Bus Quality Improvements and Local Commuter Mode Share

Justin Tyndall

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justin.tyndall@sauder.ubc.ca
Sauder School of Business,
University of British Columbia,
2053 Main Mall, Vancouver, BC,
Canada, V6T 1Z2

Abstract

The choice to use bus transit over a rival mode of transportation is a consequence of many variables. The importance of bus service quality on mode share is often considered but rarely measured explicitly. This study presents a novel temporal data set of geolocated buses from New York City. The merger of locational vehicle data with public schedule data allows for the estimation of bus dependability across neighbourhoods. This study uses plausibly exogenous spatial variation in the introduction New York City's Select Bus Service program to explore the relationship between the policy intervention, bus service quality and changes in commuter mode share. A propensity score matching procedure compares bus reliability and mode share in tracts that received Select Bus Service to a control group. A sizeable treatment effect is found. The policy intervention significantly increased service frequency and improved bus arrival reliability. Additionally, bus mode share amongst commuters in treatment neighbourhoods increased substantially. Select Bus Service was responsible for an increase in local bus mode share of 1.9 percentage points, with bus mode share in the median tract rising from 9.6% to 11.5%. Female commuters are found to be more responsive to the service improvements than males.

Public Transportation; Service Quality; Mode Share; Reliability; Headway; Bus Rapid Transit

1 Introduction

Implicit in the decision to take a bus is the choice to accept the possibility of delay or uncertainty in journey duration. Frequent stops and the necessity to navigate urban traffic cause bus transit to be particularly susceptible to delays (Lin et al., 2008). The importance of providing reliable bus service in supporting bus patronage is well accepted in the theoretical literature (Bates et al., 2001). Rider surveys also support the hypothesis that bus reliability is important to patrons (Diab and El-Geneidy, 2012; Eboli and Mazzulla, 2007; Kou et al., 2017).

Many cities have enacted programs to improve the quality of bus service (Currie and Wallis, 2008). The recent introduction of the *Select Bus Service* (SBS) initiative in New York City (NYC) will be used as a source of quasi-random variation in local service quality. A unique opportunity for identification provides causal estimates of the effect of bus quality improvement on neighbourhood commuter behaviour. Results of a statistical matching procedure demonstrate that the policy intervention led to significantly improved adherence to scheduled arrival times and a reduction in arrival volatility. Results also show that tracts which received SBS treatment experienced an increase in commuter bus mode share of 1.9 percentage points, with bus mode share in the median tract rising from 9.6% to 11.5%. These estimates may hold lessons for similar initiatives elsewhere.

Analysis will rely on detailed automatic vehicle location (AVL) data collected from GPS enabled NYC buses. AVL systems communicate the location of vehicles in real time. Several previous studies have suggested methods for transforming AVL data into dependability metrics (Bullock et al., 2005; Chen et al., 2009; Diab and El-Geneidy, 2012; Mazloumi et al., 2009; Uno et al., 2009). This study will estimate bus dependability statistics directly by combining a large AVL data set with publicly available schedule information.

The paper will proceed as follows. Section 2 reviews relevant literature. Section 3 presents data sources. Section 4 provides details on NYC's SBS program. Section 5 introduces the propensity score matching identification strategy. Section 6 presents results and section 7 concludes.

2 Related Literature

There exists a wealth of research on the theory of optimal trip scheduling in an environment with uncertainty. Small (1982) provided the orthodox formulation of the problem. Noland and Small (1995) expanded the model and argued that uncertainty in arrival time can carry large negative utility costs for commuters. A recent and detailed literature review of work estimating the value of travel time reliability in general can be found in Carrion and Levinson (2012). The current section will limit its focus to works specific to the effect of bus quality on mode choice or works with relevance to AVL data applications.

The impact of bus service quality on mode choice has received empirical attention primarily in the analysis of stated preference (SP) survey data (Bates et al., 2001; Diab and El-Geneidy, 2012; Kou et al., 2017; Prashker, 1979). Prashker (1979) was an early investigation into the attitudes of transit riders regarding service dependability. Results from a Chicago based survey showed that high variability in the arrival time of transit vehicles represented a strong source of disutility for urban travellers.

Bates et al. (2001) provided a vital synthesis of theory relating to the importance of reliability in mode choice. Bates et al. (2001) expressed scepticism regarding the validity of SP analyses due to issues such as sensitivity to the wording of questions and findings of implausibly high implied valuations of reliability. Bates et al. (2001) posited that survey respondents may overstate the disutility they receive from transit unreliability as a way to express frustration and "protest" low quality service. In relation to barriers to conducting revealed preference investigations Bates et al. (2001) noted, "there are serious problems of finding real choice situations with sufficient variation to allow statistically reliable estimates."

A starting point to conducting revealed preference analysis of the effect of bus quality on ridership can be through the comparison of locations that received improved bus service to locations that did not see an improvement in service. Kain and Liu (1999) used variation through time and across cities in bus service levels and fares to argue that the rise in bus ridership in San Diego and Houston observed in the 1980s and 1990s was explainable primarily through improved service levels. Currie and Delbosc (2011) analysed detailed bus service and ridership data from Australia. The study compared conventional bus routes, superior quality Bus Rapid Transit (BRT) routes, and so-called "smart-routes," which featured only a subset of the quality improvements of the BRT system. The heterogeneity in service quality across locations facilitated a disaggregation of the relative importance of various components of bus quality on ridership. Consistent with prior research, Currie and Delbosc (2011) found service frequency and reliability to be drivers of high ridership. In particular, the presence of dedicated bus lanes were found to increase ridership. The current study will similarly use variation in the timing and location of service improvements to identify effects.

Kou et al. (2017) conducted a detailed SP study to estimate the determinants of bus mode choice in Beijing. Kou et al. (2017) found reliability differences to be a relatively more important factor in mode choice than observed differences in average travel time. Kou et al. (2017) noted the valuation of reliability is heterogeneous across socio-economic groups, with high income earners having a stronger preference for reliability, and therefore being more likely to avoid the uncertainty associated with bus travel.

Bhat and Sardesai (2006) investigated mode choice in Austin, Texas and found large valuations for reliability, particularly for those with rigid work schedules. Analysis relied on data from an online survey. Eboli and Mazzulla (2007) employed a combination of stated and revealed preference data collected from university students in Italy to estimate a structural model of characteristics that affect rider satisfaction with bus service. Model results suggested that the design of the bus network and service reliability were central to influencing user satisfaction. Characteristics associated with rider comfort and the physical upkeep of vehicles and stops were found to be significant but less important. Eboli and Mazzulla (2011) presented further evidence regarding passenger perceptions of service quality, conducting a SP analysis of commuter bus riders in Italy. Results confirmed the primacy of route design and reliability to user satisfaction.

An international summary of bus improvement initiatives is provided by Currie and Wallis (2008). The authors present evidence that past initiatives to expand the frequency, reliability or spatial coverage of bus service have resulted in increases to bus patronage in the range of 10-20%. Interventions focused on improvements to the cleanliness and comfort of vehicles and bus stops were shown to result in smaller patronage gains. A main result of the current study is that SBS caused a 20% rise in local commuter bus mode share. The current paper differs from past estimates due to its focus on commuters, the particular causal identification strategy employed and the unique characteristics of SBS. Though not directly comparable to estimates found in Currie and Wallis (2008), the estimated magnitude is generally consistent.

There is a substantial methodological literature regarding the use of AVL bus data to estimate service dependability (Bullock et al., 2005; Camus et al., 2005; Chen et al., 2009; Diab and El-Geneidy, 2012; Mazloumi et al., 2009; Uno et al., 2009). The current paper attempts to operationalize AVL data to generate meaningful estimates of bus frequency and dependability. As AVL technology becomes more common, and if data collection becomes more prevalent, the application of AVL data to answer transit demand questions appears promising. This study represents a step towards embedding AVL data into mode share estimation.

Bertini and El-Geneidy (2004) served as a precursor to AVL applications by employing detailed bus dispatch data to estimate the factors determining bus route trip time. Chen et al. (2009) contributed an array of AVL compatible dependability metrics, including a bus stop level metric capturing the probability of a bus arrival exceeding a lateness threshold relative to the typical headway. El-Geneidy et al. (2011) provided an attempt to apply AVL data to the estimation of bus reliability. The study employed AVL data from a single bus route in suburban Minneapolis to estimate a detailed model of bus travel time and reliability. Among practical recommendations to improve bus service was the consolidation of bus stops. Bus stop consolidation is one feature of the SBS system.

Diab and El-Geneidy (2012) provided a paper that is closely related to the current study. AVL data was used to analyse the effect of several bus service improvements along two routes in Montreal. The study combined AVL data with SP data to demonstrate strong positive responses in rider perceptions to service improvements. The study stopped short of estimating the partial effect of improved service on ridership due to data limitations. A contribution of the current paper will be to leverage AVL data from a large number of bus routes (169) to enable the comparison of bus service quality across neighbourhoods. Diab and El-Geneidy (2012) found that a combination of bus service improvements led to a substantial reduction in bus run times. The consolidation of bus stops was found to reduce running time by 10.8% in Montreal. Rather than measure run times, the current study will demonstrate the ability of the SBS system to lower headways and reduce arrival volatility.

Several papers have analysed the effect of dedicated bus lanes on ridership (Chalak et al., 2016; Diab and El-Geneidy, 2012; Gibson et al., 2016; Surprenant-Legault and El-Geneidy, 2011). The literature is generally consistent in finding that initiatives which isolate bus service from traffic lead to improvements in service and increases in ridership. Surprenant-Legault and El-Geneidy (2011) used AVL data from Montreal to investigate the impact of a newly introduced reserved bus lane on travel time and reliability. Analysis revealed the reserved lane significantly reduced run times and increased the odds of a bus being no more than 3 minutes late by 65%. The ability of SBS to reduce uncertainty in arrival time may be largely attributable to the construction of reserved lanes.

As articulated by Berry et al. (1990) generally, or Bonsall (2004) as well as Eboli and

Mazzulla (2011) in relation to transport, human perceptions of quality and reliability have psychological dimensions that are not easily captured in statistical models. The current paper will embrace this agnosticism to mode choice mechanics. While a causal connection between service quality and mode choice is hypothesized, the details of the choice mechanism will be abstracted in favour of delivering empirically founded, reduced form estimates of the partial effect of improved service on local bus mode share. A qualitative study of mode choice in Porto, Portugal was undertaken in Beirão and Cabral (2007). While the authors identified transit speed and reliability as universally important components of mode choice, the study highlighted disparate opinions between those with cars relative to those reliant on transit. Frequent bus users were found to have a more positive opinion of buses compared to those who did not take the bus. Qualitative evidence from a survey of Belfast residents is presented in Mahmoud and Hine (2013, 2016). Results in Mahmoud and Hine (2013, 2016) confirmed a heightened level of satisfaction with bus service among frequent users. Additional results suggested that the satisfaction of infrequent bus users was more sensitive to travel time and reliability characteristics than frequent users. This qualitative research suggests that policy should work to communicate the merits of bus transit to infrequent riders, if ridership is to be expanded. The marketing of SBS as a “premium” bus service may have held appeal to travellers who previously ignored buses as a viable mode.

3 Data

The Metropolitan Transportation Authority (MTA) is the primary transit operator for NYC. The MTA provides an AVL data feed for bus routes. The purpose of this data feed is to communicate bus arrival information to system users in real time. Information can be accessed through a web interface and the data feed is incorporated into many third party smartphone applications. This study repurposes this data feed to construct a historical record of bus locations. Data collection was conducted for a full year, from January 1, 2016 to December 31, 2016.

AVL data was recorded at the unique route-stop level. A looping program automatically recorded the status of a sample of 14,623 NYC route-stops, approximately every four minutes. For each query, the program returned a binary observation for each route-stop: 1 if there was a bus of the corresponding route at or approaching the stop and 0 otherwise. Each query was precisely timestamped and accompanied by a unique bus identifier. This method provided longitudinal data for each route-stop in the sample. Given the four minute gap between observations, data construction relied on the assumption that sequential observations of a unique bus at nonsequential stops entailed the bus passed intermediate stops during the time between observations.

Data collection relied on the proper operation of vehicle GPS equipment, public servers, and internet connectivity. Interruptions to any of this infrastructure caused periods of incomplete data. Interruptions are rare and will not meaningfully impact service dependability estimates, which will be averaged across 2016 at the census tract level.

The MTA provides machine-readable bus schedule data. By combining timestamped AVL bus locations with scheduled arrival times, statistics pertaining to bus dependability can be calculated. The use of schedule data allows AVL data to be normalized to accord to scheduled headway variations between routes, and across time of day.

As of the study period, the MTA bus system was comprised of 307 bus routes. The MTA only provided machine readable schedule data for 199 routes. 30 routes provided insufficient observations across the period of study for statistics to be estimated. 169 bus routes remain in the final sample. Though data fails to capture the entire universe of NYC bus activity, the sample provides detailed variation across neighbourhoods. In order to accord with the study of commuter behaviour, bus arrival statistics will be further limited to periods of significant commuting, defined as weekdays from 6 am to 10 am and 4 pm to 8 pm.

It is assumed that observed vehicles intended to arrive at a stop at the scheduled time that is closest to the observed arrival time. Buses running severely off schedule are difficult to match to schedule data. To clean the data of erroneous observations, analysis is limited to cases where a bus arrived within 15 minutes of a scheduled arrival time. Trimming the data in this way eliminates outliers and focuses the analysis on buses that were at least somewhat correspondent to the public schedule. However, the 15 minute threshold likely removes some observations that were legitimately running more than 15 minutes off schedule. To the extent that these observations were legitimate, the omission of these observations will cause the aggregate dependability estimates to overstate reliability.

Table 1 provides summary statistics pertaining to AVL data. 112 million instances of a bus passing a stop along its route are recorded. Linking consecutive observations allows for the calculation of headways. Public schedule data allows for the calculation of bus lateness. The average non-SBS bus in the sample ran with a 16.40 minute headway, was systematically late by 0.14 minutes, and missed the scheduled arrival time by an average of 2.58 minutes. Buses that were subject to the SBS initiative are found to have substantially superior average performance. The average SBS observation ran with an 11.07 minute headway. SBS observations showed no evidence of being systematically late or early. The average discrepancy between scheduled and observed arrival of a SBS bus was 1.37 minutes, 47% less than non-SBS routes.

Table 1: AVL Summary Statistics

	Non-SBS Routes		**SBS Routes**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Headway (min)	16.395	13.478	11.068	10.882
Lateness (min)	0.138	0.402	-0.007	0.085
Arrival discrepancy (min)	2.577	1.561	1.370	0.514
N	109,907,510		2,410,885	

Each observation corresponds to a bus passing a stop on its route. For example, a single bus completing a route 30 stops long would yield 30 observations. The arrival discrepancy is the absolute value of lateness.

The MTA provides locational coordinates for bus stops. Bus stops are assigned to census tracts through use of the US Federal Communication Commission, Census Block

Conversion API. Dependability statistics are derived from all observed bus stops within a particular census tract.

Census tract mode share and demographic variables are taken from the American Community Survey (ACS), five-year estimates. The five-year estimates are necessary as the three-year or one-year ACS products do not provide relevant variables at the census tract level. Analysis will look for changes in bus mode share and other variables that can be attributed to the introduction of SBS. The pretreatment data is taken from the 2009 ACS five-year estimates and the posttreatment data is from the 2015 five-year estimates. The assignment of treatment status will be discussed in section 5.

In order to facilitate a consistent sample across estimates, tracts without any observed bus stops or without complete 2015 ACS data are omitted from analysis. AVL bus data and 2015 ACS data are jointly available for 1,534 NYC census tracts. NYC has a total of 2,140 populated tracts. Of the 606 tracts dropped due to missing data, 379 are dropped due to having no bus stop data, 225 are dropped due to missing ACS home price or rental price data, and two are dropped due to other missing ACS variables. Mode share and bus dependability estimates were repeated with the inclusion of tracts with missing rent or home value variables and results proved robust.

Table 2 provides summary statistics at the census tract level. The median tract experienced a mean bus headway, averaged across its route-stops, of 14.8 minutes. The interquartile range was 13.0-17.5 minutes. Analysis will consider the mean and standard deviation of observed bus arrivals relative to scheduled arrivals. The mean schedule adherence is calculated for each census tract by taking the average of all observed bus arrivals. Only 16% of tracts experienced buses which ran, on average, early. Figure 1, panel A shows the mean difference between observed arrivals and scheduled arrivals across census tracts.

Table 2: Census Tract Summary Statistics

Variable	Mean	Std. Dev.
Bus mode share	0.118	0.077
Mean of arrival discrepancy (min)	0.170	0.275
Std. dev. of arrival discrepancy (min)	3.085	1.535
Average headway (min)	15.792	4.610
Subway entrances	0.945	2.371
Unique subway lines	0.702	1.645
Closest subway station (km)	0.990	1.306
2nd closest subway station (km)	2.062	2.711
Dist. to city hall (km)	12.620	5.913
Population	4052	2168
Population density (per km^2)	19484	13033
Share of homes, detached	0.131	0.186
Under 20 years of age pop share	0.236	0.078
20-34 years of age pop share	0.246	0.079
Over 65 years of age pop share	0.129	0.058
White pop share	0.448	0.304
Black pop share	0.261	0.313
Asian pop share	0.138	0.170
Hispanic pop share	0.242	0.215
High school completion rate	0.814	0.119
College completion rate	0.349	0.208
Labour force participation	0.637	0.085
Unemployment rate	0.093	0.048
Median income ($)	61332	30118
Median rent ($)	1259	422
Median home value ($)	572857	282813
SNAP recipiency rate	0.196	0.147
Public assistance recipiency rate	0.040	0.036
N	1534	

Income, rent and home value variables are represented in 2015 US dollars.

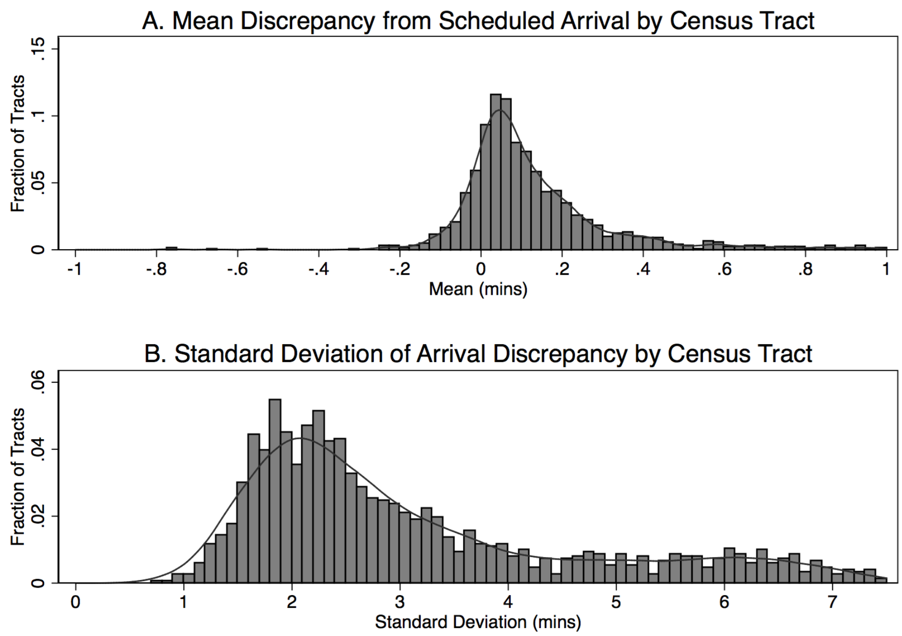

Figure 1: Histograms of bus arrival characteristics with a kernel density plot overlay.

The distribution of arrival discrepancies within a tract provide data to estimate the standard deviation of arrival discrepancy, which serves as a measure of local bus dependability similar to Jackson and Jucker (1982) and Senna (1994). Figure 1, panel B shows the standard deviation of arrival discrepancy across census tracts. A standard deviation of zero would suggest local buses always arrive off-schedule by precisely the same amount of time. The average tract experienced a standard deviation of 3.1 minutes. The standard deviation of arrival discrepancy has a long upper tail, 15% of tracts experience a standard deviation in excess of 5 minutes.

Considering that commuters complete identical trips with regularity, if a route runs off schedule by a consistent and predictable margin, users may internalize this information when forming trip plans. Hensher et al. (2011) pointed out the potential importance of this type of "conditioning." Benezech and Coulombel (2013) provided a precise mathematical model to evaluate the cost savings associated with reduced variance in transit arrival and travel time. Benezech and Coulombel (2013) noted that travellers will form an optimal strategy to minimize the expected disutility of delays. Such a strategy will be a function of prior beliefs regarding the probability distribution of delays. The mean arrival discrepancy may therefore have a limited valence for commuters while the standard deviation likely represents an important component of service quality.

4 Select Bus Service

Beginning in 2008, the MTA began to introduce new high performance bus routes branded as *Select Bus Service*. The routes share some characteristics with BRT systems. SBS routes include many features meant in improve reliability, speed and comfort. Features include more frequent buses, dedicated bus lanes, traffic signal priority, greater distances between stops, new vehicles, off-board ticketing and multiple door boarding. A press release from the MTA proffered, “the chief goal of the SBS program is to make the buses faster, more reliable and easily identified as a premium service” (MTA, 2013b).

Barr et al. (2010) studied the implementation of the first SBS route in NYC (Bx12). The report pointed to high levels of customer satisfaction with the new service. Analysis also found increased overall bus ridership within the corridor surrounding the Bx12 route. Weekday bus ridership increased by 11.4% after SBS was introduced. Barr et al. (2010) estimated that SBS service curtailed travel times by roughly 19% as compared to the prior bus service. Wan et al. (2016) conducted a large survey of SBS users to determine the service components that users found valuable. Service frequency and reliability were relatively more important to respondents than other quality improvements such as ticketing conveniences or on board comfort. Wan et al. (2016) found commuting to be the most common trip purpose among SBS riders.

Estimation in the current study benefits from more recent data, the incorporation of AVL statistics, and the use of propensity score matching to identify causal effects. Consistent with Barr et al. (2010) and Wan et al. (2016), results show a rise in both service quality and bus use. The main estimation result of the current study is that bus mode share amongst local commuters rose by 1.9 percentage points on account of SBS. The estimate is not directly comparable to Barr et al. (2010). However, a rough conversion demonstrates broad consistency. Tracts receiving SBS stops on the Bx12 route contained a working population 48,453 according to the 2009 5-year ACS. The ridership figures provided in Barr et al. (2010) imply that the 1.9 percentage point rise in commute mode share would translate to a 4.1% rise in ridership on the Bx12 route. This is generally consistent with Barr et al. (2010)'s estimate of an 11.4% rise in ridership, as Barr et al. (2010) captures additional ridership increases from non-commuters and non-locals.

The staggered introduction of SBS service across NYC neighbourhoods offers the possibility of identifying quasi-random variation in bus service quality that may be related to changes in bus mode share. This study will analyse the effect of the initial six SBS routes (Bx12, Bx41, M15, M34, M34A and S79), which were introduced between 2008 and 2013. As of February 2018 there were 17 SBS routes in operation and additional routes in various stages of planning.

The capital cost of constructing the initial six SBS routes was reported to be $70.5 million (MTA, 2013b). These expenses represented 0.53% of the MTA's annual budget (MTA, 2013a). The combined length of these routes exceeded 60 km and served a wide selection of NYC neighbourhoods. As a point of comparison, a recent subway extension in NYC extended a line (No. 7) by 2.4 km and included a single subway station at a total cost of $2.42 billion (MTA, 2017), or 33 times the cost of the six SBS routes, adjusted for inflation. Prior research has generally concluded that BRT systems are cost effective relative to other public transit modes. Tirachini et al. (2010) developed and applied a theoretical framework to compare the efficiency of BRT, light rail and heavy rail systems. Using data from Australian cities the authors found BRT to be the most efficient due to low operating costs and high service levels. In evaluating a BRT line in Los Angeles, Callaghan and Vincent (2007) found the BRT route was able to carry more riders at significantly lower cost than a commensurate light rail line.

5 Propensity Score Matching Procedure

A simple comparison of census tracts with SBS service to those without would fail to yield a causal estimate of the effect of SBS on service quality or mode share. Results would be erroneous due to the likely fact that the characteristics of neighbourhoods that received SBS service were considerably different from those that did not. Indeed, during the pretreatment period bus mode share in the tracts that would receive SBS service averaged 15.0%, while bus mode share in tracts that would not receive SBS averaged only 13.4%. This study proposes using propensity score matching to remedy the bias associated with the endogenous selection of route location.

A tract will be considered to be "treated" by SBS if it contained at least one SBS designated stop for at least 50% of the 2011-2015 ACS observation period, there are 80 such census tracts. The propensity score matching procedure forms a control group based on neighbourhood form characteristics, demographics, economic conditions and commuter mode share variables. All matching variables are lagged, taken from the 2009 5-year ACS (with survey responses collected from 2005-2009). The 2009 5-year ACS is the earliest version available. Lagging aims to achieve covariate balance between treatment and control tracts, maintaining orthogonality to the SBS treatment effect. The full set of matching variables are displayed in Table 3. The gradual introduction of SBS beginning in mid-2008 means that ACS matching variables collected between 2005 and 2009 should not be significantly affected by SBS service. To test this assumption, analysis was repeated while omitting any tract receiving SBS service in 2008 or 2009 and results remained robust.

Treated tracts are compared to the three "nearest neighbours," or non-treated tracts that are most similar according to the propensity score matching procedure. The methodology uses a logit regression to calculate the likelihood an observation will be

Table 3: Matching Balance Test

Variable	Treatment Group		Control Group		P-value
	Mean	Std. Dev.	Mean	Std. Dev.	
Bus mode share	0.150	0.102	0.149	0.111	0.9565
Subway mode share	0.307	0.192	0.302	0.178	0.8263
Subway entrances	1.850	3.472	1.567	2.635	0.4443
Unique subway lines	1.450	3.089	1.371	2.296	0.8076
Closest subway station (log km)	-0.952	0.774	-0.877	1.270	0.6209
2nd closest subway station (log km)	0.106	1.193	0.146	1.224	0.8013
Distance to city hall (log km)	2.119	0.930	2.184	0.928	0.5838
Population density	25427	20000	25023	18777	0.8696
Housing share: detached	0.089	0.163	0.097	0.151	0.6923
Under 20 years of age pop share	0.186	0.110	0.194	0.085	0.4874
20-34 years of age pop share	0.286	0.110	0.279	0.120	0.6455
Over 65 years of age pop share	0.118	0.063	0.125	0.062	0.4059
White pop share	0.611	0.298	0.590	0.296	0.5793
Black pop share	0.117	0.172	0.129	0.185	0.5903
Asian pop share	0.124	0.157	0.114	0.134	0.5704
Hispanic pop share	0.201	0.212	0.221	0.212	0.4837
High school completion rate	0.880	0.173	0.863	0.204	0.5155
College completion rate	0.568	0.315	0.537	0.342	0.4800
Labor force participation rate	0.650	0.128	0.642	0.104	0.5806
Unemployment rate	0.077	0.061	0.079	0.052	0.8212
Median income ($)	76213	37293	72068	33782	0.3554
Median rent ($)	1315	560	1297	489	0.7825
Median home value ($)	637766	269785	611457	287893	0.4728
SNAP recipiency rate	0.889	0.131	0.869	0.141	0.2669
Public assistance recipiency rate	0.033	0.050	0.042	0.048	0.1731
Borough dummy: The Bronx	0.225	0.420	0.271	0.445	0.4195
Borough dummy: Brooklyn	0.025	0.157	0.025	0.156	1.0000
Borough dummy: Manhattan	0.538	0.502	0.517	0.501	0.7476
Borough dummy: Staten Island	0.213	0.412	0.188	0.391	0.6255
N	80		240		

All matching variables are lagged to reflect conditions in the 2005-2009 period. P-values refer to the null hypothesis of equality of means. Of 29 matching variables, none are significantly different between treatment and control groups, at the 10% level. The 240 control tracts contain duplicate observations due to the matching procedure. Control tracts are composed of 121 unique tracts.

treated, based on a vector of pre-treatment characteristics. Subsequently, the three non-treated tracts that have the most similar likelihood of treatment are selected as control tracts. Tracts without a SBS stop but with a SBS route intersecting the tract are omitted as potential control tracts. Analysis was repeated while varying the number of matches between one and five. The choice of the number of matches had very little effect on results, as will be shown in the results section. Table 3 presents the covariate balance between treatment and control tracts, using three matches. Matching is done "with replacement," allowing for control tracts to serve as the control for multiple treatment tracts. Many tracts are reused, resulting in a control group comprised of 121 unique tracts. Among 29 matching variables, none are significantly different between the groups, providing evidence the matching procedure resulted in a well balanced sample. Figure 2 maps the treatment and control census tracts.

Estimates will be the so-called average treatment effect on the treated (ATET). ATET estimates yield the causal effect of treatment for tracts actually receiving treatment and are therefore most relevant for evaluating the impact of the policy. By omitting tracts that were unlikely to ever receive SBS, propensity score matching is better able to estimate the partial effect of SBS treatment. The estimation method is shown in equation 1. Standard errors are calculated according to the methodology proposed in Abadie and Imbens (2006).

$$\text{ATET} = \mathbb{E}(Y_1 - Y_0 | T = 1) = \mathbb{E}(Y_1 | T = 1) - \mathbb{E}(Y_0 | T = 1) \tag{1}$$

Y is an outcome variable of interest, indexed by potential treatment status. T is observed treatment status. 1 represents a treated observation and 0 represents an untreated observation. $\mathbb{E}(.)$ indicates an expected value.

The use of a discrete choice model was investigated, as has become typical in mode choice analysis. However, the absence of locationally precise commuter microdata necessitated reliance on aggregated neighbourhood level mode share data. In lieu of data to estimate a discrete choice model, analysis will seek to establish the causal effect of SBS service on bus quality and mode share at the census tract level.

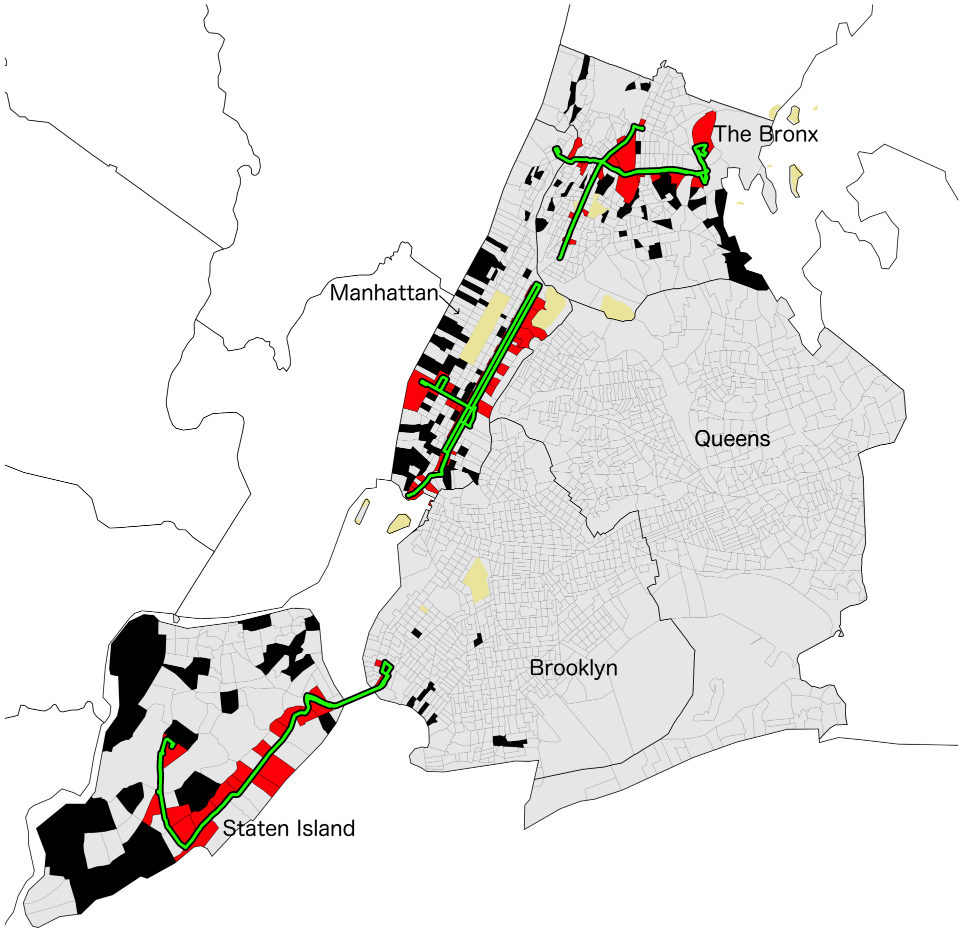

Figure 2: NYC, Treatment and Control Tract Observations

6 Results

Table 4 displays matching results for bus service outcome variables. As an initial check on the ability of the data collection process to pick up meaningful variations in bus service, column 1 provides the estimated effect of SBS service on average bus headway within a tract, post treatment. Results indicate that SBS treatment is related to a reduction in average observed bus headway of 2.15 minutes. Among treatment neighbourhoods the average headway was observed to be 15.07 minutes. This result suggests that having a SBS stop in a neighbourhood was related to a significantly higher level of bus service relative to control tracts. The result is not surprising.

Table 4: Matching Results, Effect of SBS on Bus Service

	Mean headway	Mean discrepancy of schedule adherence	Std. dev. of discrepancy
	(1)	(2)	(3)
SBS treatment	-2.146**	-.094**	-.305
	(.317)	(.004)	(.170)
# of matches	3	3	3
Mean of treated tracts	15.069	0.129	2.829

Significance levels: * : 5% ** : 1%. Outcome variables expressed in minutes. Robust standard errors are shown in parenthesis. Estimates correspond to ATET. Matching variables are displayed in Table 3.

Past literature has found service reliability to be particularly important to user satisfaction. Column 2 estimates the effect of SBS treatment on the mean discrepancy between observed and scheduled bus arrival time. Results suggest SBS treatment reduced the average gap between scheduled and observed arrival time by a highly significant 0.09 minutes. The result provides evidence that systematically late buses were less common in SBS treated tracts. Column 3 reveals the effect of treatment on the standard deviation of schedule adherence. The standard deviation of schedule adherence was reduced by 0.31 minutes, relative to a treatment group average of 2.83 minutes. Table 4 results provide strong evidence that the frequency and reliability of bus service was significantly improved by the introduction of local SBS service.

All mode share and neighbourhood change outcome variables are in first differences, using changes between the 2009 5-year ACS and the 2015 5-year ACS. Table 5 provides estimates regarding the change in commuter bus mode share attributable to the local introduction of SBS. Columns 1-3 repeat the same estimation strategy, while varying the quantity of matching observations. Three matches will be the preferred specification; however, columns 1-3 reveal that the choice of matches has only a small effect on estimates. Robustness to the choice of matching quantity is tested for other primary results, which also prove robust. Column 3 indicates that SBS treatment is associated with a sizeable and significant rise in commuter bus mode share of 1.9 percentage points.

Table 5: Matching Results, Effect of SBS Bus Mode Share

	Δ Bus Mode Share				
	(1)	(2)	(3)	(4)	(5)
SBS treatment	.024**	.024**	.019**	.015*	.034
	(.009)	(.007)	(.006)	(.008)	(.018)
Sample	All	All	All	Male	Female
# of matches	1	2	3	3	3
Median mode share, treated tracts	.115	.115	.115	.084	.148
Mean Δ mode share, treated tracts	-.014	-.014	-.014	-.012	-.014

Significance levels: ∗ : 5% ∗∗ : 1%. Robust standard errors are shown in parenthesis. Estimates correspond to ATET. Matching variables are displayed in Table 3. Δ bus mode share is the percentage point change in local bus mode share between the 2009 5-year ACS and the 2015 5-year ACS. A subset of potential control group tracts lack lagged ACS data on mode share by gender. While primary results are drawn from 80 treatment tracts and 1406 potential control tracts, columns 4 and 5 draw from 74 treatment tracts and 1272 potential control tracts. Re-estimating column 3 using the sample used in columns 4 and 5 yields an estimate of 0.025 with a standard error of 0.008.

The introduction of the SBS program occurred contemporaneously with a decline in commuter bus mode share across NYC. Even amongst tracts in the treatment group, commuter bus mode share over the study period fell by 1.4 percentage points on average. In fact, only 29 of 80 SBS treated tracts experienced an increase in bus mode share between the pre and post treatment periods. The effect of SBS treatment was largely to curtail the decline of bus mode share that was occurring across the city. A counterfactual implication is that while the median treated tract experienced a decline in bus mode share of 1.5 percentage points, bus mode share in the median treated tract would have declined by 3.4 percentage points had SBS not been introduced. Correspondingly, the median treated tract experienced a bus mode share of 11.5% after the introduction of SBS, but without SBS would have had a bus mode share of only 9.6%. There is clear evidence that improvements to bus quality led to increases in local bus mode share. Prior literature on the effects of bus quality improvements primarily focus on overall ridership changes rather than changes in commute mode share (Currie and Wallis, 2008; Currie and Delbosc, 2011; Kain and Liu, 1999). However, the conclusion that improvement to bus quality raises the popularity of bus transit is consistent with prior studies.

ACS survey data on mode share can be decomposed by gender. Table 5 provides separate bus mode share estimates for male and female commuters respectively. The ability of SBS to increase bus ridership appears to be larger among female commuters. SBS led to an increase in male commuter bus mode share of 1.5 percentage points. The effect on female commuters was a much higher 3.4 percentage points. This result points to a heterogeneous valuation of SBS characteristics between male and female commuters.

Increased bus mode share amongst commuters is likely to occur due to commuters switching from alternate modes. Table 6 provides estimates of SBS treatment on the commuter mode share of alternate modes. The mode share of subway, driving alone in a private vehicle, cycling, and walking are all tested. While all four estimates are negative, consistent with commuters switching from these modes to bus, none of the effects are statistically distinguishable from zero. Prior work often assumes that increased public transit mode share is the result of mode switching from private vehicles to public transit, for example Kou et al. (2017). Column 2 estimates an insignificant reduction in single occupancy vehicle mode share of 0.9 percentage points. Column 5 presents the effect of SBS treatment on overall public transit mode share (inclusive of bus and subway) and reports an increase of 0.9 percentage points. The result is consistent with SBS inducing mode switching form private vehicles towards transit, but large standard errors prevent any strong conclusions. The small and insignificant effect of SBS on public transit is interesting to interpreting the overall efficacy of the SBS program. While results strongly suggest SBS was successful in expanding bus mode share amongst commuters, it is not clear that the program significantly expanded overall public transit mode share. For example, a significant portion of the rise in bus mode share may have come from travellers who would otherwise have used the subway.

Substitution patterns between bus and subway can be further explored by limiting analysis to tracts that lack direct subway service. Table 7 repeats the propensity score matching exercise while limiting treatment tracts to those that have no subway stops within tract boundaries and no stops within 500 meters of the tract centroid. For tracts

Table 6: Matching Results, Effect of SBS on Alternate Modes

	Δ Subway	Δ Drove Alone	Δ Bike	Δ Walk	Δ Public Transit
	(1)	(2)	(3)	(4)	(5)
SBS treatment	-.006	-.009	-.0002	-.006	.009
	(.013)	(.008)	(.003)	(.011)	(.012)
# of matches	3	3	3	3	3
Median mode share, treated tracts	.365	.099	.000	.131	.492
Mean Δ mode share, treated tracts	.025	-.004	.004	-.004	.008

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Estimates correspond to ATET. Matching variables are displayed in Table 3. Outcome variables represent the change between the 2009 5-year ACS and the 2015 5-year ACS.

lacking direct subway service, the arrival of SBS represented a much larger increase in the quality of public transit as a whole. Among the 30 treated tracts without subway access, SBS increased commuter bus mode share by 3.5 percentage points, an effect 84% larger than the main estimate. Overall public transit mode share in these tracts experienced a significant increase of 2.2 percentage points. These results suggest that providing SBS service to transit poor environments creates substantial gains in public transit mode share.

Table 7: Matching Results, Effect of SBS on Mode Share in Tracts Without Subway Service

	Δ Bus	Δ Public Transit
	(1)	(2)
SBS treatment	.035*	.022*
	(.014)	(.011)
# of matches	3	3
Median mode share, treated tracts	.180	.417
Mean Δ mode share, treated tracts	-.012	.004

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Estimates correspond to ATET. Matching variables are displayed in Table 3. Outcome variables represent the change between the 2009 5-year ACS and the 2015 5-year ACS.

If residents place a significant valuation on transit service when making household locational decisions, it is possible that this preference will be capitalized into home prices. Unlike the installation of a subway line, where large upfront capital costs nearly ensure the service will continue to operate for a long duration, bus routes have comparatively low capital costs and their routes can be more easily adjusted. This uncertainty in future service implies that the capitalization of SBS service into land values may be limited. However, if current residents value the presence of SBS, demand for current housing should increase, which would push up local rents. Table 8, column 1 tests for the effect of SBS on local home values, but finds no statistically significant effect. Column 2, estimates the effect of SBS treatment on the change in median local monthly rent. Results show a large ($109) and significant increase in local rent attributable to SBS service. Median rent in treatment tracts was $1090 in the pretreatment period, suggesting SBS treatment increased rents by 10.0%. The presence of a positive rent effect but no home value effect is consistent with the amenity value of SBS failing to translate into significant land value capitalization due to uncertainty in its long term continuation. Rent and home value results are tentative due to the inability to control for potential changes in home quality through time, across tracts. The potential effects of SBS introduction on neighbourhood socio-economics was considered. Column 3 tests for an effect of SBS on local median income but finds no significant effect.

Table 8: Matching Results, Effect of SBS on Neighbourhood Characteristics

	Δ Home Value	Δ Monthly Rent	Δ Median Income
	(1)	(2)	(3)
SBS treatment	-15623 (25063)	108.857** (21.124)	-2253 (1683)
# of matches	3	3	3
Median values of treated tracts (post treatment)	505000	1147	74836

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis. Estimates correspond to ATET. Matching variables are displayed in Table 3. Outcome variables represent the change between the 2009 5-year ACS and the 2015 5-year ACS. Outcome variables are expressed as changes in inflation adjusted 2013 dollars. Three treatment observations are missing lagged home value data and one observation is missing lagged rent data, therefore columns 1 and 2 are estimated on restricted samples.

7 Conclusion

This study analysed the effect of a bus improvement initiative in NYC on service quality and commuter mode share. Inferring causality regarding the effect of transit service improvements is typically hindered by endogeneity of treatment relative to local characteristics. The quasi-random introduction of SBS in NYC allows for an identification opportunity through propensity score matching. The use of a large AVL data set allowed for novel estimates of bus performance. SBS service was found to be associated with observable improvements in bus service frequency and reliability. Furthermore, SBS was found to increase local commuter bus mode share by 1.9 percentage points, such that bus mode share in the median treated tract increased from 9.6% to 11.5%. The ability of SBS to expand bus mode share was found to be stronger among females than males. Point estimates indicate an overall increase in public transit mode share of 0.9 percentage points. Alternate modes of transportation did not experience significant changes in mode share as a result of SBS introduction. Mode shift effects were larger in tracts without subway service. In the median treated tract without subway service, SBS caused a significant rise in bus and public transit mode shares of 3.5 and 2.2 percentage points respectively. Additionally, results indicate SBS had no significant effect on local home values, but was associated with a 10% increase in local rents.

Low service quality of bus transit has been repeatedly identified in academic literature and in public policy as an impediment to expanding bus mode share. Despite strong priors on the importance of quality, there exists scant revealed preference empirical evidence on the relationship between service quality and mode choice. The methodology utilized herein provides useful reduced form estimates of the partial effect of a bus quality improvement program on aggregate mode share and neighbourhood characteristics. This study is limited by available data such that the valuation that users place on the components of bus quality can not be estimated individually. Further attempts to decompose quality characteristics would prove useful. Understanding the substitution patterns triggered by improved bus service in a discreet choice model would also provide complimentary information to this study's findings. The proliferation of AVL derived data sets may enable the parametrization of existing theoretical mode choice models. The current study takes a step towards this methodology. The coupling of large AVL data sets with established choice theory reveals a promising landscape for future research.

There has been a recent increase in interest regarding BRT type interventions in developed cities. Regarding NYC, the MTA has plans to further expand the SBS program beyond its current 17 routes. Generating measurable shifts in commuter behaviour towards public transit is an area of substantial policy interest. Unlike a full BRT system, SBS included relatively modest adjustments to bus service. It was unclear *a priori* if SBS would have a meaningful effect on mode choice. The mode shift effects estimated in this study provide evidence that the introduction of premium bus service significantly affects commuter decisions. The relatively low capital costs of SBS relative to rail infrastructure suggests such initiatives may provide good value.

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