Journal of the Eastern Asia Society for Transportation Studies, Vol.11, 2015

Effects of Two Fare Policies on Public Transport Travel Behaviour: Evidence from South East Queensland, Australia

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Abstract: Congestion and peak loading are key concerns for public transport agencies in Australian cities. Two fare policies, off-peak discounts and volume rebates, have been adopted in South East Queensland (SEQ) attempting to alter passengers' travel behaviour. This research examines how these two fare policies have changed passengers' travel patterns by using newly available smart card data from automated fare collection systems. The findings indicate that current off-peak discounts do not significantly alter passengers' boarding times or encourage peak spreading. Volume rebates, however, do provide incentives to encourage more use of public transport, implying that this could be a way to reduce traffic congestion should most of the additional trips be diverted from other modes. The paper concludes with suggestions for additional, more sophisticated policies to ease congestion and peak loading.

Keywords: Fare Policy, Public Transport, Smart Card Data, Travel Behaviour.

1. INTRODUCTION

Congestion and peak loading are simultaneous but distinct public transport service problems in many cities. The search for low-cost 'solutions' to such problems is a continuing challenge for transport operators/planners and policy makers. Major Australian cities have sought to increase transport infrastructure investment to increase peak hour capacity. But major road, rail and bus rapid transit investments are expensive. Investments can be deferred if more efficient use of existing public transport infrastructure is made, and options to increase these efficiencies are of growing importance (Palma and Lindesy, 2002; Merugu et al., 2009; Gomes et al., 2012). In Australia, many travel behaviour change initiatives were introduced in the late 1990s and early 2000s as part of travel demand management (TDM) programs (Meyer, 1999; Garling et al., 2002; Hensher and Puckett, 2007). These included measures to encourage changes in public transport travel behaviour.

Two specific fare policies were applied in South-East Queensland (SEQ) Australia: Off-peak discount, and Volume rebates (see Table 1). The main method for shifting peak demand on public transport has been the use of fare discounts for the off-peak period. The regional transit authority Translink offers 20% fare discounts in

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off-peak periods. In addition, a volume rebates policy is also used to encourage public transport usage and mode shift from private to public transport, introduced as part of the introduction of the 'Go-card' smart-card electronic ticketing, which allows passengers to travel on all TransLink bus, train, ferry and light rail services in SEQ.

Table 1. Go-card fare policies in SEQ

Policies	Details
Off-peak discounts	Off peak travel is 20 per cent lower than peak travel. [Travelling between 9:00am* and 3:30pm, after 7:00pm on weekdays and all day on weekends and on public holidays provides a 20 per cent saving on the Go-card fare.]
Volume rebate	Travel for free after the 9th paid journey in a 7-day period from Monday to Sunday, regardless of zones travelled.

Source: TransLink

* An extra 30 minutes was added to the off-peak morning period in March, 2014 when the definition of morning peak time zone from TransLink was changed to trips that start between 3:00am to 8:30am.

In the public transport literature, transport policies are viewed as a path to deliver sustainable transport (Legacy et al., 2012). Much of the research has focused on how public transport policies may transfer across jurisdictions (MacKinnon et al., 2008; Marsden and Stead, 2011; Lucas, 2012); decision support systems for fare policy analysis (Elvik and Ramjerdi, 2014); and choice modelling and other analysis of specific public transport policies that may assist mode shift (Palma and Lindesy, 2002; Taylor, 2007; Merugu et al., 2009; Bamberg et al., 2011; Gomes et al., 2012; Redman et al, 2013). To encourage public transport usage, evidence exists supporting the use of differentiated fare policies (Glaister, 1974; Redman et al, 2013), service frequency adjustments (Jansson, 1993) and capacity improvements (Arnott et al., 1993), and there may also be value in communications campaigns, other service quality changes, parking improvements supporting transit, and in provision of feeder services (Henn et al. 2010). In the literature on fare policies, Glaister (1974) identified optimal fare levels for the two distinct problems of congestion and peak loading, focusing on generalized consumer surplus. Cervero (1981; 1990) showed how flat fare policies were inequitable, and that differentiation by time of day and by distance can not only create more just fare arrangements, but also stimulate desired behaviour changes. Taylor (2007) showed how policies such as fare discounts have been applied in Australia to achieve both these ends.

Methodologically, many researchers have used laborious travel surveys to calibrate the effectiveness of fare policies (for example, Meyer, 1999; Garling et al., 2002; Hensher and Puckett, 2007). There are many well-known challenges regarding the validity of such surveys (does the survey itself change behavior, differing response rates, coding, questionnaire design and self-selection through the recruitment process, etc., see Stopher et al., 2007). The advent of automated fare collection technologies in the form of public transport smart cards and the availability of transaction data provides a more reliable way to evaluate efficacy of fare discount policies in lieu of conventional travel surveys.

The objective of this paper is to explore the effects of the two principal features of the fare policies applied in SEQ, using smart card transaction records. The research hypotheses are: *i)* that the off-peak fare discount policy will have peak spreading effects and relieve peak load pressures; and, *ii)* the volume rebates policy will have positive effects in encouraging more passengers to use public transport.

The paper is structured as follows. The next section provides a review of previous research on travel behaviour evaluations using public transport smart card data. This highlights issues to be considered and sets out the contribution of this paper. Following is a description of the SEQ transport study area together with a summary of the current fare systems and the methods and data of the paper. The penultimate section provides the results together with interpretations. The paper concludes with discussions and avenues for further research.

2. UNDERSTANDING TRAVEL BEHAVIOUR USING SMART CARD DATA

Recently, many studies have used smart card data to examine public transport issues, including public transport policies (Blythe, 2004; Bagchi and White, 2005; Trepanier and Morency, 2010), travel behaviour (Bagchi and White, 2004; Seaborn et al., 2009; Munizaga et al., 2010), operational performance (Morency et al., 2007), and fare policies (Pelletier et al., 2011). Pelletier et al. (2011) reviewed the use of smart card data for strategic, tactical and operational purposes. Automated fare collection systems via smart cards are increasingly being adopted by public transport agencies around the world giving rise to a new travel data source that can provide managers and/or operators with continuous trip data covering longer time periods than a traditional diary survey.

Bagchi and White (2005) identified the potential role of smart card data for travel behaviour analysis. With clear data definitions, smart card systems can provide access to larger volumes of personal travel data; link data to the individual card and/or traveller; obtain trip factors; and identify customer types (Bagchi and White, 2005). Morency et al. (2007) adopted data mining techniques to identify transit use cycle and travel patterns among card segments and to measure travel patterns for different types of passengers. These studies confirm the applicability of using smart card data for understanding travel behaviour/patterns. Pelletier et al. (2011) also highlight the potential to identify multiple links for smart card data and strategic planning with fare policies for public transport being one area of potential, such as fare reductions or volume rebates.

The literature is sparse in terms of the use of smart card data to evaluate fare policies and specifically those policies designed for peak spreading and mode shift. This is the focus of this paper, particularly for commuters. The next section presents the characteristics of the case study area in SEQ, Australia.

3. THE SEQ TRANSPORT SYSTEM

The SEQ region is in the Australian state of Queensland and has an urban population of 3.1 million (Australian Bureau of Statistics, 2015). Since the 1970s, three rapidly growing urban areas, including Brisbane, Gold Coast and the Sunshine Coast, have merged into a 200-km long city within the region (Spearritt, 2009). Public transport in SEQ is well developed and the systems comprise rail, bus, ferry, and tram services. Figure 1 shows the TransLink SEQ service areas and fare zones. TransLink, established in 2004, is a Queensland Government agency which manages public transport services covering Brisbane and SEQ. Public transport fares are integrated across all public transport modes, except for taxi, in the SEQ region. In 2008, a smart card ticketing system was introduced, branded the ‘Go-card’, which allowed passengers to travel on all TransLink bus, train, ferry and tram services.

Train

The CityRail network has 11 lines and 214, mostly 3-car, vehicles in use (Soltani et al., 2015). A large commuter rail network of just over 200 kilometres connects to the Sunshine Coast and Gold Coast. The CityRail network has relatively low ridership. Service frequencies are 30 minutes off-peak in the outer suburbs and only recently improved to 15minutes (or shorter) in the inner and middle suburbs.

Bus

The Brisbane City Council runs extensive bus services for more than one million residents in its very large municipal area, with more than 400 different bus routes[1]. Many of the bus services run on busways that Hoffman (2008) describes as ‘Quick-ways’ as they are fully segregated from other traffic, with an average stop spacing of more than one kilometre. In Greater Brisbane and outside Brisbane City’s jurisdictions, a range of private bus companies are contracted to supply operations targeting commuters and local demands. Notably, many bus services effectively parallel train services within Brisbane City with relatively low bus-rail integration.

Ferry

Brisbane Transport (a division of Brisbane City Council) provides three types of passenger ferries on the Brisbane River: *CityCat*, *CityHopper* and *CityFerry*. The *CityCat* with 9 monohull ferries serves 21 kilometres of the Brisbane River with 24 terminals within the urban area. The *CityCats* themselves are either 149 or 162 passenger catamarans that operate at a maximum cruising speed of 25 knots. The *CityHopper* is a free frequent service operating in the inner-city with 8 terminals from North Quay in the CBD to Sydney Street operating at a maximum speed of around 15 knots. Both of these routes are either supplemented by cross-river *CityFerry* services that supplement key cross river services already provided by the *CityCat* or *CityHopper* routes (Teneriffe-Bulimba; Thornton Street-Eagle St Pier), or linked to a cross-river terminal to the *CityCat* services (Norman Park-New Farm Park) (Tsai et al., 2014).

Tram

A tram system, the Gold Coast Light Rail, consists of a single 13-km route with 16 stations. As the tram system was not operating until 20 July 2014, however, the modeling in the following analysis does not include tram passengers.

The Translink fare system is a region-wide, zone-based scheme in which passengers mostly use one card for all public transport modes. Cash fares are still possible on most services but at steep additional cost. With Go-card payment fares are automatically collected based on the zones travelled. All Go-card passengers must tag on when boarding and tag off when alighting from buses or ferries, or when entering and leaving a train or tram station. Go-card readers are installed on-board or on platforms. As such, it provides origin and destination data records for each transaction (Soltani et al., 2015). Four types of Go-cards are in use: adult, child, senior and concession—the later three have 50% fare reduction as compared to the adult card.

[1]TransLink, *All Bus Timetables*TransLink, 2014 (http://jp.translink.com.au/travel-information/network-information/buses/all-timetables)

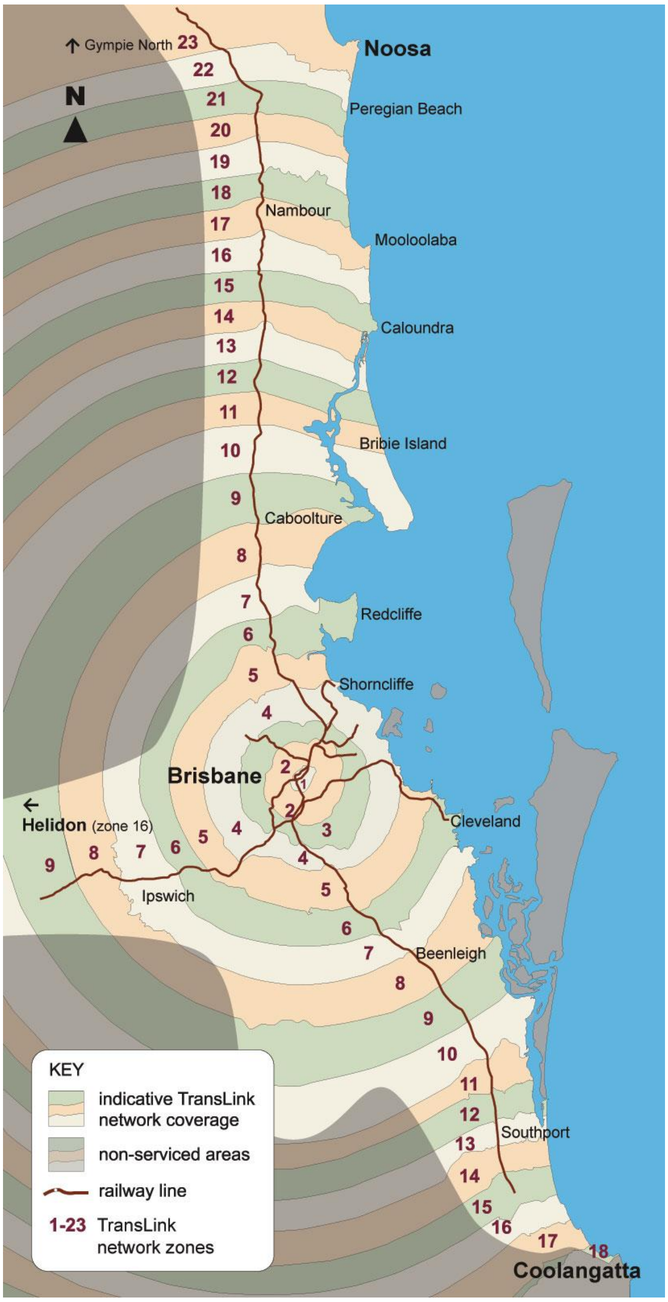

Figure 1. TransLink South East Queensland service areas and zones (Source: TransLink)

4. MODELING APPROACH AND DATA ACQUISITION

The effect of fare policies is determined by measuring passengers' travel behaviour/patterns. This study obtained travel behaviour by cardholder with spatial, temporal, operational, and trip characteristics of the passenger trip/journey from the Go-card data. This paper uses a one month[2] cross-sectional slice of Go-card transaction data, provided by TransLink which provides approximately 15 million data points. Table 2 summarises the type of information collected from the Go-card data.

[2] March 2013 is selected due mainly to no public holiday or school break in this month.

Table 2. Go-card data and its attributes

Item	Information group				
	Spatial	Temporal	Operational	Cardholder	Trip
Card number				◎	
Number of passengers				◎	
Trip ID				◎	◎
Trip origin (stop boarded)	◎				◎
Trip destination (stop alighted)	◎				◎
Zone ID*	◎				◎
Time of trip (at both origin and destination)		◎			◎
Date of trip (at both origin and destination)		◎			◎
Operator name			◎		
Route ID			◎		
Public transport mode**			◎		

* Zone ID and Public transport mode are collected from the General Transit Feed Specification (GTFS) from the TransLink.
** Public transport modes include bus, ferry and train.

It should be noted that this one month slice of data does not have before-and-after data for the off-peak discount policy: this is proxied by the boarding time zone. Trip frequency in each time zone for each passenger is used to represent the effects of off-discount policy. This means the off-peak discount policy is indirectly measured by the effect on trip frequency and in particular which time zones influence trip frequency the most. For example, if traveling in off-peak has stronger impact on trip frequency, compared with traveling in peak time, it implies that off-peak discount policy would significantly encourage passengers to travel outside peak time periods.

As the interest of this paper is to examine passengers' travel behaviour the modeling approach must be personal (Go-card ID) based rather than trip/journey based. A linear regression modeling technique is adopted for analysis purposes with the total trip number for each passenger during the research period being regarded as the dependent variable. The hypothesized relationship is shown in Eq.(1), where *S*, *T*, *I*, *O*, *P* are respectively vectors of the spatial, temporal, cardholder, and operational characteristics and policy factors.

$$T_i = f(S, T, I, O, P) \tag{1}$$

Where, the dependent variable T_i is the total trip number for passengers (*i*) in March 2013. This paper focuses on commuters, and only frequent users' data (those making a minimum of 24 trips per month[3]) were extracted since, as Bagchi et al. (2003) identifies, smart card data lacks trip purpose information.

In March 2013 alone, approximately 15 million entries were recorded. The analysis is based on a total of 412 samples randomly drawn from high frequency use

[3]In Australia, employment rate is 93.9% and 30.9% of it are part-time employment. This study use minimum 60% appointment that is approximately equal to three days a week as a standard to calculate trip frequency for commuters. This study assume that passengers who travel at least 2 trips a day and three days a week (minimum 24 trips a month) are commuters.

ID, after cleaning of the data removed 5.6% data records due to inconsistent, missing or unusable data (i.e. trips where the passenger failed to tag-off their Go-cards or tagged on-and-off quickly at the same place). A sample is used for computational reasons and to meet eligibility requirements of statistics software. The sample constitutes approximately 1.5% of the Go-card dataset including 16,520 trip based observations, or 13,151 journey based observations in March 2013. In the dataset, journey numbers needed to be recalculated from trip numbers in the Go-card dataset as the TransLink definition[4] identifies that trip and journey have different meanings:

> *"A trip is defined as the distance travelled from point of embarkation on a vehicle (or vessel) to its terminus, or to a location, prior to the terminus, where the passenger disembarks from the vehicle. A trip may be the full journey or part of the journey."*
>
> *"A journey is the distance travelled from the origin to the final destination. A journey might involve several trips using different transport modes. The sum of these trips will make up one journey."*

Spatial characteristics

The spatial characteristics of trips are captured by the zone number(s) travelled by each cardholder and it is expected that longer trips are likely to have more transfer trips and thus increase the passengers' total trip numbers (i.e., trip frequency). Because this study uses personal (Go-card ID) base analysis, the zone variable is presented as average zones travelled in March 2013. Table 3 shows the descriptive statistics of the variables, including minimum, maximum, mean, standard deviation, skewness, and kurtosis values.

Temporal characteristics

The temporal characteristics are presented by time of trip at both origin and destination for each trip (hereinafter, time zone). The time zone of boarding is used because it is the standard to identify fare and discount policy. This study divides the 24 hours a day into 48 time zones, each with 30-minute equal time periods so as to explore which time zone influences trip frequency the most with the expectation that time zones lying in peak time periods (3:00am to 8:30am and 3:30pm to 7:00pm) will be positively associated with the number of trips.

Cardholder characteristics

Cardholder characteristics include card number/ID, number of passenger, and Trip ID. Card ID in the data is a unique identity attached to each smart card, encrypted to protect customers' private information and is not used in modeling. The number of passenger indicates how many passengers travel on a single Go-card. For most transactions, this value is 1; however, it also has some negative values due to refunds, data errors or Go-card events tagged on/off on different dates. Thus, this variable is also not included in the modelling. The trip ID identifies the trip sequence within a journey, allows the derivation of journey number and transfer number—both of which are expected to be positively associated with total trip number. This is the key cardholder characteristic used in the analysis.

[4]Full Go-card journey and trip definitions can be found on the TransLink website. http://translink.com.au/tickets-and-fares/fares/go-card-journey-and-trip

Operational characteristics and policy factor

Public transport modes, including bus, train, and ferry, are used in this study to represent operational characteristics. The public transport mode variables are total trip numbers that use each mode that include bus, train, or ferry, respectively. The sample mode shares for bus, train, and ferry are 77%, 20% and 3%, respectively. Whilst different from the total mode share for SEQ for bus, train and ferry (59%, 39% and 2% respectively), the sample mode share is for commuters (or frequent travelers) for which no population statistics are available. A further policy variable, 9-journey, is introduced to investigate the effects of volume rebates policy. The 9-journey variable indicates the number of free trips of each card ID within the research period and is expected to have positive association with total trip numbers.

Table 3. Summary of descriptive statistics of variables in the model(N=412)

Variable	Unit	Definitions*	Expected signs	Min	Max	Mean	Standard Deviation	Skewness	Kurtosis
Journey	Number	Total journey numbers	n.a.**	12.00	75.00	32.83	8.10	0.56	2.96
Trip	Number	Total trip numbers	n.a.**	24.00	133.00	38.96	13.67	2.21	7.59
Transfer	Number	Total number of transfer trips	+	0.00	67.00	6.12	9.90	2.14	5.27
Zone	Average number	Average travelled zones	-	1.00	10.00	2.70	1.12	1.45	4.39
Time zone (at origin)	Dummy	For each time zone, 1= there are more than 3 trips in this particular time zone; 0 = otherwise	+/-	0	1	-	-	-	-
Public transport mode									
Bus	Number of times used	Total trip numbers that selected bus as travel mode	+	0.00	95.00	29.96	17.11	0.25	0.89
Train	Number of times used	Total trip numbers that selected train as travel mode	+	0.00	69.00	7.63	13.14	1.77	2.32
Ferry	Number of times used	Total trip numbers that selected ferry as travel mode	+	0.00	38.00	1.54	5.73	4.57	20.23
9-journey	Number of free journeys	The number of free journeys	+	0.00	30.00	2.09	3.37	4.26	24.35

* The definition of each variable is for each cardholder in March 2015

**Dependent variable

5. RESULTS

In order to evaluate the relationship between variables, correlation coefficients are calculated (Table 4). In Table 4, most variables (i.e., journey number, 9-journey number, transfer number, time zones, etc.) have a moderate positive linear relationship (r>0.7) to the dependent variable, total trip number. In contrast, the correlation coefficients between average zones travelled ("Zone" in Table 4) and other variables (i.e. journey, trip, transfer, etc.) have a weak negative linear relationship (r<-0.3). Operational variables, train and bus, have a moderate negative linear relationship, suggesting that these two modes exist in a competitive relationship in nature.

Using the selected explanatory variables (Table 3), a number of linear regression models are estimated. The regression results of the preferred model are summarised in Table 5. The adjusted R-square is 0.957, suggesting that 95.7 percent of the variation in trip frequency can be explained by the explanatory variables. In general, all variables present the correct signs as expected with the trip frequency being lower with more average zones travelled and all other variables (temporal, cardholder, and operational characteristics, and policy factor) show significant positive effects on trip frequency.

Table 4. Correlation coefficients of variables

	Trip	Journey	Transfer	Zone	Morning peak time zone						Afternoon peak time zone				Off-peak hour	Bus	Train	Ferry	9-journey
					6:00-6:29	6:30-6:59	7:00-7:29	7:30-7:59	8:00-8:29	8:30-8:59	16:00-16:29	16:30-16:59	17:00-17:29	17:30-17:59					
Trip	1																		
Journey	0.70**	1																	
Transfer	0.81**	0.15**	1	-															
Zone	-0.15**	0.05	-0.24**	1															
6:00-6:29am	0.52*	0.33**	0.11**	-0.02*	1														
6:30-6:59am	0.79**	0.45**	0.73**	-0.17**	0.32**	1													
7:00-7:29am	0.61**	0.62**	0.33**	-0.06	0.21**	0.42**	1												
7:30-7:59am	0.43**	0.51**	0.18**	0.02	0.33*	0.23**	0.54**	1											
8:00-8:29am	0.80**	0.47**	0.72**	-0.12*	0.35**	0.64**	0.27**	0.15**	1										
8:30 8:59am	0.80**	0.46 **	0.73**	-0.12*	0.22**	0.66**	0.28**	0.15**	0.97**	1									
16:00-16:29pm	0.72**	0.39**	0.68**	-0.12*	0.73**	0.50**	0.21**	0.11*	0.78**	0.75**	1								
16:30-16:59pm	0.74**	0.50**	0.61**	-0.15**	0.61**	0.79**	0.53**	0.29**	0.51**	0.52**	0.39**	1							
17:00-17:29pm	0.40**	0.49**	0.15**	0.03	0.24*	0.20**	0.48**	0.89**	0.13**	0.13**	0.10*	0.26**	1						
17:30-17:59pm	0.81**	0.43**	0.77**	-0.17**	0.11**	0.87**	0.36**	0.20**	0.74**	0.76**	0.57**	0.69**	0.18**	1					
Off-peak hour	0.49**	0.58**	0.21**	-0.01	0.09**	0.27**	0.65**	0.83**	0.17**	0.18**	0.13**	0.34**	0.74**	0.24**	1				
Bus	0.62**	0.39**	0.53**	-0.06	0.46**	0.53**	0.41**	0.34**	0.47**	0.49**	0.40**	0.46**	0.32**	0.52**	0.34**	1			
Train	0.25**	0.19**	0.18**	0.001	0.02*	0.15**	0.12*	0.03	0.21**	0.20**	0.23**	0.18**	0.02	0.17**	0.07	-0.55**	1		
Ferry	-0.02	0.04	-0.06	-0.18**	0.00	-0.03	-0.04	-0.04	0.00	0.00	0.00	-0.02	-0.06	-0.01	-0.01	-0.27**	-0.09	1	
9-journey	0.70**	0.76**	0.35**	-0.12*	0.21**	0.49**	0.37**	0.22**	0.59**	0.58**	0.50**	0.50**	0.21**	0.50**	0.27**	0.34**	0.26**	0.08	1

Note: * indicates 0.05 level of significance; ** indicates 0.01 level of significance.

Table 5. Regression results (N=412)

	Coefficient	t-value	Tolerance	VIF
Constant	19.032	9.020***	-	-
Zone	-0.260	-2.511**	0.936	1.068
Time of Trip				
7am-7:29am	3.420	4.543***	0.458	2.181
7:30am-7:59am	3.774	3.911***	0.213	4.689
16:30pm-16:59pm	4.858	2.844***	0.249	4.013
17:00pm-17:29pm	4.896	4.874***	0.177	5.652
Off-peak hour	3.084	6.195***	0.548	1.825
Transfer	9.736	6.933***	0.375	2.664
Transport mode				
Bus	0.310	3.473***	0.148	6.742
Train	0.308	3.541***	0.217	4.602
9-journey	0.610	4.167***	0.563	1.777
R	0.958			
R^2	0.957			
Durbin-Watson	2.137			

Note: ** indicates 0.05 level of significance; *** indicates 0.01 level of significance.

The OLS regression residuals demonstrated heteroscasdasity and hence the results presented have used the White (1980) correction to make the errors become heteroscedasticity-consistent standard errors. Table 5 presents the VIF for each variable, suggesting little issue with multicollinearity and the Durbin Watson statistic, being close, suggests little presence of serial correlation.

For spatial characteristics, the average number of zones travelled has negative impact on trip frequency. Figure 2 displays the relationship between average zones travelled and trip numbers. It indicates that, on average, passengers travelling longer distances (more zones) will not necessarily make high trip numbers. Figure 3 further shows the relationship between transfer numbers and average zones travelled. From Figure 3, the longer travel distance is, the lower the trip number and transfer number are, implying that long-distance travels tend to be direct travel, without interchange.

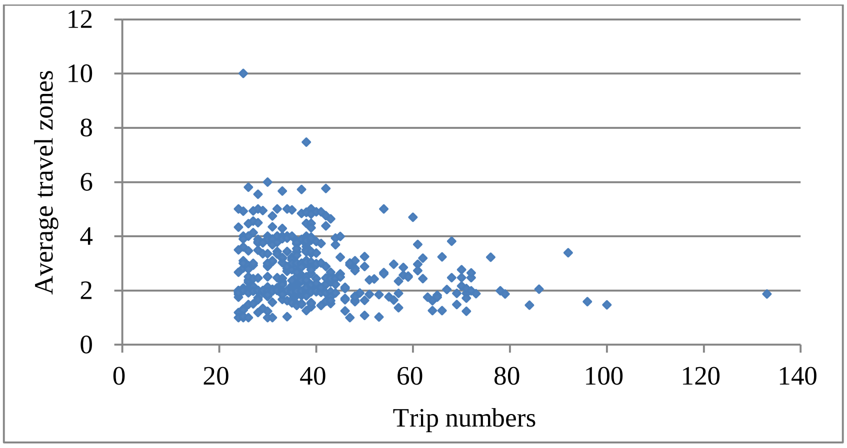

Figure 2. Relationship between trip numbers and average zones travelled (N=412)

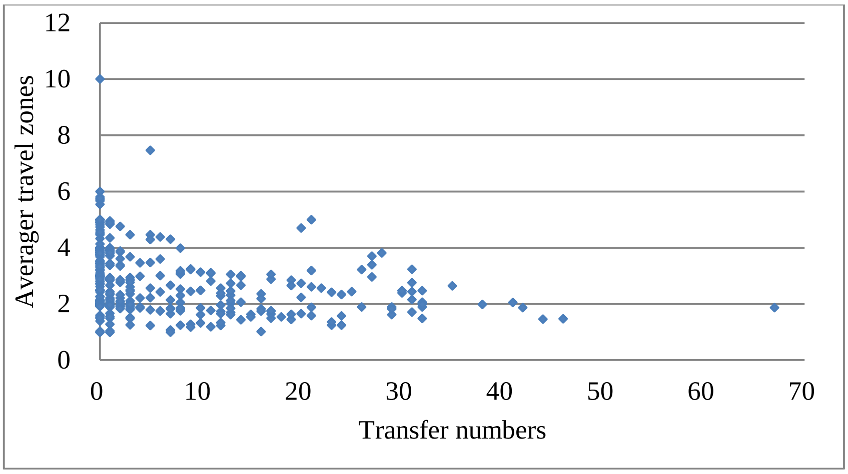

Figure 3. Relationship between transfer numbers and average zones travelled (N=412)

For temporal factors, only five time zones have significant effects on trip frequency, including two morning peaks (7:00-7:29am and 7:30-7:59am), two afternoon peaks (16:30-16:59pm and 17:00-17:29pm) and off-peak time. More than 57% trips are taking place in these five time zones (Figure 4). Although there are 19 time zones in peak time periods and 29 time zones in off-peak time period, this study only uses one off-peak time variable to include all off-peak time zones due to the fact that only 12% trips occur in off-peak time period and many off-peak time zones (e.g. 12:00am-3:00am) do not have any trips. The results in Table 5 indicate that peak time periods have a higher influence on trip number (4.896-4.402) than off-peak time period does (3.084). Even with an off-peak discount policy, travelling during the peak hours is still the major activity, contributing to peak traffic congestion and overload situations.

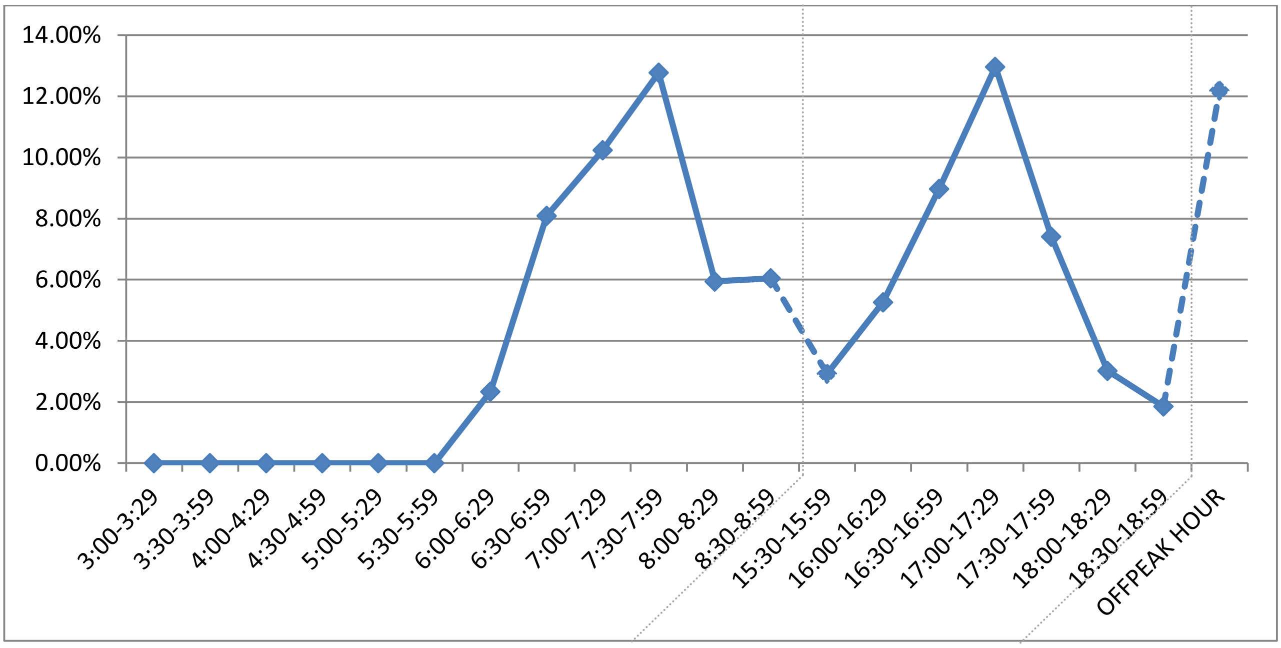

Figure 4. Percent of trip numbers in different (boarding) time zones (N=412)

Cardholder/trip characteristic is presented as the number of transfers for each Go-card user. This variable shows significant positive influence on trip frequency. For operational characteristics among three transport modes (bus, train and ferry), only bus and train are significant modes that have positive effects on trip frequency. Among them, bus has higher impact on trip frequency than does train which is likely to be as a result of the extensive bus network in Brisbane. The policy factor, 9-journey, in the model also has a positive impact on trip frequency. It indicates that volume rebates policy in SEQ are boosting public transport usage.

6. DISCUSSIONS

Two public transport policies, off-peak discount and volume rebates, have been adopted in SEQ, Australia to encourage mode shift and to spread out peak hour congestion. To measure the effects of these two fare policies, this study makes use of public transport smart card data, in lieu of conducting a traditional travel survey, to analyse high frequency public transport users' travel behaviour for a one-month period. Based on the regression results, the findings and some policy implications are further discussed as follows.

First, for the off-peak discount policy, the model results show that five different time zones have a significant effect on trip frequency. Four of these are in peak-hour periods (morning and afternoon) and their influence on total trip numbers are larger than the off-peak time zone. It suggests that peak-hour travelling is still the main generator of trip frequency. Even with the off-peak discount policy, more than 80% of the high frequency users still take public transport in peak time zones (Figure 4). This indicates that the motivation of shifting time of travelling from peak to off-peak may not be strong enough or that these passengers do not have sufficient flexibility in their travel times; in other words, the current off-peak discount policy gives passengers only small rewards should they change their times of travelling. Alternative or complimentary approaches may be required to achieve greater peak spreading. One avenue where active transport programs have experienced successes is via so-called 'gamification' schemes, which harness known social-psychological effects in competitive games (Deterding et al., 2011). These are designed to encourage travel behaviour change to achieve 'rewards/behaviour incentives' within the gamified environment (Merugu et al., 2009; Pluntke and Prabhakar, 2013). Other approaches beyond the purview of transport agencies may include flexible employment practices.

Furthermore, although there are 19 peak time zones in total, only 4 have significant effects on trip frequency. These four peak time zones are continually the time zones (two in the morning and two in the afternoon) where the peak frequencies are highest (Figure 4), suggesting that there still is noticeable peak traffic volume within the morning and afternoon peak time periods. If a peak time period can be further divided into three time zones—peak time, peak shoulder time and off-peak time as shown in Figure 5, then offering differentiated discounts (e.g., 0%/20%/40%) to different users in peak time/peak shoulder/off-peak time may prove more effective in mitigating peak-load situations. It is possible that such a multi-stage dynamic fare scheme may lead to more effective spreading effects as the peak time or peak shoulder time users will then have more incentive to shift to travel in earlier/later time zones.

As for the volume rebates policy, the model results confirm that the 9-journey policy has provided incentives to encourage passengers to use public transport more often. From the model result (Table 5), 9-journey policy brings significant positive impacts to trip numbers. This imply that once passengers who activate the 9-journey policy are incentivised to use public transport more because of free trips. This also suggests peak on-road traffic congestion be eased to some extent if these extra public transport journeys are being shifted from other modes and are within peak hour.

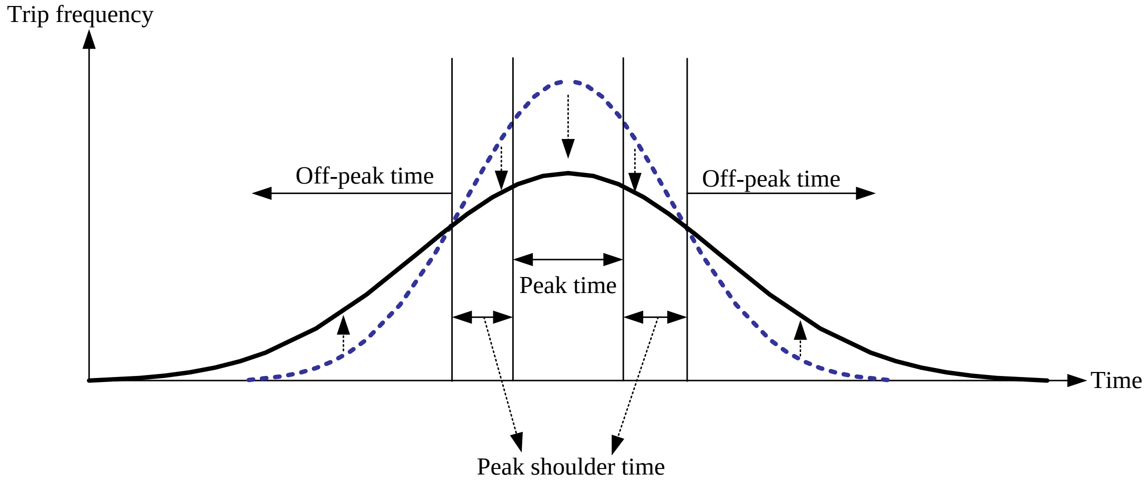

Figure 5. Peak spreading effects by multi-stage dynamic fares scheme

Another variable, transfer number, is less significant than peak hour factor because transfer number has a larger impact than peak hour variables in Table 5. In SEQ, no discount is provided to any inter-or intra-mode transfer. Passengers have to pay full additive fees for trips by different modes that belong to a single journey. In many countries, a transfer discount policy has been proven to have positive effects on increasing public transport usage. In Taiwan, for example, where a quite different ticking regime is in place, a NT$8 (about US$0.25) discount is provided to each bus transit user transferring to or from Taipei Metro. This transfer discount has significantly raised both Metro and bus ridership. Since transfer numbers do have a significant positive influence on trip frequency, a favourable transfer discount policy is suggested to help increase public transport patronage overall.

Finally, the research results also indicate transport modes to be significant variables, especially for bus (Table 5). In SEQ, a busway network is provided (Figure 6), which separates buses from general traffic. Like a train network, the TransLink busway network has offered commuters faster, more frequent and reliable bus services. Some busways even operate parallel to train lines, e.g. the South East Busway. To some extent, these two transport modes are competing with each other. Busways can provide a wider coverage of service (more than 100 routes operate in the South East Busway) with higher accessibility and more service frequency. In contrast, train lines (e.g., the Beenleigh Line parallel to the South East Busway), which are not serviced well by feeder buses, only serve limited stations with lower accessibility and less service frequency (30-minutes frequency for most lines). Consequently, busways can help uplift bus service quality and make bus a more significant influence on trip frequency than other public modes.

Figure 6. Busways network (source: TransLink)

7. CONCLUSIONS

This paper has investigated how off-peak discount and volume rebates policies affect travel behaviour/patterns in SEQ, Australia. It contributes to the literature by providing additional evidence from an Australian case and by making use of smart card data instead of conducting a cumbersome survey for analyzing fare policy effects. The empirical findings in general have confirmed that the two fare policies in the study area do influence passenger travel behaviour/patterns, especially with the volume rebates policy (9-journey). It seems that passengers do not perceive sufficient incentive to alter their boarding times out of the morning and afternoon peak time periods and it is suggested that further disaggregating the peak time period into several time zones and offering multi-stage differentiated fare discounts could further spread out a high peak. Moreover, a transfer discount between bus, train and ferry could be introduced to encourage increases in overall public transport ridership.

Future research will focus on the investigation of other potential determinants that may influence travel behaviour, including the role of social demographic characteristics. Policy effects for low and medium frequencies users are unexplored using these methods. Other modelling approaches, such as geographically weighted regression, can be attempted to account for spatial dependency among different stops; or choice modeling can be used to analyze passenger mode choice or measure policy effects. A further segmentation of the peak/off-peak time periods will also be considered as ways of improving model fit and interpretations of fare policies. The current fare calculation is based on zones travelled for each journey. Instead of using the personal (Go card ID) based analysis of this study with the sample of 412 IDs, a journey based analysis might reveal more in terms of the financial effects of fare policies since the fare system is broadly zonally based. Other relevant variables, such as public transport frequencies, service coverage, connections, pricing structure, land use types, and built environment attributes, are of potential interest in explaining and controlling public transport travel behavior/patterns, which can be explored in future studies.

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