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

Geneviève Boisjoly,
Emily Grisé,
Meadhbh Maguire,
Marie-Pier Veillette,
Robbin Deboosere,
Emma Berrebi &
Ahmed El-Geneidy

School of Urban Planning, McGill University
Suite 400, 815 Sherbrooke St. W.
Montréal, Québec, H3A 2K6, Canada
Tel.: 514-398-4058
Fax: 514-398-8376
E-mail: ahmed.elgeneidy@mcgill.ca

January 4th 2018

Word Count: 5,160, 3 Tables, 2 Figures

For Citation please use: Boisjoly, G., Grisé, E., Maguire, M., Veillette, M., Deboosere, R., Berrebi, E., & El-Geneidy, A. (2018). *Invest in your riders: A longitudinal analysis of the determinants of public transport ridership in 25 North America cities.* Paper presented at the 97th Annual Meeting of the Transportation Research Board, Washington D.C., USA.

ABSTRACT

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 model suggests that vehicle revenue kilometers and car ownership are the main determinants of transit ridership. External factors such as the presence of ride-hailing 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 can be a key factor to mitigate the decline in transit ridership or sustain and increase it. While the results of this study demonstrate 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 in a North American context as well as the associated financing challenges.

Keywords: Ridership, Public transportation, Operations, Ride-hailing, Bicycle sharing

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 & van Ommeren, 2016; Beaudoin & Farzin, 2015; LaBelle & Stuart, 1996). Throughout the 1990's and 2000's, transit ridership has steadily increased in most cities (American Public Transportation Association, 2010; El-Geneidy, Hourdos, & Horning, 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 & Weikel, 2016). 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, Rifaat, Tay, & De Barros, 2016; Taylor, Miller, Iseki, & Fink, 2009; Thompson, Brown, & Bhattacharya, 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 & 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 scenario analysis is then conducted to shed light on the interrelationship between operations, fare policy 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 in a North American context as well as the associated financing challenges.

LITERATURE REVIEW

Determinants of Public Transport Ridership

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, Varley, & Chen, 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 & 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, Bartholomew, Li, Paez, & Habib, 2014; Grimsrud & El-Geneidy, 2013; Jacques, Manaugh, & El-Geneidy, 2013; Krizek & 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 & Phung, 2007, 2008; Iacono, 2006; Kain & Liu, 1999; Liu, 1993), while some others tried to do a mix between the micro and macro levels (Guerra & 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.

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 & 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, Flannelly, Flannelly, & Behnke, 1991; Taylor et al., 2009). Gas price, by contrast, has produced mixed results, 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.

For internal factors, it is evident within the literature that fares are found to hold a negative, statistically significant relationship with transit ridership (Chen et al., 2011; Kain & 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). Both of 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. Guerra and Cervero (2011) used two calculated variables, VRM/VRH and additionally VRM/directional route miles. The general consensus within these studies is that increased service levels, however they are measured, have positive impacts on overall transit ridership. Ridership was 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 & Liu, 1999; McLeod et al., 1991; Taylor et al., 2009).

Previous studies have used NTD data to assess the determinants of transit ridership, and in these instances the adopted modelling 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 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 area in the US, their observations range from 2000 to 2009. Given the new 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 including new variables associated with the mobility transformation that many cities are currently undergoing, namely the presence of ride-hailing 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 fourth relates to the incorporation of major Canadian cities within the study as Canadian cities have been excluded from previous work. Finally, a scenario analysis addressing the relationship between VRK, fare and ridership is conducted to shed light on the financing challenges a transit authority can face when trying to increase ridership through different approaches, this scenario analysis is derived from the models.

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, Badami, & El-Geneidy, 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.

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

Metropolitan Area	Core city	Metropolitan Population	Transit Agency	Modes
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

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, fare revenues and VRK 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].

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

[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.

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.

Statistical Analysis

To explore the determinants of ridership over time, we conducted a multilevel longitudinal mixed-effect models, using ridership (number of unlinked passenger trips) as the independent variable. We nested each observation in its respective transit agency, to account for the differences imposed by the agency. 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 model use total ridership (number of unlinked passenger trips) as its dependent variable, and ridership was transformed through the natural logarithm function to obtain a normally distributed dependent variable. The model includes all 25 transit agencies and assesses the relationship between total ridership (across all modes), VRK and fare, while controlling for external variables. All independent numerical variables were also transformed with the natural logarithm function, to ensure ease of interpretation and comparison across coefficients. The results were nonetheless consistent in terms of statistical significance, direction and magnitude using a semi-log model, 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) respectively, and were accordingly removed from the model. 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-hailing system, as it is the first major company that operated in North America, with a share of 40% of the US ground transportation market (which includes Lyft, Uber, taxi and rental car companies) in 2015, compared to less than 3% for Lyft (Hagan, 2017).

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 model, 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.

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 model. 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.

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. This data was however 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 model without these years, where the model 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.

Nevertheless, the stability of the model 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.

TABLE 2 Description of variables and summary statistics

	Source	Variable definition and construction	Unit	Mean	Std dev.	Min.	Max.
	Continuous variables						
Ridership	NTD CUTA	Number of unlinked passenger trips*	Trips (million)	325	611	24	3510
Vehicle Revenue Kilometers (VRK)	NTD, American Community Survey CUTA, Statistics Canada	Number of kilometers travelled by vehicle in revenue service*	Kilometers (million)	102	135	12	728
Fare	NTD 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 Statistics Canada	CMA population‡	Person (million)	4.96	3.82	1.73	20.2
Area	American Community Survey, US Census Bureau Statistics Canada	CMA geographic area‡	Squared kilometers	13169	6080	2883	22854
Percent of household without a car	American Community Survey 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 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 Statistics Canada	Per capita real GDP by metropolitan area†	2015 USD/ capita	65456	14161	27119	112851
Gas Price	US Energy Information Administration	Average retail prices for gasoline†	2015 USD/liter	0.84	0.20	0.46	1.42

	Source	Variable definition and construction	Unit				
	Statistics Canada						
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.

RESULTS

Ridership and Operations Trends

Figure 1 shows how ridership has evolved over the years[2]. The graph shows that ridership has increased over time, although pronounced drops are present in some years. Most notably, after an important increase in ridership between years 2010 and 2012, total ridership has remained relatively stable, suggesting that efforts are needed to increase ridership levels in the future.

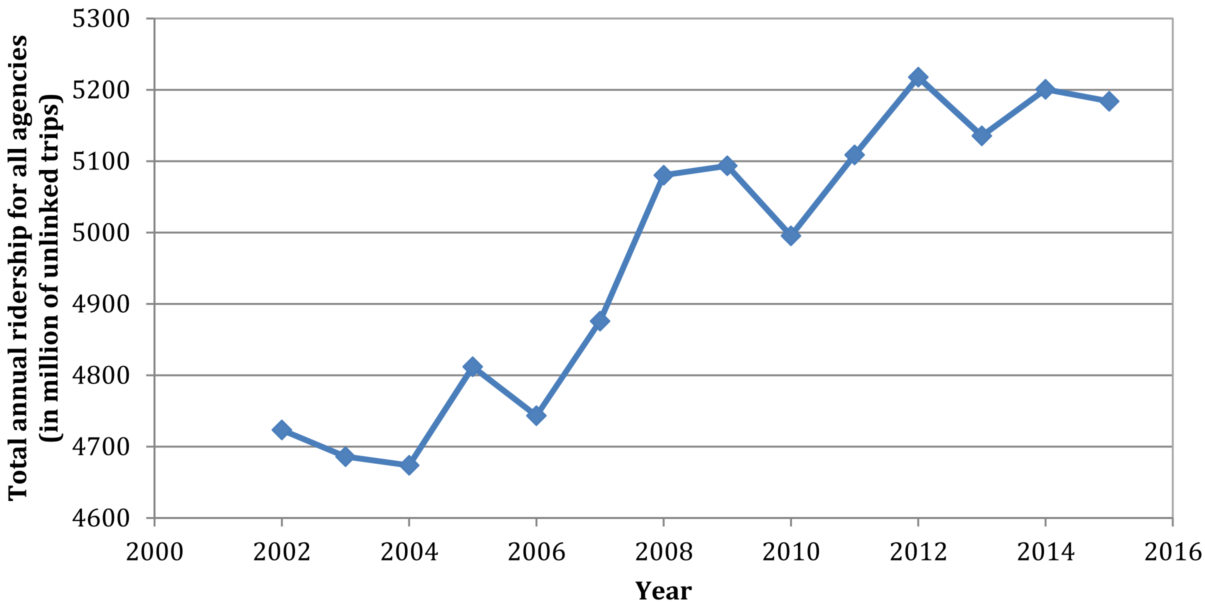

FIGURE 1 Ridership per year (total for all transit agencies)

Figure 2 shows the relationship between total annual ridership and total annual VRK, each point representing a year[3]. The graph suggests the following trend: in years where operations where overall higher (higher VRK), ridership was also higher. It thus suggests a positive association between operations and ridership. However, 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 a multilevel longitudinal regression model.

---

[2] Note that MTA New York City Transit data is not included in this graph. New York ridership is as an outlier in the distribution of the ridership and was thus removed to avoid skewing of the graph.

[3] Ibid

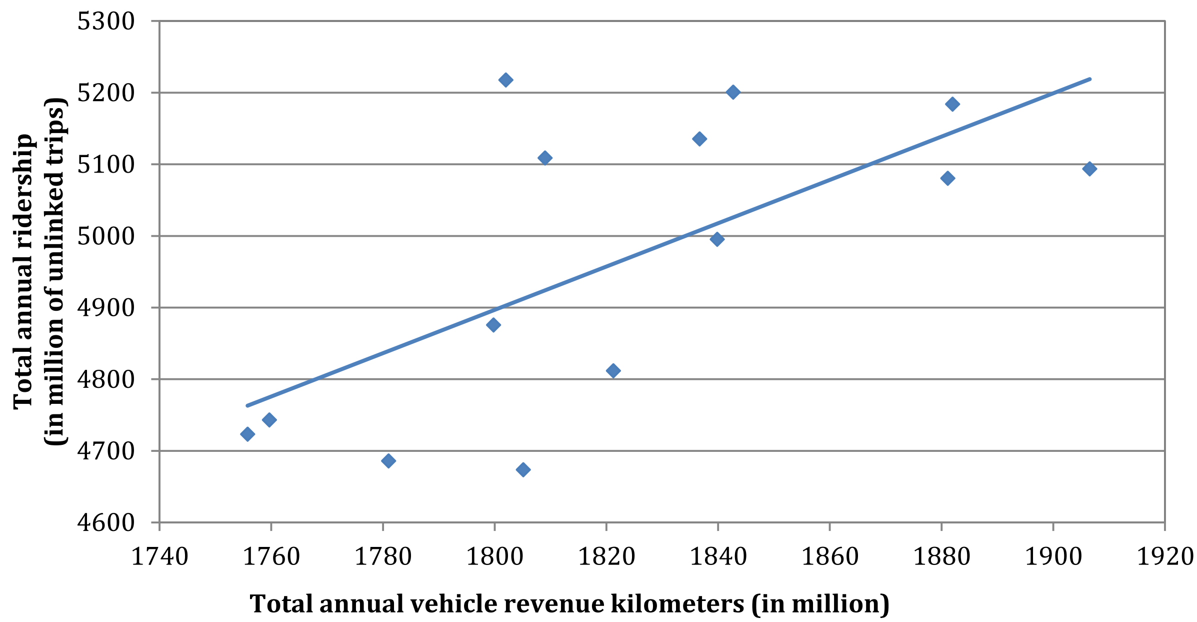

FIGURE 1 Ridership and vehicle revenue kilometers (VRK) per year.

Results of the Statistical Model

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 8.10% 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 2.14% 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. This suggests that multimodality, or the presence of alternatives to the private vehicle can contribute to, rather than deteriorate, ridership. In a survey of North American car sharing members, Martin and Shaheen (Martin & Shaheen, 2011b) found mixed results regarding the impact of car sharing systems on transit use. While many individuals reduced their use of transit after joining a car sharing organization, a large number of individuals, albeit slightly lower, also increased their use of transit. Our results suggest that ride-hailing systems, similar to car sharing services, can provide a complement to transit networks, and might overall contribute to an increased number of trips when aggregating the changes in behavior of all individuals. While these aspects are considered with dummy variables in this study, further studies could use more detailed variables (e.g.: number of trips made with Uber and bicycle-sharing systems) to test 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 & Fink, 2009), suggesting that higher gas prices result in lower ridership, as the private vehicle becomes less competitive financially. The magnitude of the relationship is, however, relatively small, the coefficient of gas price (0.067) 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 3.58% increase in ridership. In other words, increasing the number of individuals residing in an area (and therefore population density) is associated with more trips. Inversely, a 10% increase in the geographic size of the CMA is associated with a 2.92% 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).

TABLE 3 Results of the longitudinal multilevel mixed-effect regression modelling public transport ridership (number of unlinked passenger trips) (log-transformed)

Variable	Coeff.	Sig.	Conf. interval[†]	
Internal variables				
Revenue vehicle kilometers. (ln)	0.810	***	0.726	0.894
Average fare (ln)	-0.214	***	-0.286	-0.142
External transport-related variables				
Presence of private bus operator	0.115	***	0.081	0.150
Presence of Uber	0.023		-0.004	0.051
Presence of bicycle sharing system	0.005		-0.028	0.038
Proportion of carless households (ln)	0.440	***	0.268	0.613
Gas price (ln)	0.067	**	0.022	0.111
Other external variables				
Population (ln)	0.358	***	0.189	0.526
Area (ln)	-0.292	**	-0.487	-0.097
Constant	2.491	*	0.096	4.886
AIC		-630		
BIC		-584		
ICC		0.90		
Log-likelihood		327		
Observations		348		
Number of groups		25		

* 95% significance level | ** 99% significance level | *** 99.9% significance level
[†] 95% confidence interval

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.

Figure 2 conceptualizes the relationship between internal factors, external factors, ridership and the transit agency's revenues and subsidies as we observed it in our model 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 Figure 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 model, transit agencies and municipalities wishing to increase their ridership should consider improving their service through investments in their operations, while limiting the 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 to 25% to 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. A scenario analysis is conducted in the next section to assess this relationship between operation costs, fare and 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 variable 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 suggests that such program might overall contribute to higher levels of ridership. 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, ride-hailing 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 & Shaheen, 2011a; Martin, Shaheen, & Lidicker, 2010; Ter Schure, Napolitan, & Hutchinson, 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 ride-hailing 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.

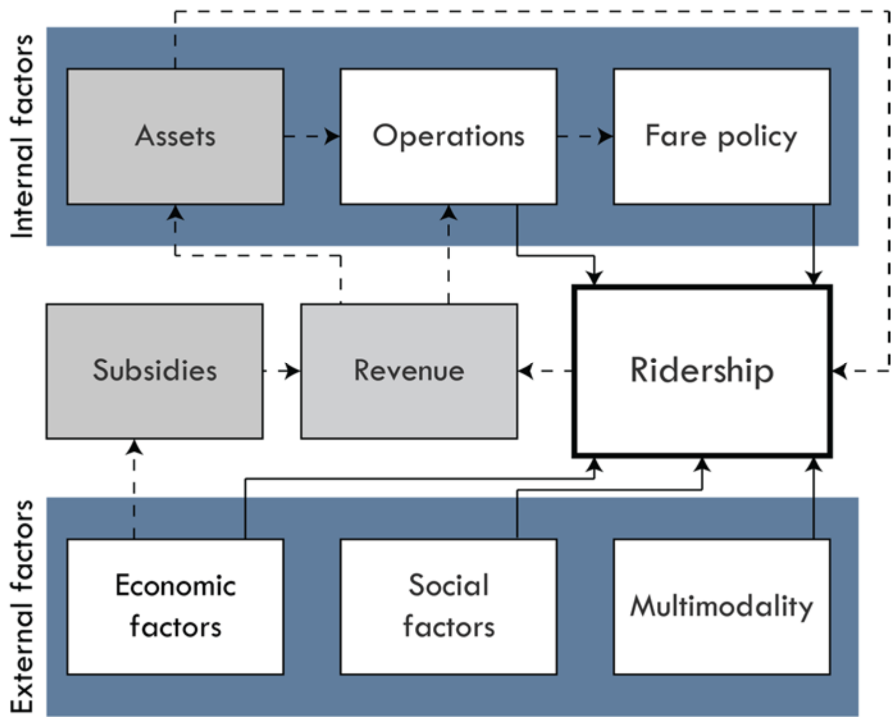

FIGURE 2 Determinants of ridership.

Scenario Analysis – Ridership, Operations and Fare Policy

To provide a greater understanding of how operations, fare policy and ridership are related, a scenario analysis derived from the statistical model coefficients is conducted. The aim is to understand how various increases in VRK and fare are associated with increase in ridership. This was performed by predicting change in ridership as a function of VRK and fare increases. Nine scenarios were considered. Firstly, holding the fare constant, the increase is ridership is calculated for three increases in VRK (5%, 10% and 15%). Since these increases in VRK are generally associated with greater operation expenses, further scenarios were developed to account for the fare increases required to secure additional revenues. More specifically, for each increase in VRK (5%, 10%, 15%), two scenarios are considered. The first calculates a fare increase that covers half of the additional expenses associated with the increase in operation, while the second calculates a fare increase that covers the full additional operating expenses. Operating expenses are calculated based on the average operating costs from all agencies ($6.71/km). An iterative process was then conducted by changing the value of the fare to obtain an additional revenue that corresponds to the (half or full) additional operating expenses. The additional revenue was calculated by multiplying the ridership by the fare before and after the fare increase, while the additional operating expenses were calculated by multiplying the added VRK by the average operating costs (ΔVRK*$6.71/km).

Figure 3 illustrates the results of the scenario analysis, presenting the increase in ridership as a function of increases in VRK and fares. The increase in VRK is indicated on the x-axis, and the fare increase is presented with a numerical value in each bar. The change in ridership is presented on the y-axis. Firstly, holding fares constant, a 1% increase in VRK results in a 0.8% increase in ridership, as found in the model. For example, a 10% VRK increase is associated with a 8% increase in ridership. Considering the other scenarios, we see that the increases in ridership associated with increases in VRK are offset by losses in ridership from fare increases. For example, to cover a 10% increase in operating expenses, a 24.7% increase in fare is required, and reduces the increase in ridership from 8% to 3%. Furthermore, the required increase in fare is substantial and accordingly highly unlikely to be implemented.

Overall, the scenario analysis demonstrates that it is very difficult to sustain large increases in ridership through fare increases. Our study shows that greater VKM with limited fare increase 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.

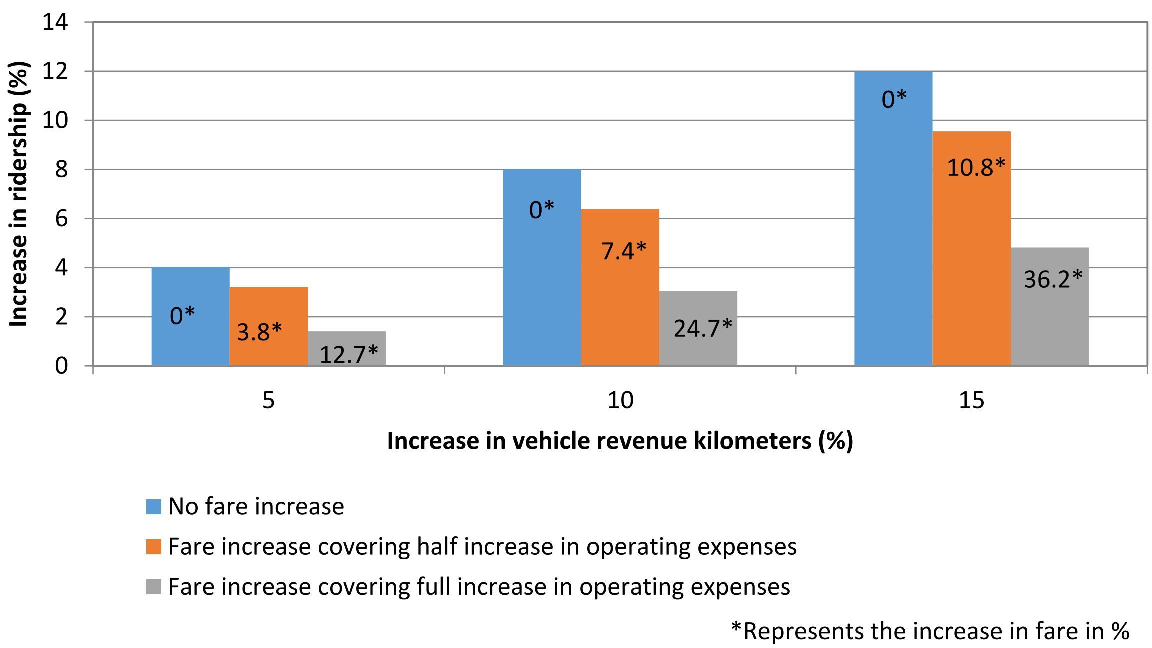

FIGURE 3 Increase in ridership as a function of increase in vehicle revenue kilometers (VRK) and fare[4].

[4] Values were predicted for an agency with the following characteristics: presence of purchased transportation for bus services, presence of Uber, presence of a bicycle-sharing system, 10% of

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 ride-hailing services and gas prices (Bliss, 2017; CISION, 2017; Levinson, 2017). However, the findings of this study reveal that internal factors, rather than ride-hailing and gas price, are key determinants of ridership. Whilst ridership is not independent of external factors, the reduction in 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 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 fare increases cannot support large increases in ridership through investments in operations. 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, Revéret, & Gendron, 2012; Enoch, Potter, & Ison, 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 ride-hailing 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 financial challenges associated with investments in operations. The findings of this study are relevant to researchers and policy-makers wishing to better understand the levers of transit ridership.

ACKNOWLEDGMENTS

This research was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) discovery program and the Social Sciences and Humanities Research Council of Canada (SSHRC). The authors would like to thank Lauren Rudko from the Canadian Urban Transit Association (CUTA) for providing us the data. The authors also acknowledge Prof. David Levinson, University of Sydney and Prof. Richard Schearmur, McGill University for their input on the analysis.

---

households without a car, CMA population of 4.09 million inhabitants and area of 11.50 km^2, with a gas price of \$0.82/liters. Those values correspond to the mean of the log-transformed variables. The increase in ridership is calculated relative to the base scenario, with a ridership of 163.03 million unlinked trip, an average fare of \$0.95 and 66.20 million vehicle revenue kilometers.

REFERENCES

Abdel-Aty, M. (2001). Using ordered probit modeling to study the effect of ATIS on transit ridership. *Journal of Planning Literature, 16*(2), 236-319.

Adler, M., & van Ommeren, J. (2016). Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes. *Journal of Urban Economics, 92*, 106-119.

American Public Transportation Association. (2010). *2009 Public transit fact-book*. Retrieved from Washington, D.C.: http://www.apta.com/resources/statistics/Documents/FactBook/APTA_2009_Fact_Book.pdf

Beaudoin, J., & Farzin, Y. (2015). Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. *Research in Transportation Economics, 52*, 15-22.

Bliss, L. (2017). What's Behind Declining Transit Ridership Nationwide? Retrieved from https://www.citylab.com/transportation/2017/02/whats-behind-declining-transit-ridership-nationwide/517701/

Canadian Urban Transit Association. (2017). *2000-2015 Canadian transit fact book*. Retrieved from Toronto, Canada:

Chen, C., & McKnight, C. (2007). Does the built environment make a difference? Additiona evidence from the daily activity and travel behaviour of homemakers living in NYC and suburbs. *Journal of Transport Geography, 15*(5), 380-395.

Chen, C., Varley, D., & Chen, J. (2011). What affects transit ridership? A dynamic analysis involving multiple factors, lags and asymmetric behaviour. *Urban Studies, 48*(9), 1893-1908.

CISION. (2017). Poll suggests UberX is decreasing TTC and GO transit ridership Retrieved from http://www.newswire.ca/news-releases/poll-suggests-uberx-is-decreasing-ttc-and-go-transit-ridership-529475091.html

Currie, G., & Phung, J. (2007). Transit ridership, auto gasoline prices, and world events. *Transportation Research Record, 1992*, 3-10.

Currie, G., & Phung, J. (2008). Understanding the link between transit ridership and auto gasoline prices: US and Australian evidence. *Transportation Research Record, 2063*, 133-142.

Curry, B. (2016). Where have all the transit riders gone? *The Globe and Mail*. Retrieved from https://www.theglobeandmail.com/news/politics/drop-in-transit-ridership-has-officials-across-canadastumped/article30178600/

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of Public Transportation, 12*(4), 3.

Drzymala, L., Revéret, J., & Gendron, C. (2012). *Recensement des sources de financement alternatives et innovantes du transport collectif en milieu urbain en rapport avec les préceptes de la théorie de l'économie de l'environnement*: Prosperité durable (Université d'Ottawa).

El-Geneidy, A., Hourdos, J., & Horning, J. (2009). Bus transit service planning and operations in a competitive environment. *Journal of Public Transportation, 12*(3), 39-59.

Enoch, M., Potter, S., & Ison, S. (2005). A strategic approach to financing public transport through property values. *Public Money and Management, 25*(3), 147-154.

Farber, S., Bartholomew, K., Li, X., Paez, A., & Habib, K. (2014). Assessing social equity in distance based transit fares using a model of travel behaviour. *Transport Research Part A, 67*, 291-303.

Federal Transit Administration. (2017). National Transit Database. Retrieved from https://www.transit.dot.gov/ntd/ntd-data

Fitzsimmons, E. (2017, 2017/02/23). Subway Ridership Declines in New York. Is Uber to Blame? *The New York Times*. Retrieved from https://www.nytimes.com/2017/02/23/nyregion/new-york-city-subway-ridership.html?rref=collection%2Ftimestopic%2FMetropolitan%20Transportation%20Authority%2C%20N.Y.

Gómez-Ibáñez, J. (1996). Big-city transit ridership, deficits and politics. *Journal of the American Planning Association, 62*(1), 30-50.

Governing. (2017). State Gas Tax Revenue Data. Retrieved from http://www.governing.com/gov-data/transportation-infrastructure/gas-tax-revenue-data-by-state-inflation-adjusted.html

Grimsrud, M., & El-Geneidy, A. (2013). Driving transit retention to renaissance: Trends in Montreal commute public transport mode share and factors by age group and birth cohort. *Public Transport, 5*(3), 119-241.

Guerra, E., & Cervero, R. (2011). The effects of densities and fixed-guideway transit ridership and costs. *Journal of the American Planning Association, 77*(3), 267-289.

Hagan, S. (2017). Uber takes majority of ground transport market for U.S. business travelers. Retrieved from https://www.bloomberg.com/news/articles/2017-01-26/uber-takes-majority-of-ground-transport-market-for-u-s-business-travelers

Iacono, M. (2006). *Modeling the Cost Structure of Public Transit Firms: The Scale Economies Question and Alternate Functional Forms.* University of MinnesotaMajor: Civil engineering.

Jacques, C., Manaugh, K., & El-Geneidy, A. (2013). Rescuing the captive [mode] user: An alternative approach to transport market segmentation. *Transportation, 40*(3), 625-645.

Kain, J., & Liu, Z. (1999). Secrets of success: assessing the large increases in transit ridership achieved by Houston and San Diego transit providers. *Transportation Research Part A, 33*, 601-624.

Krizek, K., & El-Geneidy, A. (2007). Segmenting preferences and habits of transit users and non-users. *Journal of Public Transportation, 10*(3), 71-94.

LaBelle, S., & Stuart, D. (1996). Diverting automobile users to transit: Early lessons from the Chicago Transit Authority's Orange Line. *Transportation Research Record, 1503*, 79-87.

Lee, B., & Lee, Y. (2013). Complementary pricing and land use policies: Does it lead to higher transit use? *Journal of the American Planning Association, 79*(4), 314-328.

Levinson, D. (2017). On the predictability of the decline of transit ridership in the US. Retrieved from https://transportist.org/2017/03/20/on-the-predictability-of-the-decline-of-transit-ridership-in-the-us/

Linton, J. (2016). What Factors Are Causing Metro's Declining Ridership? What Next? Retrieved from http://la.streetsblog.org/2016/01/29/what-factors-are-causing-metros-declining-ridership-what-next/

Liu, Z. (1993). *Determinants of public transit ridership: analysis of post World War II trends and evaluation of alternative networks.* (PhD), Harvard University, Cambridge, M.A.

Martin, E., & Shaheen, S. (2011a). The impact of carsharing on household vehicle ownership. *ACCESS Magazine, 1*(38).

Martin, E., & Shaheen, S. (2011b). The impact of carsharing on public transit and non-motorized travel: An exploration of North American carsharing survey data. *Energies, 4*(11), 2094-2114.

Martin, E., Shaheen, S., & Lidicker, J. (2010). Impact of carsharing on household vehicle holdings: Results from North American shared-use vehicle survey. *Transportation Research Record: Journal of the Transportation Research Board*(2143), 150-158.

McLeod, M., Flannelly, K., Flannelly, L., & Behnke, R. (1991). Multivariate time-series model of transit ridership based on historical, aggregate data: the past, present and future of Honolulu. *Transportation Research Record, 1297*, 76-84.

Nelson, L., & Weikel, D. (2016). Billions spent, but fewer people are using public transportation in Southern California. *Los Angeles Times*. Retrieved from http://www.latimes.com/local/california/la-me-ridership-slump-20160127-story.html

Pasha, M., Rifaat, S., Tay, R., & De Barros, A. (2016). Effects of street pattern, traffic, road infrastructure, socioeconomic and demographic characteristics on public transit ridership. *KSCE Journal of Civil Engineering, 20*(3), 1017-1022.

Taylor, B., & Fink, C. (2009). *The factors influencing transit ridership: a review and analysis of the ridership literature*. Retrieved from Los Angeles, C.A.: http://www.reconnectingamerica.org/assets/Uploads/ridersipfactors.pdf

Taylor, B., Miller, D., Iseki, H., & Fink, C. (2009). Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. *Transportation research part A: policy and practice, 43*(1), 60-77.

Ter Schure, J., Napolitan, F., & Hutchinson, R. (2012). Cumulative impacts of carsharing and unbundled parking on vehicle ownership and mode choice. *Transportation Research Record*(2319), 96-104.

Thompson, G., Brown, J., & Bhattacharya, T. (2012). What Really Matters for Increasing Transit Ridership: Understanding the Determinants of Transit Ridership Demand in Broward County, Florida. *Urban Studies, 49*(15), 3327-3345.

U.S. Department of Transportation. (2000). *Changing Faces of Transportation*. Retrieved from Washington D.C.:

United States Federal Reserve System. (2017). Historical Rates for the Canadian Dollar. Retrieved from https://www.federalreserve.gov/releases/h10/hist/dat00_ca.htm

Verbich, D., Badami, M., & El-Geneidy, A. (2017). Bang for the buck: Toward a rapid assessment of urban public transit from multiple perspectives in North America. *Transport Policy, 55*, 51-61.