the different sources of funding and transit ridership.

In addition to new sources of revenues, local and regional governments need to explore multimodality and car ownership policies to support transit ridership. While using simple data, our study sheds light on the potential contribution of ridesourcing and bicycle-sharing systems. In this regard, more efforts are needed to assess the effect of new mobility trends, including car-sharing, with detailed data. This paper contributes to disentangling the role of internal and external factors in determining ridership, while exploring the related trends in rail and bus operations. The findings of this study are relevant to researchers and policy-makers wishing to better understand the levers of transit ridership.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2018.07.005.

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