Exploring the Impacts of Transit Priority Measures Using Automatic Vehicle Monitoring (AVM) Data

Graham CURRIE, Kelvin Chun Keong GOH, Majid SARVI

Department of Civil Engineering, Monash University, VIC 3800, Australia

Email for correspondence: kelvin.goh@monash.edu

ABSTRACT

This paper measures the operational performance of a series of transit priority initiatives using an empirical analysis of Automatic Vehicle Monitoring (AVM) data on trams in Melbourne, Australia. Very little previous research has modelled factors influencing the performance of priority schemes and none has explored the relative performance of space (or lane) based measures compared to time (or traffic signal) measures.

An after-before comparison of priority schemes showed that on average both space and time priority measures reduced run time (average -0.18 mins or 1.6% and -0.05 mins or 0.005% respectively). They also reduce run time variability. On average, the space based priority measures studied covered 1.97 kms or 61% of average route section lengths. Time based measures covered on average 1.91 or 25% of the junctions on each route section studied.

A regression model explained 83.5% of run time and 51.8% of the variation in run time. The most influential factors affecting running time were; route length (β=0.59), scheduled running time (β=0.41), space priority (β=-0.16), weekday (β=0.09), direction of travel (β=0.07), and time priority (β=-0.03). Results suggest a kilometre of space priority results in a 7.1% reduction in run time whereas a time priority measure at one junction yields a 1.7% decrease in run time. Results also suggest space priority (over 1 km) will reduce run time variability by 10.0% while time priority (at a single junction) will reduce run time variability by 5.4%.

Both space and time priority measures produce a greater effect on run time variability than run time suggesting impacts on service reliability are larger. The paper discusses the implications of these findings on transport policy and explores areas for future research.

Keywords: Running time, Variability, Tram, Automatic Vehicle Monitoring, Operational performance

1 INTRODUCTION

Public Transport (or transit) priority aims to provide a more efficient allocation of road space or time to public transport vehicles because they have higher occupancy levels and lower net emissions per passenger compared to private vehicles (University of Southampton, 2002). There is much evidence that the use of priority initiatives is increasing as a means to address growing congestion in cities (Smith et al., 2005). However a major gap exists in research demonstrating the impacts of specific types of transit priority initiatives. While a handful of before and after studies of the performance of transit priority have been undertaken few are based on a robust statistical analysis. Most studies in the field have been based on simulation tools (e.g. Tétreault and El-Geneidy, 2010, Lee et al., 2005). A major barrier to progress in understanding the impacts of specific transit priority measures is a lack of extensive empirical data upon which initiatives can be assessed.

This paper aims to measure the operational performance of a series of transit priority initiatives using an empirical analysis of Automatic Vehicle Monitoring (AVM) data on trams in Melbourne, Australia. It is part of a wider research program designed to develop new methodologies to optimise the design and implementation of transit priority schemes[1].

This paper starts with a review of previous research with a focus on previous studies examining the performance of priority initiatives and factors influencing on-road public transport operational performance. The research aims are then outlined followed by a description of the Melbourne tram priority case study. The data and analytical methodology is then described followed by a detailing of the major study findings. A discussion and conclusions finalise the paper.

2 RESEARCH CONTEXT

Research literature is reviewed with a focus on empirical studies of factors influencing the operational performance of on-road public transport and specifically those concerned with transit priority schemes.

2.1 Impact of Transit Priority Measures on Transit Performance

There are a wide range of studies of the operational performance of on-road public transport and priority initiatives based on traffic micro-simulation studies (e.g. Tétreault and El-Geneidy, 2010, Lee et al., 2005, Currie et al., 2007, Robertson, 1985, Jepson and Ferreira, 1999). While there are clear experimental benefits of micro-simulation approaches, lack of real world evidence will always act to suggest these approaches are rather theoretical. This paper focuses on the few studies of real world evidence rather than experimental approaches.

Regarding transit priority schemes associated with allocation road space to buses/trams, a wide range of travel time benefits are reported for busways associated with Bus Rapid Transit Systems (e.g. Levinson et al., 2003). However evidence concerning impacts on travel time

[1] *Australian Research Council Industry Linkage Program project LP100100159, 'Optimising the Design and Implementation of Public Transport Priority Initiatives' Institute of Transport Studies, Monash University in association with the Transport Research Group, University of Southampton, UK. The Principal Chief Investigator is Professor Graham Currie the Chief Investigator is Dr Major Sarvi and the Partner Investigator is Dr Nick Hounsell. Mr Goh is one of two APAI PhD students on the project. The Industry Sponsors include VicRoads and the Victorian Department of Transport.*

variability are rare and few of those reported concerning travel time reductions have a strong statistical base (Kimpel et al., 2004).

For rail systems, Van Oort and Van Nes (2009) studied the impact of RandstadRail, a new light rail transit (LRT) system in the Netherlands, that is operated based on a three-step operations control philosophy which includes a range of measures including transit priority at intersections to improve reliability of its service. Since its operations in 2007, the proportion of trips departing with a deviation of between −1 and +1 min has increased from 70% to 95% while the average dwell time improved from 28 to 24 seconds per stop (Van Oort and Van Nes, 2009). While these findings are relevant to the current research they do not specifically relate to transit priority initiatives since a range of wider measures were implemented at the same time including headway management and operations planning measures. Hence it is difficult to isolate the impact of priority measures from this analysis.

The success of traffic signal priority (TSP) initiatives in reducing running time delay for transit vehicles is also widely recognised in the literature. Kimpel at al. (2004) carried out one of the few empirical analysis of bus data using AVM data from TriMet's Bus Dispatch System in Portland, Oregon. In their study, the operational performance was evaluated based on the changes in mean and variance of running times, scheduled running time, passenger wait time and in-vehicle times. The authors found that the expected benefits of TSP are not consistent across routes and time periods, nor are they consistent across the various performance measures. A regression analysis was also carried out to determine the factors that influence running time which included consideration of the impacts of TSP. TSP measures were found to reduce running times by 14.2 seconds per trip, holding all other variables at their mean values. However the authors note that 'In truth, it cannot be stated that this reduction is solely due to TSP since other factors are at least partially responsible for the decrease'. In addition this study did not explore impacts on travel time variability. Interestingly, the study found that mean and variance of headways as well as the on-time performance decreased overall which was primarily due to buses shifting from either on-time or late towards being early. This implies an important need to adjust schedules following priority implementation.

In evaluating the impact of providing signal priority to bus delays, Furth and Muller (2000) tested various signal priority strategies at one of the busiest intersections in Eindhoven and found that providing absolute (full and unconditional) priority to buses could reduce bus delays by as much as 89%. The downside was that delays to the general traffic doubled. Providing conditional priority for buses was found to be more effective, as delays to buses reduced by about 40% while general traffic performance remained generally unchanged. Although this study provides one of the few comprehensive analytical assessments of priority impacts no modelling of the factors driving operational performance including transit priority was undertaken.

Overall therefore it can be seen that there are few empirical studies exploring the drivers of transit priority performance. None have considered the relative influence of road space and time based priority schemes and only one concerns trams (or light rail). However a wider range of empirical studies have examined factors influencing on-road transit run time and its variability.

2.2 Factors Affecting Run Time and its Variability

One of the earliest attempts to understand key factors affecting on road public transit run time, Abkowitz and Engelstein (1983), developed a regression model relating mean running times of two transit routes in Ohio to various explanatory variables and found that segment length, the

number of boarding and alighting passengers, proportion of parking restrictions along the route, number of signalised intersections, time of day and direction of travel were statistically significant in accounting for changes in running time. Route length and the running time deviation upstream were also found to have an influence on running time deviation. Strathman and Hopper (1993) used multinomial logit modelling to assess the contribution of various potential determinants on the on-time performance of buses in the Portland metropolitan area. Amongst the variables that were investigated, the number of boardings, shorter headways, weekday trips and bus driver experience were found to have a positive effect on on-time performance. The number of stops was found to be statistically insignificant but this was reasoned to be redundant due to the strong correlation with passenger activity variables. In a subsequent paper, Strathman et al. (1999) found that route characteristics, direction of travel and time of day had an impact on run time variability.

Analysing the underlying distributions of bus travel and arrival times at timing points has been one avenue used by researchers to understand the causes of travel time variability. Kimpel et al. (2004) have shown that travel time distribution can also be used by transit planners to develop timetables to achieve optimal on-time performance. Mazloumi et al. (2010) also analysed travel time distributions to identify that both earliness and lateness of bus arrival at timing points are also causes of travel time variability. This study used a regression analysis to establish that land use, route length, number of traffic signals, number of bus stops and departure delay relative to the scheduled departure time were factors contributing to the variability of travel time variability.

In general, there is much consistency in factors found to be significant in affecting run time and its variability from the above studies. The only noteworthy exception concerns the weather. Hofmann and O'Mahony (2005), showed that rainy days had significant impact on bus travel time. Travel time variability was also found to be impacted thought to a lesser extent.

Significantly none of the above studies was specifically focused on transit priority initiatives and those that have (reported earlier) are limited in scope and number. This paper aims to address these gaps in knowledge.

3 RESEARCH AIMS

This research aims to examine the effects of two distinct types of priority measures, i.e. space allocation vs. time allocation measures on tram run time and run time variability using an empirical analysis. It also aims to identify key factors that affect the performance of run time and its variability including the relative influence of time and space priority measures.

4 CASE STUDY CONTEXT

4.1 Melbourne Trams

Melbourne has one of the largest tram systems in the world and is also the world largest 'streetcar system' where trams operate in mixed traffic in the middle of roads (Currie and Shalaby, 2007). Melbourne has some 167kms/ 104miles of mixed track running, centre lane operations, and as a result low operating speeds (average speed is 15 kph) and poor service reliability. Poor operating performance is associated with a high level of car ownership and increasing levels of traffic. Car travel in Melbourne is growing at a rate of 1.9% per annum with urban congestion increasing. Tram speeds are reported to have fallen as a result of these factors (Currie and Shalaby, 2007).

Two classes of priority scheme are examined; space allocation and time allocation measures.

4.2 Space Allocation Measures

Transit priority in terms of space allocation involves providing road right of way to transit vehicles. This can be achieved by reallocating existing space to transit or increasing carriageway width to add a new carriageway for transit. Various forms of priority treatments fall under this category. The most common would be a bus lane or transit-way, where road space is allocated for use by transit vehicles. When the highest level of priority is to be accorded to transit vehicles, transit ways are to be used by transit vehicles only, i.e. general traffic would not be permitted to use this road space. At lower priority levels, transit ways could be designed to allow for shared use or exclusive use by transit vehicles only. Other forms of space allocation priority measures include prohibited parking.

In the Melbourne case study area all cases of space allocation are in the form of transit ways provided for trams. All are cases where existing road space is reallocated to trams (rather than expansion of road space) and all are part-time tram lanes operating only in the peak. This includes prohibited parking on the kerbside (called clearways) which increases the available roadspace for traffic. In all cases trams operate in the median or centre lanes of the road. Lanes are not physically segregated, rather yellow lines on the road demark the bounds of the lane. Traffic is permitted to enter the tram lane only to make turns from locations up to 100m from intersections but selected signal priority measures are included in a package of tram lanes to clear turning traffic from the tram right of way in most cases.

4.3 Transit Signal Priority Measures

The application of transit signal priority (TSP) is growing internationally (Smith et al., 2005). Melbourne trams have one of the largest traffic signal priority system in Australasia with over 600 intersections providing active signal priority including early green and extended green phases (Currie, 2006). The system interacts with the SCATS traffic control system (Lowrie, 1992) and has been operating for at least 20 years. As such the technologies used are considered old and potentially outdated. System actuation is based on road based transponders rather than GPS and the priority provided is not conditional; rather early running trams get signal priority and it is provided regardless of the level of congestion at intersections (Currie, 2006).

4.4 Melbourne Tram Priority Measures Studied

A list of priority measures implemented for trams was compiled covering the period from 2005 to 2010 (where AVM data for trams was available). Table 1 shows the schemes identified and the priority treatments they comprise. In total priority schemes from nine tram routes were identified. Figure 1 shows the locations of these routes within Metropolitan Melbourne.

All nine routes radiate from the city centre and operate on a frequency of 4 to 12 minutes (average 7.5 mins) in the morning peak. Three of the priority schemes identified included both space and time (signal) priority while the others had either only space or only time priority. In general all priority initiatives were located on busy inner urban congested streets leading to the busy central business district of Melbourne.

Table 1: Details of Tram Priority Measures Implemented in Melbourne

Route	Priority Measure			Implementation Date
	Description	Time	Space	
24	Part-time tram lane, signal priority and right-turn ban for general traffic at 1 intersection	✓	✓	Apr-10
48		✓	✓	Apr-10
6	Part-time tram lane for city-bound direction and signal priority at 4 intersections	✓	✓	Sep-10
67	Signal priority for tram at 3 intersections	✓		Oct-10
70	Signal priority for tram at 1 intersections	✓		Jan-08
16	Signal priority for tram at 1 intersection	✓		Jan-08
86	Part-time tram lane for city-bound direction		✓	Aug-06
112	Part-time tram lane for city-bound direction		✓	Aug-06
19	Part-time tram lane for both directions		✓	Dec-05
	Number of Routes (Total =9)	6	6	

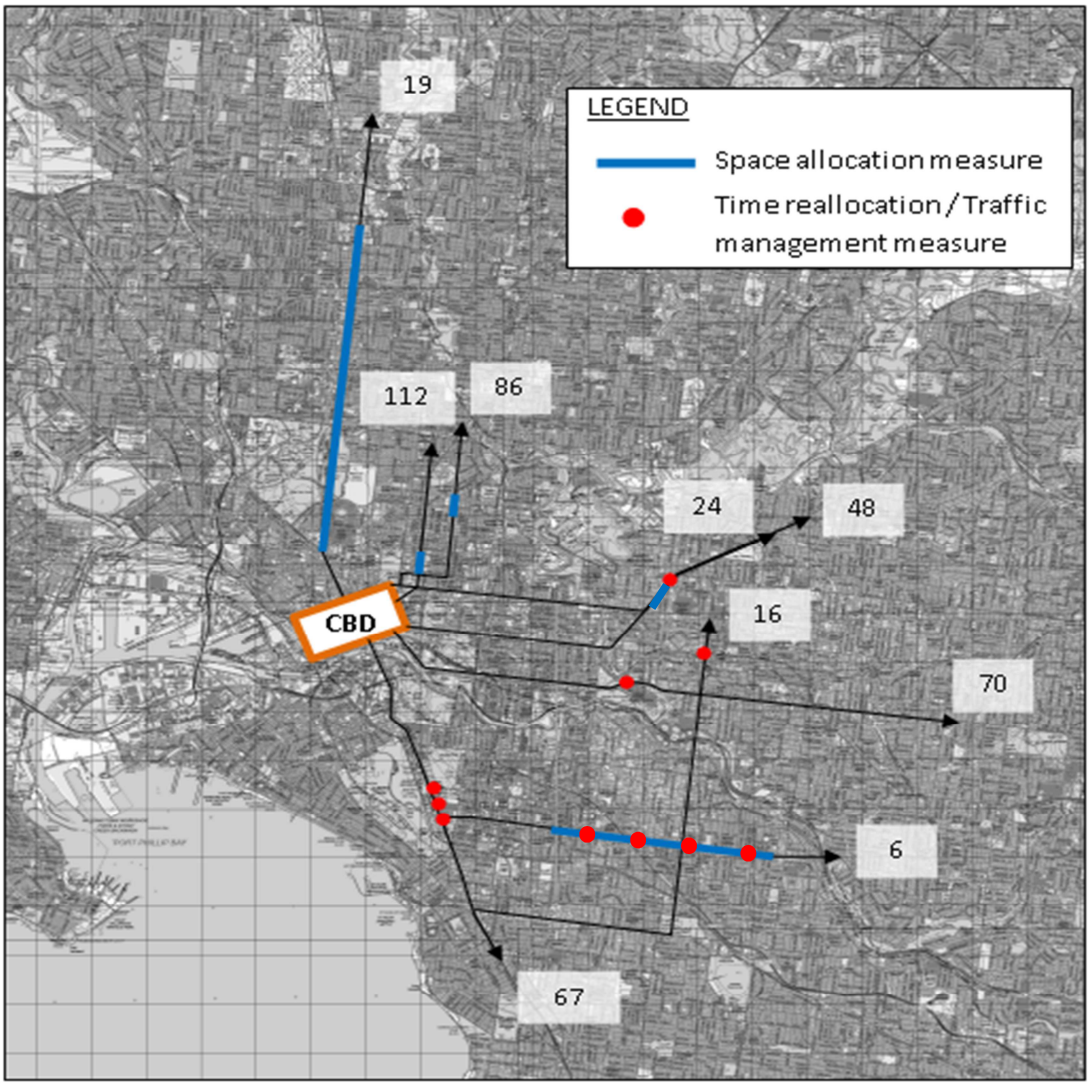

Figure 1: Map of Tram Routes (route numbers indicated) with Priority Measures Implemented (Source: Department of Transport, Victoria)

5 METHODOLOGY AND DATA

5.1 Data

AVM system data was collated for a month's worth of morning peak period (07:00 to 09:00hrs) tram travel time for both direction of travel in each of the "before" and "after" periods. AVM data for the start and ending timing points for each route were selected covering the nearest geographical locations to the route sections where priority measures were implemented. To account for any possible seasonality effect, the same month was used in the "before" and "after" period. To cater for any ramp up in operation, the month selected was also at least three months before and after the implementation of the priority measure. In total, travel data from 11,959 completed trips were used.

5.2 Measures

To establish the average run time of all trips by direction of travel and time period in a route, the recorded arrival and departure times of trams at timing points along the stretch under study were extracted and computed (Equation 1). Various measures for travel time variability have been used in the literature. For this study, the more commonly used measure, standard deviation of travel times, is used (Equation 2):

$$Mean\ Run\ Time,\ \theta_{rdwp} = \frac{1}{M}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\left(TOA\right)_{n+1} - \left(TOD\right)_{n}\right)_{m} \tag{1}$$

$$Run\ Time\ Deviation,\ Dev(\theta_{rdwp}) = \sqrt{\frac{1}{M-1}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\left(TOA\right)_{n+1} - \left(TOD\right)_{n}\right)_{m} - \left(\theta_{rdwp}\right)_{m}} \tag{2}$$

where θ_{rdwp} = Run time for route r in direction d, day of week w and period p
TOA = Time of Arrival at timing point
TOD = Time of Departure at timing point
n = Timing point number
m = run number

5.3 Analytical Approach

Two analysis methods were employed. Firstly data was compiled for before and after priority periods and average performance measures computed and compared to assist in understanding the general characteristics of the data.

Secondly a regression based analysis model was developed with the aim of establishing the relative influence of space and time priority measures relative to other influences on operational performance. Two models were developed, one exploring the relative influences on run time and the other on run time variability.

The models for run time and run time variability were set up using the results from equations (1) and (2) as dependent variables. The independent variables, which capture route and temporal characteristics as well as account for the effects of implementing priority treatments, were chosen for inclusion in these models based on the literature. (Abkowitz and Engelstein, 1983, Strathman and Hopper, 1993, Tétreault and El-Geneidy, 2010, El-Geneidy et al., 2011). The definition and description of each variable are tabulated in Table 2, while reasons for considering the independent variables and expected results are discussed in the following paragraphs.

Table 2: Definition and Description of Variables used in the Regression Models

Variables	Description
Dependent Variables	
Model 1: RT	Average Run Time (min) Equation 1
Model 2: RTDev	Run Time Deviation (min) Equation 2
Independent Variables	
DIST	Section Length (km)
JUNCTS	Number of signalised junctions along section under study
SCH	Scheduled travel time along section based on timetable (min)
RAIN	Average rainfall amount per day (mm)
INBOUND	Direction of travel (1 if city-bound and 0 otherwise)
WKDAY	1 if weekday (Monday to Friday) and 0 otherwise
SPACE	Length of priority provided along corridor of tram's route (km)
TIME	Number of priority measures provided along tram's route

Route section length (DIST) and the number of junctions (JUNCTS) are route characteristics that have consistently been shown to be significant in determining run time and its variability (Abkowitz and Engelstein, 1983, Strathman and Hopper, 1993, Tétreault and El-Geneidy, 2010, El-Geneidy et al., 2011). For the former, it is theorised that longer section lengths would lead to longer run times and increased run time variability, given that the tram would need to overcome greater distance including factors such as roadside friction caused by parked vehicles, entering and exiting traffic from side roads, etc. A larger number of junctions on a route, is assumed to result in slower run times and larger variation in on-time arrivals at timing points, hence increasing run time variability. As such, positive signs are expected for both coefficients.

Tram drivers are also strongly influenced by pre-defined scheduled travel time between timing points in how they operate trams. Given that the scheduled time for travelling along a same stretch of route differs in this study, a variable SCH is included to account for any behavioural influence which tram drivers might exhibit to explore if this acts to affect run time. Longer run times and larger run time variability is expected with increasing scheduled times.

Previous research also indicates that rainy days (RAIN) have a negative impact on ridership and travel time (Guo et al., 2007, Hofmann and O'Mahony, 2005). In terms of run time, it is expected that rainy days would cause tram drivers to be more cautious and slow down. As for run time variability, it could be argued that rainy days resulting in reduced ridership would lead to greater variations in run time, as trams would arrive at the next timing point earlier. However, the increased congestion on roads caused by the rain could negate this effect. For this study, run time variability is expected to reduce on rainy days.

The direction of travel (INBOUND) was also included in the list of variables to account for the likelihood that outbound travel conditions would be more favourable than inbound (city-bound). A dummy variable is used to define the trip, with 1 indicating the inbound direction and 0 outbound. In line with past research (Abkowitz and Engelstein, 1983), a negative correlation is expected between run time / run time variability and run time on inbound trips with all other things being equal. The same reasoning applies and results expected for trips made during a weekday vs weekend.

The implementation of priority measures for trams is addressed by the use of dummy variables with separate measures for space priority measures (SPACE) and time or signal priority measures (TIME). It is hypothesized that both space and time priority measures bring about

favourable traffic conditions for tram operations and therefore lead to reduced run times and run time variability. All other factors that are not taken into account are captured in the constant variable in the models. These include patronage, traffic flow, accidents and driver characteristics. While these variables are known to influence operational performance they remain unexplored in this analysis due to time and data access limitations.

Two least-squares, linear regression models were developed to relate the two outcomes (run time and run time variability) to the set of independent variables in Table 2. A base model, where all variables are included, is firstly adopted then a backward stepwise selection technique was used to discard insignificant variables until only significant variables exist in the final model. The adjusted R^2 is used to assess the overall statistical fit of the models.

For comparative purposes, alternative model formulations explore different variable combinations for the final model.

Analyses also considered the linear model assumptions of linearity, homoscedasticity and normality. To ensure these are concerns are not violated, variables with VIF values exceeding ten were deemed to be highly correlated with other variable(s) and disregarded. The models were also subjected to a White's Test to ensure no heteroscedasticity exists and scatterplots of the dependent variable and independent variables were examined to ensure they were evenly distributed.

6 RESULTS

6.1 Before/After Descriptive Data Analysis

Table 3 shows a summary of average before and after space and time priority initiatives using measures of performance (run time and run time variability) and measures of descriptive data for each of the explanatory variables examined in the analysis (Table 2). Table 3 also shows the scale of source data records available for each section of the analysis.

Table indicates that:

- On average both space and time priority measures show a reduction in run time between the after and before periods.
- Space based priority measures achieve a higher net reduction in run time with average run time reductions more than three times larger for space based initiatives, (average -0.18 mins) than time based measures (-0.05 mins).
- In percentage terms, space based measures on average reduced run times by 1.6% and time based measures by half of one percent.
- Both space based and time based priority initiatives act to also reduce run time variability with again a higher reduction for space based measures (average -0.14) than time based measures (-0.03).
- To put the above into perspective, average space based priority measures covered 1.97 kms or 61% of average route section lengths. Time based measures covered on average 1.91 or 25% of the junctions on each route section studied. From this observation, the larger operational impact of space based measures might be as expected given their relative scale.
- There is a relatively even spread of records in the before and after periods and also for space and time priority initiatives. With almost 12,000 records, the analytical basis of the data is considered robust.

Table 1: Average Descriptive Statistics of Tram Trips – Before/After Priority Measures

	Priority Measures					
	Space Priority		**Time Priority**		**Total**[1]	
Number Recorded Vehicle Trips						
Before	3,475		3,686		5,960	
After	3,501		3,678		5,999	
Total	6,976		7,364		11,959	
BEFORE THE INTRODUCTION OF PRIORITY MEASURES						
Regression Explanatory Variables						
Descriptive Statistics – Discrete	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Run Time (RT, min)	11.59	6.61	10.37	5.58	11.90	6.04
Run Time Deviation[2] (RTDev mins)	1.37	0.71	1.58	1.13	1.63	1.01
Section Length (DIST, km)	3.24	1.81	2.93	1.34	3.28	1.51
Number of Junctions (JUNCTS)	9.56	6.46	7.58	4.88	9.34	5.80
Scheduled Time (SCH, mins)	12.81	6.81	10.35	4.78	12.37	5.94
Rainfall/Day (RAIN, mm)	1.45	4.42	1.83	4.24	1.72	4.46
Space allocation measure (SPACE, km)	-	-	-	-	-	-
Time measure (TIME, junctions)	-	-	-	-	-	-
Descriptive Statistics – Boolean	**Number of Recorded Vehicle Trips**					
City-Bound (INBOUND=1)	2,842		2,411		4,201	
Out-Bound (=0)	633		1,275		1,759	
Weekday(WKDAY=1)	3,029		3,045		5,070	
Weekend(=0)	446		641		890	
AFTER THE INTRODUCTION OF PRIORITY						
Descriptive Statistics – Discrete	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Run Time (RT, min)	11.41	6.42	10.32	5.52	11.79	5.84
Run Time Deviation[2] (RTDev mins)	1.23	0.63	1.55	1.18	1.57	1.04
Section Length (DIST, km)	3.32	1.82	2.94	1.33	3.33	1.52
Number of Junctions (JUNCTS)	9.85	6.53	7.58	4.85	9.48	5.85
Scheduled Time (SCH, mins)	13.14	7.11	10.36	4.71	12.53	6.14
Rainfall/Day (RAIN, mm)	1.24	4.08	2.44	5.42	1.64	4.41
Space allocation measure (SPACE, km)	1.97	1.83	0.41	0.91	1.15	1.70
Time measure (TIME, junctions)	0.90	1.38	1.91	1.05	1.17	1.24
Descriptive Statistics – Boolean	**Number of Recorded Vehicle Trips**					
City-Bound (INBOUND=1)	2,786		2,402		4,161	
Out-Bound (=0)	715		1,276		1,838	
Weekday(WKDAY=1)	3,049		3,085		5,126	
Weekend(=0)	452		593		873	
CHANGE IN DISCRETE VARIABLE STATISTICS – BEFORE AND AFTER[3]						
Descriptive Statistics – Discrete	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Run Time (RT, min)	-0.18	-0.19	-0.05	-0.06	-0.11	-0.20
Run Time Deviation[2] (RTDev mins)	-0.14	-0.08	-0.03	0.05	-0.06	0.03
Section Length (DIST, km) [4]	0.08	0.01	0.01	-0.01	0.05	0.01
Number of Junctions (JUNCTS)[4]	0.29	0.07	0.00	-0.03	0.14	0.05
Scheduled Time (SCH, mins)	0.33	0.30	0.01	-0.07	0.16	0.20
Rainfall/Day (RAIN, mm)	-0.21	-0.34	0.61	1.18	-0.08	-0.05
Space allocation measure (SPACE, km)	1.97	1.83	0.41	0.91	1.15	1.70
Time measure (TIME, junctions)	0.90	1.38	1.91	1.05	1.17	1.24

Note: (1) - Given that some routes had both space and time measures, figure reported in this column will not relate to those reported under the space allocation and time / traffic management measures.

(2) – Standard deviation of run time, as computed in equation (2).

(3) - Changes in section length, number of junctions and scheduled time are due to unequal number of trips in the before and after periods

(4) – Some variables appear to make unusual changes in the after period e.g. increases in number of junctions or changes in section length. This is due to changes in the service levels of trams in the after period. It results in a changes in computed averages and does not reflect changes in actual junctions or route lengths

6.2 Modelling Results

Tables 4 and 5 summarize the results of the run time and run time variability models respectively.

Table 4: Results of Mean Running Time Model

Variables (X_i)	Model 1: ln(RT) = Constant + f(Xi)		
	Base	Model 1A	Model 1B
Constant	0.964	0.964	0.897
DIST	0.240	0.240(0.594)	0.387(0.956)
JUNCTS	#	#	#
SCH	0.041	0.041(0.406)	-
RAIN	^4.8×10^{-5}	-	-
INBOUND	0.097	0.097(0.073)	0.120(0.09)
WKDAY	0.146	0.146(0.085)	0.273(0.159)
SPACE	-0.074	-0.074(-0.162)	-0.064(-0.14)
TIME	-0.017	-0.017(-0.03)	-0.041(-0.07)
Goodness of Fit			
Adjusted R^2	0.835	0.835	0.813

Note: # - JUNCTS disregarded due to high correlation with DIST
Figures in parenthesis are standardized coefficient (β) values
Except for ^, all coefficient values presented above are significant at P<0.05

Table 5: Results of Running Time Deviation Model

Variables (X_i)	Model 2: ln(RTDev) = Constant + f(Xi)		
	Base	Model 2A	Model 2B
Constant	-0.433	-0.436	-0.466
DIST	0.151	0.150(0.458)	0.217(0.661)
JUNCTS	#	#	#
SCH	0.019	0.019(0.228)	-
RAIN	^-0.001	-	-
INBOUND	0.162	0.162(0.151)	0.173(0.161)
WKDAY	0.506	0.506(0.363)	0.564(0.405)
SPACE	-0.105	-0.105(-0.283)	-0.100(-0.27)
TIME	-0.054	-0.055(-0.117)	-0.065(-0.14)
Goodness of Fit			
Adjusted R^2	0.518	0.518	0.511

Note: # - JUNCTS disregarded due to high correlation with DIST
Figures in parenthesis are standardized coefficient (β) values
Except for ^, all coefficient values presented above are significant at P<0.05

Results are presented for the base models, where all variables are included, and final models (1A/B and 2A/B) which only comprise variables that are found to be statistically significant. Results of the VIF values showed that the DIST and JUNCTS variables were highly correlated. Hence, the latter was dropped in both the base and final models. In addition, the dependent variables RT and RTDev had to be log-transformed to ensure normality in the regression models.

Overall, the Model 1A and 2A modes explained more variability in the data; 83.5% of run time data and 51.8% of run time variability data.

The following variables are the most influential on running time (in order of relative significance); route length (β=0.59), scheduled running time (β=0.41), space priority (β=-0.16), weekday (β=0.09), direction of travel (β=0.07), and time priority (β=-0.03).

The following variables are the most influential on running time variability (in order of relative significance); route length (β=0.46), weekday (β=0.36), space priority (β=-0.28), scheduled running time (β=0.23), direction of travel (β=0.15), and time priority (β=-0.12).

Previous research (Hofmann and O'Mahony, 2005, Mazloumi et al., 2010) suggests that more rainfall leads to longer run times and acts to lower run time variability. Findings in this analysis were generally consistent with these patterns however rainfall was found not to be a statistically significant so was omitted in the final output models.

It is possible to generalise the findings of the models to estimate the generalised effects of different types of priority initiative:

- Based on results from Model 1A, a kilometre of space allocation priority measure results in a change of $\exp^{-0.074}$ or a 7.1% reduction in run time whereas a time related measure at one junction yields a change of $\exp^{-0.017}$ or a 1.7% decrease in run time.
- Similar observations can be made in the model 2A, where the impact of providing a unit space allocation and time measure result in a 10.0% and 5.4% reduction in run time variability.
- The results also suggest that the benefits of implementing space allocation outweighs that of time measures on a per unit basis however units (kms of bus lane or a junction of signal priority) are not necessarily comparable. Certainly in the source data the extent of space priority measures implemented is larger than the time priority measures hence larger impacts might be expected.
- Another noteworthy observation is that both sets of space and time priority measures produce a greater effect on run time variability than run time. This is an interesting observation because, as noted earlier, it is common to omit measurement of run time variability effects of priority schemes when it can be argued these are more influential to critical issues such as transit operational reliability.

7 DISCUSSION AND CONCLUSIONS

This paper measures the operational performance of a series of transit priority initiatives using an empirical analysis of Automatic Vehicle Monitoring (AVM) data on trams in Melbourne, Australia. A review of the research literature has established very few analytical studies using a robust data set which have attempted to model factors influencing the performance of priority initiatives on operational run time or run time variability. None have explored the relative impacts of space (or lane based) priority and time (or signal based) priority. None have concerned the performance of priority on tram or streetcar systems.

Data including some 11,959 AVM run time records for priority measures on 9 tram routes covering a representative month before and after the implementation of priority initiatives. Two analyses were undertaken including a descriptive analysis of the average impact of priority schemes and a least squares regression model exploring factors influencing run time and run time variability including space priority measures, time priority measures and other variables

including section length, rain, scheduled running time, the number of junctions, direction of travel and day of week.

The descriptive analysis of after-before comparisons of priority schemes showed that on average both space and time priority measures reduced run time. Space based priority measures achieve a higher net reduction in run time with average run time reductions (average -0.18 mins or -10.8 seconds more than three times larger than time based initiatives, (-0.05 mins or -3 seconds). In percentage terms, space based measures on average reduced run times by 1.6% and time based measures by half of one percent. Both space based and time based priority initiatives act to also reduce run time variability with again a higher reduction for space based measures (average -0.14) than time based measures (-0.03). To put the above into perspective, average space based priority measures covered 1.97 kms or 61% of average route section lengths. Time based measures covered on average 1.91 or 25% of the junctions on each route section studied. On this basis, the larger operational impact of space based measures might be as expected given their relative scale.

The best performing regression model explained 83.5% of run time data and 51.8% of run time variability data. The most influential factors affecting running time were (in order of relative significance); route length (β=0.59), scheduled running time (β=0.41), space priority (β=-0.16), weekday (β=0.09), direction of travel (β=0.07), and time priority (β=-0.03). Results suggest a kilometre of space allocation priority measure results in a 7.1% reduction in run time whereas a time related priority measure at one junction yields a 1.7% decrease in run time.

The most influential factors explaining running time variability were (in order of relative significance); route length (β=0.46), weekday (β=0.36), space priority (β=-0.28), scheduled running time (β=0.23), direction of travel (β=0.15), and time priority (β=-0.12). Results suggest that providing a unit of space priority measures (over 1 km) will reduce run time variability by 10.0% while a unit of time priority (at a single junction) will reduce run time variability by 5.4%.

Both space and time priority measures produce a greater effect on run time variability than run time.

There are numerous ways in which research of this type can be expanded. Firstly there is considerable scope to expand the range of schemes to which such methods can be applied to increase our understanding of the operational performance of priority measures. Secondly there is much scope to explore a wider range of explanatory measures which might act to explain operational performance outcomes from priority schemes. Ridership, stop dwell time and traffic volume data would be useful additions to the regression models. Thirdly and lastly there would be much scope to explore the performance of individual types priority measures to a higher degree of detail and at a more disaggregate level. This is an aim of the wider research program of which this paper is a part. However due to a lack of monitoring data and the limited number of individual priority schemes of specific types, the research program will explore these issues using a micro-simulation approach.

Overall the paper has provided a more robust basis for estimating the benefits achieved in providing both space and time based priority measures. Continued research of this type is required to support the case for investments in transit priority to address the considerable future mobility challenges expected in cities worldwide.

8 ACKNOWLEDGEMENT

The authors would like to thank the Australian Research Council for financial support of the research and also to the Victorian Department of Transport and VicRoads for both providing financial and information relating to the tram priority measures implemented in Melbourne. Appreciation also goes to the Bureau of Meteorology for supplying the weather data used in this research. The team would also like to thank the Land Transport Authority of Singapore for providing Mr Gohs time inputs to the research. We would also like to thank Alexa Delbosc for assistance in reviewing technical aspects of the paper. Any omissions or errors in the paper are the responsibilities of the authors.

9 REFERENCES

ABKOWITZ, M. D. & ENGELSTEIN, I. 1983. Factors affecting running time on transit routes. *Transportation Research Part A: General,* 17**,** 107-113.

CURRIE, G. 2006. Assessing Australian Transit Signal Priority Against World Best Practice. *Australian Road Research Board National Conference.* Canberra, Australia: ARRB.

CURRIE, G., SARVI, M. & YOUNG , W. 2007. A New Approach to Evaluating On-Road Public Transport Priority Projects: Balancing the Demand for Limited Road Space. *Transportation,* Volume 34 Number 4 pp 413-428.

CURRIE, G. & SHALABY, A. 2007. Success and Challenges in Modernising Streetcar Systems – Experience in Melbourne and Toronto. *Transportation Research Record,* Volume 2006**,** pp 31-39

EL-GENEIDY, A. M., HORNING, J. & KRIZEK, K. J. 2011. Analyzing transit service reliability using detailed data from automatic vehicular locator systems. *Journal of Advanced Transportation,* 45**,** 66-79.

FURTH, P. G. & MULLER, T. H. J. 2000. Conditional bus priority at signalized intersections: Better service with less traffic disruption. *Transportation Research Record***,** 23-30.

GUO, Z., WILSON, N. & RAHBEE, A. 2007. Impact of Weather on Transit Ridership in Chicago, Illinois. *Transportation Research Record: Journal of the Transportation Research Board,* 2034**,** 3-10.

HOFMANN, M. & O'MAHONY, M. The impact of adverse weather conditions on urban bus performance measures. Intelligent Transportation Systems, 2005. Proceedings. 2005 IEEE, 13-15 Sept. 2005 2005. 84-89.

JEPSON, F. & FERREIRA, L. 1999. Assessing Travel Time Impacts Of Measures To Enhance Bus Operations *Road & Transport Research* Vol 8 No 4 Dec 1999 pp 41-54.

KIMPEL, T., STRATHMAN, J., BERTINI, R., BENDER, P. & CALLAS, S. 2004. Analysis of transit priority using archived TriMet bus dispatch system data. *Transportation Research Board 82nd Annual Meeting***,** 156-166.

LEE, J., SHALABY, A., GREENOUGH, J., BOWIE, M. & HUNG, S. 2005. Advanced Transit Signal Priority Control with Online Microsimulation-Based Transit Prediction Model. *Transportation Research Record: Journal of the Transportation Research Board,* 1925**,** 185-194.

LEVINSON, H. S., ZIMMERMAN, S., CLINGER, J., GAST, J., RUTHERFORD, S. & BRUHN, E. 2003. TCRP Report 90: Bus Rapid Transit. Washington DC: Transportation Research Board of the National Academies.

LOWRIE, P. R. 1992. SCATS - A Traffic Responsive Method of Controlling Urban Traffic. Sydney, Australia: Traffic Authority of NSW.

MAZLOUMI, E., CURRIE, G. & ROSE, G. 2010. Using GPS Data to Gain Insight into Public Transport Travel Time Variability. *Journal of Transportation Engineering,* 136**,** 623-631.

ROBERTSON, G. D. 1985. BLAMP - AN INTERACTIVE BUS LANE MODEL. *Traffic Engineering & Control,* 26**,** 366-369.

SMITH, H. R., HEMILY, B. & IVANOVIC, M. 2005. *Transit Signal Priority (TSP): A Planning and Implementation Handbook*, ITS Amercia, Washington D.C.

STRATHMAN, J., DUEKER, K., KIMPEL, T., GERHART, R., TURNER, K., TAYLOR, P., CALLAS, S., GRIFFIN, D. & HOPPER, J. 1999. Automated Bus Dispatching, Operations Control, and Service Reliability: Baseline Analysis. *Transportation Research Record: Journal of the Transportation Research Board,* 1666**,** 28-36.

STRATHMAN, J. G. & HOPPER, J. R. 1993. Empirical analysis of bus transit on-time performance. *Transportation Research Part A: Policy and Practice,* 27**,** 93-100.

TÉTREAULT, P. R. & EL-GENEIDY, A. M. 2010. Estimating bus run times for new limited-stop service using archived AVL and APC data. *Transportation Research Part A: Policy and Practice,* 44**,** 390-402.

UNIVERSITY OF SOUTHAMPTON 2002. Public Transport Priority: State of the Art Review. *PRISCILLA Bus Priority Strategies and Impact Scenarios - Deliverable 2.* University of Southampton.

VAN OORT, N. & VAN NES, R. 2009. Control of public transportation operations to improve reliability: Theory and practice. *Transportation Research Record***,** 70-76.