WAITING FOR THE BUS:
SERVICE DEPENDABILITY AND COMMUTER MODE CHOICE

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Proceedings of the 52nd Annual Conference
Canadian Transportation Research Forum

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 causes 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). Due to data limitations, empirical revealed preference (RP) analysis connecting observed vehicle reliability and bus mode choice have not been widely attempted.

This paper will present detailed Automatic Vehicle Location (AVL) data on New York City (NYC) buses from 2016. Several previous studies have suggested metrics 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 from a large AVL data set. Subsequently, the metrics will be taken to mode share data in order to relate bus dependability to local variation in bus ridership. Results suggest service dependability is an important determinant of local bus mode share amongst commuters.

2. Related Literature

There is a depth of research analysing the impact of travel time uncertainty on the relative attractiveness of driving a private vehicle (Small et al., 2005). The relative lack of RP analysis on the effect of travel time uncertainty in public transit is in part tied to a lack of available data on the reliability of transit vehicles. A detailed literature review of work estimating the value of travel time reliability can be found in Carrion and Levinson (2012). The current section will not attempt to replicate a full review, but provide a brief description of the most relevant papers.

Service dependability is robustly identified in the literature as an important stated preference (SP) of transit users (Nash, 1967; Kou et al., 2017). The impact of bus dependability on mode choice has received empirical attention primarily in analysis of survey data (see Bates et al. (2001); Kou et al. (2017); Prashker (1979)). Prashker (1979) was an early investigation into the attitudes of transit riders regarding service dependability. Prashker (1979) found that variability in the arrival time of transit vehicles was particularly aggravating for urban travellers.

Bhat and Sardesai (2006) noted that “few empirical studies consider reliability as an attribute affecting commute travel decisions.” Studies commonly elect to simply consider differences in expected travel time. Bhat and Sardesai (2006) investigated mode choice in Austin, Texas and found low deviation in private vehicle travel times increased the likelihood of choosing that mode.

Eboli and Mazzulla (2007) relied on a combination of stated and revealed preference data to estimate a structural model of characteristics that affect rider satisfaction of bus service. Eboli and Mazzulla (2007) estimated bus service reliability to be among the most important factors affecting satisfaction.

Chen et al. (2009) provided an array of dependability metrics, including a bus stop level metric capturing the probability of a bus arrival exceeding a lateness threshold relative to the typical headway. The current study is similarly based on bus stop level analysis, but pulls from a large data set allowing for the derivation of dependability variation across neighbourhoods.

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

Hess et al. (2004) is a unique example of an empirical revealed preference (RP) study looking specifically at willingness to pay for avoided wait time at a bus stop. Hess et al. (2004) found that the student sample in their study were willing to pay only $8.50 per hour for avoided wait time. Hess et al. (2004) does not estimate willingness to pay for avoided uncertainty.

There is a substantial methodological literature regarding the use of AVL bus data to estimate service dependability (Bullock 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 provide meaningful estimates regarding the actual importance of bus dependability on mode choice.

As described by Chang and Stopher (1981) as well as Bonsall (2004), the human motivations underlying travel mode choice are rooted in perceptions of reliability that may have psychological dimensions that are not easily captured in statistical models. The current paper will share this agnosticism to mode choice mechanics. While a causal connection between reliability and mode choice is assumed, the details of the choice mechanism will be abstracted in favour of delivering empirically founded estimates of the partial effect of reliability on mode share.

3. Data

This study will make use of exclusive AVL data of bus locations from NYC across 2016. The Metropolitan Transportation Authority (MTA) is the primary transit operator for NYC. The MTA provides a real-time GPS data feed for bus routes. The purpose of this data feed is to communicate bus arrival information to system users. This study repurposes this resource to construct a historical record of bus locations.

Data collection was executed from January 1, 2016 to December 31, 2016. Collection relies on the proper operation of vehicle GPS equipment, public servers, and internet connectivity, meaning interruptions in any of this infrastructure will cause periods of incomplete data. These events are sufficiently rare that they should not meaningfully affect service dependability estimates, which will be averaged across 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, roughly every 4 minutes. At each check, the system returns a binary observation for each route–stop: 1 if there is a bus of the corresponding route at the stop and 0 otherwise. This method provides panel data for each route-stop, with timestamps indicating when the stop was observed. Data construction relies on the assumption that chronologically sequential observations of a bus at non-sequential stops entails the bus passed the intermediate stop during the time between observations. Instances where bus service is interrupted, or the AVL service is interrupted, result in periods where the gap between subsequent buses may appear artificially long. To clean the data of such outliers, cases where a bus appeared to arrive more than 15 minutes after the most recent scheduled arrival time are dropped from analysis. In order to accord with the study of commuter behaviour, bus arrival statistics will be limited to periods of significant commuting, defined as 6 am to 10 am and 4 pm to 8 pm.

The MTA also 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 particular metrics will be described in the subsequent section.

As of the study period, the MTA bus system was comprised on 307 bus routes. The MTA only provides 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. The fixed-effect, controlled regression approach described in the methodology section will limit the importance of missing routes by basing estimation on observed deviation from scheduled arrivals, while controlling for differences across geographic and demographic dimensions.

Data is collapsed to the census tract level for analysis. Dependability statistics are derived from all observed bus stops within the census tract. Census tract demographic variables are taken from the 2015 American Community Survey (ACS), five-year estimate. The five-year estimate is necessary to provide relevant mode choice variables at the census tract level. Data matching is imperfect temporally as ACS survey responses are gathered between 2011 and 2015, while the AVL data is collected in 2016. The misalignment of data sets necessitates the assumption that neighbourhood composition and mode choice between 2011 and 2015 is a reasonable proxy for these characteristics in 2016. AVL bus data and ACS data are available for 1,535 census tracts within New York City. Table 1 provides summary statistics at the census tract level.

Figure 1 displays the average number of daily buses observed across census tracts. The average tract in the sample saw 617 buses pass through the tract during an average day. Limiting the sample to commuting hours produces an average bus throughput of 278 buses. Both of these measures will serve as covariates in regressions to control for the supply of bus service to the tract.

Table 1: Summary statistics

Variable	Mean	Std. Dev.
Bus mode share	0.118	0.077
Mean lateness	3.86	1.178
Std. dev. of lateness	2.98	0.737
Average daily buses	617.498	464.586
Average rush hour buses	277.779	207.044
Subway entrances	0.944	2.37
Unique subway lines	0.702	1.645
Closest subway station	0.99	1.305
2nd closest subway station	2.062	2.71
Dist. to city hall	12.62	5.911
Population density	19471.234	13037.716
Housing share: detached	0.131	0.186
Housing share: 1 unit attached	0.095	0.116
Housing share: 2 unit attached	0.181	0.149
Housing share: 3-4 unit attached	0.128	0.121
Housing share: 5-9 unit attached	0.069	0.095
Housing share: 10-19 unit attached	0.052	0.064
Housing share: 20-49 unit attached	0.123	0.13
Housing share: 50+ unit attached	0.218	0.248
Population	4050.418	2168.614
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	0.447	0.305
Black pop share	0.261	0.313
Asian pop share	0.138	0.17
Hispanic pop share	0.242	0.215
High school completion rate	0.814	0.119
College completion rate	0.349	0.208
Labor force participation	0.637	0.085
Unemployment	0.093	0.048
Median income	61342.522	30110.678
Median rent	1259.207	421.665
Median home value	572705.668	282783.045
Poverty rate	0.187	0.12
SNAP recipiency rate	0.196	0.147
Share receiving public assistance	0.04	0.036
N	1535	

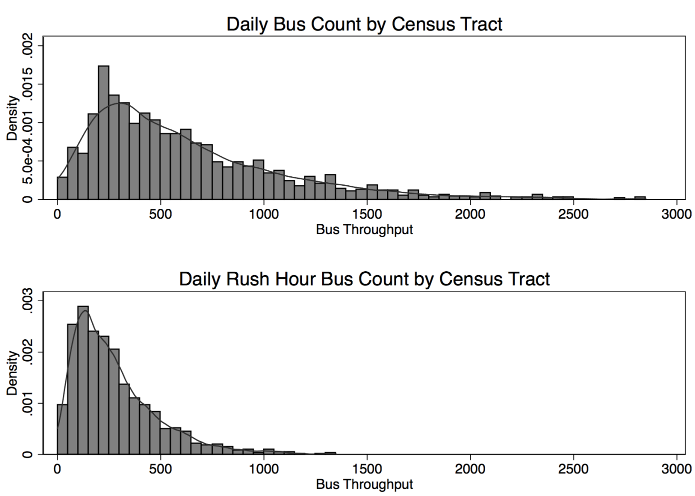

Figure 1: Histograms with kernel density plot overlays.

4. Methodology

The primary approach to capturing bus dependability will be through measurement of the standard deviation of bus lateness. In a scenario where riders have information about past bus dependability, perhaps through personal interaction with the service, there is little disutility derived from a bus which is late by a constant and predictable amount of time. For example, if a route consistently runs five minutes behind schedule, users can internalize this information when forming trip plans. A discussion of such consideration appears in Bates et al. (2001). This assumption seems particularly reasonable given the current study's focus on commuters. For commuters, who attempt identical trips with regularity, consistent lateness will be learned, while volatility will remain a source of disutility. Hensher et al. (2011) points out the potential importance of this type of "conditioning."

This paper will take a regression approach with similarities to Jackson and Jucker (1982) and Senna (1994). The mean lateness of local bus arrivals will be used as a term in regressions. Primarily, the inclusion of mean lateness is to control for otherwise unobserved heterogeneity in bus service characteristics across tracts. This control allows for the more precise identification of the effect of volatility.

The use of a multinomial logit model was investigated, as is typical of mode choice analysis. However, the absence of locationally specific commuter microdata necessitated reliance on aggregated neighbourhood level mode share data. A "BLP" (Berry et al., 1995) framework was considered, however due to limited data on alternative modes, unobserved prices, and the likelihood of strong preference heterogeneity across travellers who select rival modes, BLP could not provide reasonable identification of the effect of dependability.

The variable of interest is local mode share of bus transit. This variable is transformed using an inverse hyperbolic sine transformation. This transformation has similar properties to a log transformation but preserves zero values, of which there are 21 instances out of 1,535 tracts. This transformation substantially increases the R^2 of the model as compared to a linear specification. The transformed dependent mode share variable is distributed roughly normally, suggesting an ordinary least squares (OLS) regression approach should provide reasonable estimates of partial effects.

$$B_i = \alpha + \theta \overline{L_i} + \beta\sigma_i + X_i + \Phi_i + \varepsilon_i \quad (1)$$

Equation 1 provides the basic model to be estimated. B_i is the transformed mode share of bus transit in census tract i, $\overline{L_i}$ is the average observed bus lateness, σ_i is the standard deviation of lateness observations, X_i is a vector of tract specific attributes and Φ_i is a fixed effect for the tract's county. NYC is composed of five counties, which are contiguous with boroughs.

Despite the inclusion of fixed effects, a valid estimation concern will be the possible presence of omitted variable bias. If high bus arrival uncertainty is a result of unobserved heterogeneity between tracts, estimates may be biased. Additionally, the possible presence of reverse causality could mean that high bus ridership is itself affecting bus reliability, conditional on covariates. The most plausible mechanism for reverse causality would be high patronage routes suffering from poor quality service due to delays related to accommodating large numbers of patrons. The presence of reverse causality would not explain results, as it would work in the opposite direction to central findings. To the extent that this mechanism persists in the specification, the results herein are an underestimation of the true effect of bus reliability on mode share.

Controlled regression estimates will be observed to have a strong stability relative to the introduction of control variables, suggesting the model is well identified. However, without truly exogenous variation in bus dependability, concerns over omitted variable bias and reverse causality affecting estimates may persist. Section 6 will extend the methodology to a matching procedure, contrasting tracts that received government investment in improved transit service over the period of study to tracts that did not receive this investment, but were otherwise similar. Results are consistent with variations in dependability causing significant and sizeable mode share effects.

5. Results

Figure 2 shows the mean bus lateness experienced across census tracts. The average tract in the sample experienced a mean lateness of 3 minutes and 52 seconds. The assumptions necessary to infer lateness from the data gathering process suggest a need for caution in assuming unbiasedness in summary results. However, this aggregate bias will be differenced out in the regression procedure.

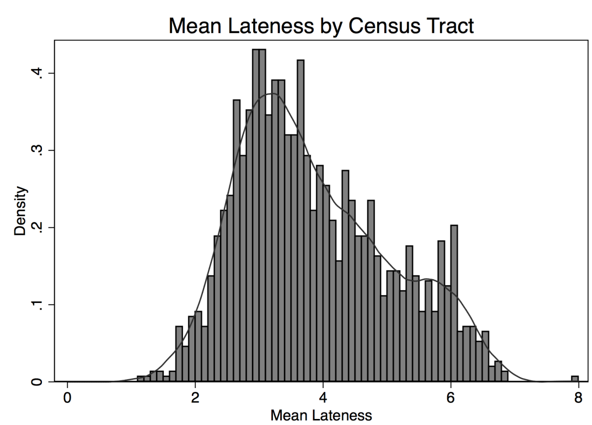

Figure 2: Histogram with kernel density plot overlay.

Figure 3 shows the standard deviation of bus lateness across census tracts. A standard deviation of zero would suggest local buses always arrive off-

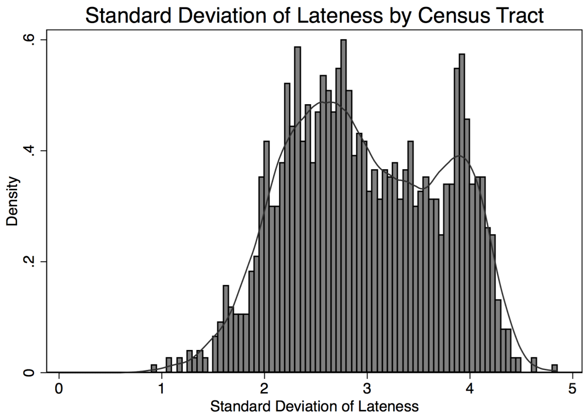

Figure 3: Histogram with kernel density plot overlay.

schedule by precisely the same amount of time. The average tract experiences a standard deviation of bus lateness equal to 2 minutes and 59 seconds.

Table 2 shows the main regression results. Column 1 simply regresses bus mode share on mean lateness ($\bar{L_i}$) and the standard deviation of lateness (σ_i). The effect of uncertainty is highly significant and of the expected direction. To ease interpretation, results will relate prospective partial effects to a hypothetical tract possessing the median bus mode share of 10.7%. Considering the standard deviation of σ_i is 0.737 (44 seconds), the naive estimation of column 1 suggests a one standard deviation decrease in uncertainty (σ_i) correlates with a large rise in bus mode share in the median tract from 10.7% to 21.8%, a 105% increase. The effect of mean lateness is positive, suggesting that tracts with late buses posses a higher bus mode share. A likely contributor to the positive effect is omitted variable bias. Tracts with late buses may share characteristics that correlate with high bus mode share.

Column 2 adds fixed effects for the tract's county. Fixed effects cause a substantial reduction is the estimated effect of bus arrival uncertainty. A one standard deviation reduction in uncertainty in the median tract is now related to a rise in mode share from 10.7% to 15.4%, a 45% increase. The inclusion of fixed effects reduces the effect of mean lateness to a value statistically indistinguishable from zero, consistent with the strong positive effect in column 1 being explainable through omitted variable bias.

The local presence of subway service presents an important alternative mode for riders that should be controlled for. Column 3 adds a vector of public transit controls. Variables for the average number of buses passing through the tract in a day, the number of buses passing through the tract during rush hours, the number of subway entrances within the tract, the number of unique subway lines passing through the tract, the distance from the tract's centroid in km to the closest subway station, the distance to the second closest subway station and the distance to New York's city hall are all entered as controls. The effect of the inclusion of this vector of transit controls further reduces the parameter of interest, reducing the estimated effect of a standard deviation decrease in σ_i to a 33.4% rise in bus mode share.

Column 4 adds a vector of controls for the built environment, detailed in Table 2. Column 5 adds additional controls for local socio-economic conditions. Interestingly, the iterative inclusion of additional controls has very little effect on the central parameter of interest. If results were an artefact of omitted variable bias it would be expected that the inclusion of a large array of control variables would substantially dampen the estimated effect, however, the effect retains its magnitude and strengthens in statistical significance.

The regression with the full set of controls indicates that a one standard deviation decrease in uncertainty would increase bus mode share in the median tract from 10.7% to 14.1%, a 32% increase. As a further interpretation, each minute reduction in the standard deviation of lateness is estimated to increase bus mode share by 46%.

A placebo test is performed on the column 6 regression as a robustness check. The full regression is repeated, but with the replacement of the dependent variable. Rather than bus mode share, subway mode share, private vehicle mode share and cycling mode share are used as the dependent variable in separate regressions (not shown). There is no statistically significant effect of bus reliability on any of the three placebo dependent variables, at the 10% level. This test builds confidence that the estimates are not driven by spurious correlations but are true responses to differing levels of service dependability.

The possibility of reverse causality remains a concern. The marginally positive coefficient on mean lateness is possibly explainable by high bus use causing delays. The negative coefficient on the standard deviation of lateness appears less subject to this explanation; it is not clear that high bus use would cause lowered standard deviation in arrival times. Nevertheless, the following section will utilize a policy change affecting service dependability to establish causality more strongly.

6. Select Bus Service

Beginning in 2008, the MTA began to introduce new high performance bus routes branded as Select Bus Service (SBS). The routes share characteristics with Bus Rapid Transit (BRT) systems. SBS routes included many features meant in improve reliability and speed, including off-board ticketing, multiple door boarding, dedicated bus lanes and greater distances between stops. 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" (New York City Department of Transportation, 2013). The staggered introduction of this service across neighbourhoods offers the possibility of identifying quasi-random variation in bus reliability that may be related to changes in bus ridership.

Table 2: Bus Mode Share, Commuters

	(1)	(2)	(3)	(4)	(5)	(6)
Std. dev. of lateness	-.969**	-.498	-.390	-.428	-.371*	-.380**
	(.231)	(.358)	(.177)	(.173)	(.130)	(.105)
Mean lateness	.665**	.200	.189	.249	.189	.198
	(.205)	(.328)	(.155)	(.158)	(.102)	(.087)
Log daily buses			.228	.173	-.092	-.175
			(.097)	(.136)	(.180)	(.194)
Log rush hour buses			-.048	.013	.234	.317
			(.107)	(.124)	(.173)	(.185)
Subway entrances			-.005	.011	.014	.011
			(.013)	(.015)	(.016)	(.015)
Unique subway lines			-.074*	-.064*	-.053*	-.043
			(.022)	(.020)	(.015)	(.020)
Log dist. to nearest subway stn.			.132*	.191*	.160*	.163**
			(.031)	(.042)	(.050)	(.032)
Log dist. to 2^{nd} nearest subway stn.			.075	.150	.184**	.163**
			(.106)	(.102)	(.045)	(.049)
Log dist. to city hall			.551*	.520*	.359	.277**
			(.167)	(.170)	(.140)	(.039)
Constant	3.208**	3.599**	.989	1.218	.412	1.512
	(.312)	(.262)	(.588)	(2.200)	(1.630)	(1.410)
County FE?	N	Y	Y	Y	Y	Y
Urban form controls?	N	N	N	Y	Y	Y
Age/demographic controls?	N	N	N	N	Y	Y
Socio-economic controls?	N	N	N	N	N	Y
Obs.	1535	1535	1535	1535	1535	1535
R^2	.050	.031	.324	.385	.492	.540

Significance levels: $*$: 5% $**$: 1%. Robust standard errors, clustered at the county level are shown in parenthesis. Urban form controls: population, population density, housing stock composition (share of homes that are detached, single unit, two unit, 3-4 unit, 5-9 unit, 10-19 unit, 20-49 unit, 50+ unit). Age/demographic controls: race and ethnicity shares (white, black, Asian, Hispanic), age shares (<20, 20-34, >65). Socio-economic controls: high school completion rate, college completion rate, labour force participation rate, unemployment rate, median income, median rent, median home value, poverty rate, SNAP recipiency rate, public assistance recipiency rate.

The commuter bus mode share for census tracts that had at least one SBS bus stop during the period of study was 13.1%, while other tracts within New York City demonstrated only a 11.7% share. Furthermore, the standard deviation of lateness was 2.7 minutes for SBS containing tracts and 3.0 minutes for non-SBS tracts. Drawing conclusions from these statistics would be subject to severe omitted variable bias: the decision of where to locate SBS routes was a consequence of local differences in use and demand for bus service, as observed by local transit planners. To overcome this identification barrier, this paper will propose and execute a matching procedure.

This section will consider a tract to be "treated" by SBS if it had at least one SBS designated stop, for at least 50% of the 2011-2015 ACS observation period, there are 90 such census tracts. The matching procedure uses propensity score matching with matches based on neighbourhood form characteristics, demographics, socio-economic conditions and a lagged measure of bus ridership taken from the 2010 5-

year ACS. Matching variables are detailed in Table 3. Treated tracts are compared to three "nearest neighbours," or non-treated tracts that are most similar according to the propensity score matching procedure.

Table 3 displays matching results. Column 1 estimates the effect of SBS treatment on the standard deviation of late times. Results suggest SBS treatment reduced the standard deviation of lateness by a highly significant 0.13 minutes, or 18% of a standard deviation. Column 2 estimates the effect of SBS treatment on bus mode share. Results indicate SBS treatment led to an increase in ridership of 16%. Both estimates are so-called treatment on the treated effects, and would not necessarily apply to tracts that are dissimilar to the treated tracts.

According to Section 5 estimates, a 0.13 minute reduction in the standard deviation of lateness should result in only a 5.2% increase in ridership. The disparity in estimates is consistent with the reality that SBS encouraged ridership through characteristics other than dependability alone, such as reduced travel time and boarding conveniences.

Table 3: Effect of SBS, Matching Method

	Std. dev of Lateness	Bus mode share
	(1)	(2)
SBS treatment	-.134*	.150*
	(.057)	(.060)
# of matches	3	3

Significance levels: * : 5% ** : 1%. Robust standard errors are shown in parenthesis. Estimates show the average treatment on the treated. Matching variables: lagged bus mode share; and all covariates from Table 2, column 6, omitting mean lateness and bus throughput variables, but including county dummy variables.

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). Related literature is generally consistent in finding that initiatives which improve bus service reliability lead to increases in ridership.

7. Conclusion

Low service dependability 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 dependability, there has been scant RP empirical evidence on the relationship between mode choice and measured dependability. This study leverages a large data set on bus locations to provide cross-neighbourhood estimates of the impact of bus dependability on mode share. Regressions suggest uncertainty in bus arrival times put significant downward pressure on bus mode share. The preferred OLS estimation indicates that a one standard deviation reduction in bus arrival uncertainty is related to a 32% increase in bus mode share–increasing mode share in the median tract from 10.7% to 14.1%.

The introduction of SBS in NYC led to observable improvements in bus service reliability and increases in local bus mode share. The quasi-random introduction of SBS allows for an empirical identification strategy that can relate bus dependability to bus mode share.

The proliferation of AVL technology can enable the parameterization of existing theoretical mode choice models through the collection of real vehicle travel data. The coupling of large AVL data sets with established choice theory reveals a promising landscape for future research.

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