Temporal variations in usage of Melbourne's bike paths

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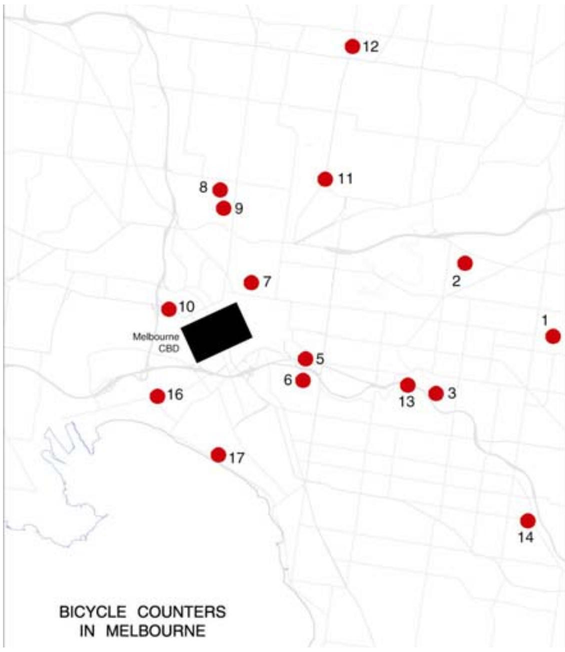
1 Introduction

Growing community concerns over climate change, congestion, obesity, and rising fuel prices is translating into increased interest in cycling. Recent statistics highlight that for the first time, sales of bicycles in Australia have outstripped new motor vehicles (Cycling Promotion Fund, 2006). Transport authorities are responding with initiatives to provide better infrastructure, supportive policies and behavioural programs to promote use. While not unique to cycling, one recurring challenge is the lack of data on which to formulate plans and measure the effectiveness of a range of initiatives. Traditional reliance on irregular cross-sectional travel surveys and temporary link counts has often presented challenges for studies of bicycle use. The research reported here has only been possible because of the investment made by VicRoads to continuously collect usage data on Melbourne's bike paths.

Beginning in November 2005, VicRoads began installing automatic counting equipment at selected locations on Melbourne's off-road bike path network. This comprises inductive loops and recording equipment (Figure 1). While the inductive loops have been installed at 17 sites, the permanent recording equipment has been limited to a subset of those sites (Figure 2). The automatic counters provide hourly aggregate two-way counts (aggregated from 15 minute raw counts) of the number of bicycles using the facility.

Figure 1: Automatic counter installation on a bike path (Source: VicRoads)

Barton (2006) presented an initial analysis of the usage patterns evident in the first five months of data collected by the loops. This study extends Barton's (2006) work by covering the period from November 2005 to November 2006 and adds value to that raw loop data by enhancing understanding of the extent of temporal variations which exist in the usage of Melbourne's off-road bicycle paths and the factors which contribute to those variations. The analysis presented here sheds new light on the impact of local weather effects on use of bicycle facilities and demonstrates how insight into prevailing trip purposes can be gleaned from analysing patterns in usage statistics. This research has implications in the context of modelling the demand for use of bicycle facilities and for the development of adjustment factors to estimate seasonal demand as a function of daily counts.



Site	Trail Name	Distance to Melbourne Town Hall (km)
1	Anniversary Trail	8.3
3	Main Yarra Trail No. 1	6.2
4	Koonung Trail	12.2
5	North Bank	2.0
6	South Bank	2.0
7	Canning Street	2.6
8	Upfield Railway	4.2
9	Capital City Trail	3.7
10	Footscray Road "Capital City Trail"	3.7
11	St. Georges Road	5.4
13	Gardiners Creek	5.0
16	Tram 109 Trail	2.5
17	Bay Trail	5.4

Figure 2: Automatic Counter Locations (Source: VicRoads)

The structure of this paper is as follows. Section 2 summarises existing knowledge about factors affecting variability in bicycle path use and highlights strengths and weaknesses of results reported in the literature. Section 3 quantifies the aggregate variability in usage of Melbourne's bike paths across facilities, days, weeks and months of the year, it also segments the trails on the basis of the distributions of bicycle traffic throughout the day. Section 4 enhances understanding of the factors contributing to that variability by calibrating and interpreting a multivariate demand model. The conclusions and research directions are presented in Section 5.

2 Factors affecting Bike Path Usage

The level of bicycling in a city is a function of the bicycling infrastructure provided; the safety of bicycling on that infrastructure; the costs and levels of service provided by alternative transport modes; income levels; climate; city size, demographics and density of development, as well as the public image enjoyed by bicycling and the underlying attitude and culture in relation to bicycling (Pucher et al, 1999). Researchers have drawn on different types of data in order to understand the relative contributions of those different factors and this study focuses on only a subset of those factors.

Using census data from 42 US cities, Dill and Carr (2003) extended the analysis of Nelson and Allen (1997), to examine the factors which explain the extent of commuter cycling. Their aggregate analysis found that higher levels of bicycle infrastructure were positively and significantly correlated with higher rates of bicycle commuting (measured by the percentage of commuter trips undertaken by bicycle). Specifically each additional mile of on-street bicycle lane (per square mile) was found to result in about a one per cent increase in the share of commuter bicycling. Bicycle commuting was found to reduce with increasing car ownership. A significant weather effect was also identified with each additional day of rain (from historical average data) resulting in a reduction of 0.01 per cent in the percentage of commuter bicycle trips. In Dill and Carr's (2003) modelling, it was only the extent of on-street bicycle lanes which was significantly correlated with the extent of commuter cycling. They could not find a significant relationship with the extent of off-road paths.

There are mixed results reported in the literature about the extent to which the provision of off-road facilities encourages commuter bicyclists. Aultman-Hall et al (1997), drawing on a disaggregate survey of commuter cyclists route choices found that high-quality direct off road paths were used infrequently by commuter cyclists in Guelph (Canada). In contrast, Gutttenplan and Patten (1995) report results from the Baltimore-Washington area in the USA where 45 per cent of respondents in a survey indicated they used off-road trails primarily for transportation which covered commuting to work, school or shopping. Of course it is not only the nature of the bicycle facilities but the extent to which they provide a connected network suitable for accessing activity centres which will govern their use.

Keay (1992) collected observational data on cyclist volumes, classified by gender, during one hour periods on weekends over a 40 month period. His surveys providing a time series of 164 survey days of data which were then correlated with rainfall and temperature data recorded during the observational surveys. Scattergram plots confirm that higher rainfall reduced cyclist volumes however, while slight rain reduced the number of female cyclists by half, the decline in male cyclists was delayed until there was appreciable rainfall. Keay also noted a decline in cyclist numbers at temperatures greater than 30C and less than 10C, and at wind speeds greater than 50 km/h, although he acknowledged that further data was required to confirm the statistical significance of those relationships.

Nankervis (1999) reported results of a pilot study conducted in Melbourne where a survey was used to examine the effects of weather and climate on bicyclists' decisions to commute to three Melbourne universities over the course of the year. The small sample size (less than 50 respondents), and the fact that a cross sectional survey was employed rather than a time series or panel survey, suggests that caution should be exercised when interpreting the results. Only weak statistical associations could be found between weather/climate and the level of cycling although a decrease in cycling was observed over the winter months. Heavy rain was found to be the largest weather deterrent for cyclists with 67 per cent of respondents indicating they will not ride under those conditions. Nearly all (90 per cent) of those who would not ride indicated they would use an alternative mode with the remainder indicating they simply wouldn't make the trip. In contrast light rain or low temperatures resulted in clothing changes and high temperatures or wind made no impact on the travel decisions of 70 to 80 percent of regular riders. Commuting by bicycle decreased towards the end of the working week. Nankervis speculated that reflected after work social activities at the end of the week which prompted the use of other modes.

More recently, Burke et al (2006) highlighted that our understanding of the impact of climatic conditions on non-motorised demand is not well advanced. There is broad recognition that demand for those modes has a 'seasonal' dimension, and as cited in Burke et al (2006), 'bad weather' is often nominated as a reason for not walking or cycling (Martin and Carlson, 2005; National Highway and Traffic Safety Administration and Bureau of Transportation Statistics, 2003). Hahn and Craythorn (1994) identified reduced walking and cycling trip-making due to diminishing daylight availability. Burke et al (2006) examined the impact of climate (temperature, humidity, rainfall and hours of daylight) and topography (specifically variation in elevation) on walking trips in Brisbane. They found that walking trip rates per person per day did not vary as a function of changes in daylight availability, rainfall, temperature, humidity or local topography. However, that study relied on cross-sectional survey data and the results may be a reflection of the relatively limited variability in the explanatory variables (particularly climate) measured over a survey period spanning late 2003 to early 2004.

Drawing on the rich time series data base provided by the VicRoads bicycle path loop counters, the results presented in the following section provide insight into the variability in bicycle path usage. By correlating the usage data with climate information it is then possible to identify factors which contribute to that variability.

3 Variability in use of Melbourne's off-road bicycle paths

Usage variability can be examined:

- across paths,
- by time of day,
- by day of week, and
- by month of year.

The loop data provides a basis for quantifying the underlying variability in bicycle path usage. In this section we illustrate the extent of the underlying variability while in the following section we examine the factors contributing to that variability. The dataset on which this analysis is based consists of time series of hourly volume data from the 13 sites covering a period of approximately one year. Missing data was present in the dataset, but accounted for only about 13% of the total hourly observations, and did not adversely affect our ability to examine the underlying relationships.

3.1 Variability in usage across paths

The Average Annual Daily Traffic (AADT) provides a measure of the variability in usage across the paths. AADT values for each counter location, computed for weekdays, and weekends and public holidays are shown in Table 1.

Table 1: Average Annual Daily Traffic across sites

	Average Annual Daily Traffic (AADT)			
Site	All days	Weekdays	Weekends & Public Holidays	Ratio of Weekday to Weekend & Public Holiday volumes
Anniversary Trail	251	204	341	0.60
Bay Trail	1106	973	1359	0.72
Koonung Trail	450	386	583	0.66
Main Yarra Trail	456	365	620	0.59
Canning Street	1247	1577	619	2.55
Capital City Trail	603	666	483	1.38
Footscray Road	1065	1215	782	1.55
Gardiners Creek	1576	1741	1290	1.35
North Bank	1722	1895	1404	1.35
South Bank	884	975	713	1.37
St. Georges Road	663	799	411	1.94
Tram 109	602	647	516	1.25
Upfield Railway	450	529	301	1.76

The first four sites (the Anniversary, Bay, Koonung and Main Yarra Trails) have more riders on weekends and public holidays than weekdays (at a ratio of 2:3) whereas the remaining sites exhibit the exact opposite pattern with a ratio of about 3:2. This result suggests that there are two groupings of paths. Austroads (1999) classifies off-road paths based on their functionality; one type is to cater for commuter cyclists and the other for recreational riding. The first group of sites have a "Recreational Trail" character since usage is approximately 50 per cent higher on weekends and public holidays than on weekdays. The second group can be characterised as "Commuter Trails" since their highest volumes are on weekdays. The basis for this segmentation of the trails into two distinct types is examined in greater detail in the sections which follow.

3.2 Variability in use by time of day and day of week

Cyclist volumes not only vary across sites as seen in the previous section, but they also vary by time of day. To illustrate the difference an indexed volume is used for each site, with 100 equalling the 24 hour average. This gives a clearer comparison of the time of day variability across sites over the use of aggregate volumes, which were discussed in the previous section. Figures 3 and 4 highlight the differences across groups. These figures were created by aggregating all the sites within the particular grouping to create a volume weighted average profile for the two types of paths for both weekdays and weekends. The variation within group was minimal so these figures provide a reliable indication of the extent of hourly variation across path types.

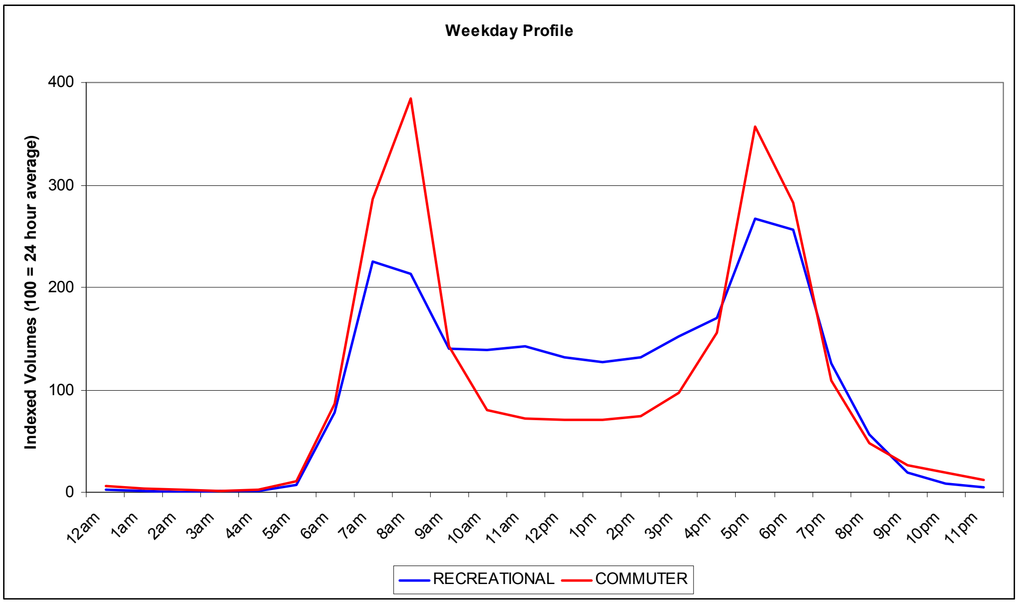


Figure 3: Weekday Profile

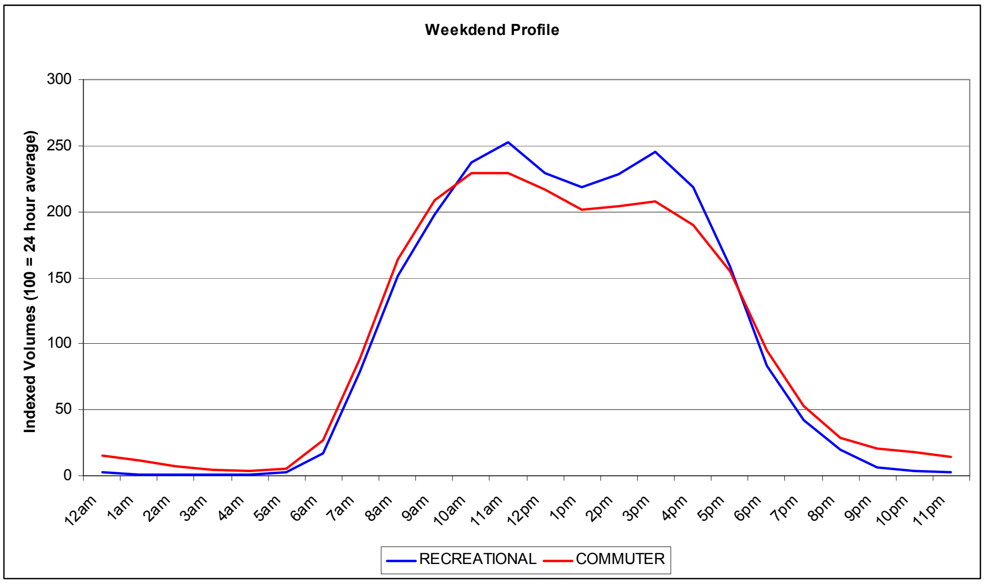


Figure 4: Weekend Profile

Figure 3 highlights that usage of the commuter trails exhibit two very distinct peaks on weekdays and a substantial drop in volumes during the off-peak. Recreational trails have two less pronounced peaks. Weekend profiles, illustrated in Figure 4, are indistinguishable implying that both commuter and recreational paths cater for recreational riding at that time. Using this data time of day (TOD) conversion factors can be computed to enable practitioners who undertake manual bicycle counts at any particular time of the day to approximate the volumes outside of their survey period. Those conversion factors are shown in Tables 2 and 3. In those tables, 'AM', 'PM' and 'Off Peak' refer to weekdays, and 'Night' refers to both weekday and weekend night-time. To illustrate the application of these factors, consider a short term count conducted on a weekday during the AM peak which was used to calculate an average hourly flow on a commuter trail. Using the values shown in Table 3, the weekend hourly flow could then be estimated as 54 per cent of that hourly flow and the off-peak weekday flow as 26 per cent of that hourly flow.

Table 2: TOD Conversion Factors (Recreational Trails)

		TIME OF SURVEY (RECREATIONAL TRAILS)				
		AM Peak	Off Peak	PM Peak	Weekend	Night
CONVERSION	AM Peak (7AM – 9AM)	1.00	1.59	0.95	1.14	13.05
	Off Peak (9AM – 4PM)	0.63	1.00	0.60	0.72	8.21
	PM Peak (4PM – 7PM)	1.05	1.68	1.00	1.21	13.76
	Weekend (7AM – 7PM)	0.87	1.39	0.83	1.00	11.41
	Night (7PM – 7AM)	0.08	0.12	0.07	0.09	1.00

Table 3: TOD Conversion Factors (Commuter Trails)

		TIME OF SURVEY (COMMUTER TRAILS)				
		AM Peak	Off Peak	PM Peak	Weekend	Night
CONVERSION	AM Peak (7AM – 9AM)	1.00	3.86	1.26	1.84	15.06
	Off Peak (9AM – 4PM)	0.26	1.00	0.33	0.48	3.91
	PM Peak (4PM – 7PM)	0.79	3.05	1.00	1.45	11.93
	Weekend (7AM – 7PM)	0.54	2.10	0.69	1.00	8.20
	Night (7PM – 7AM)	0.07	0.26	0.08	0.12	1.00

3.3 Variability in use by month of year

Figures 5 and 6 show the trends in monthly weekday and weekend volumes respectively. There is a difference between the commuter and recreational trails during the week but little difference on weekends. There is a clear decline over the winter months in the middle of the year. For commuter routes on weekdays the peak ridership months typically record cyclist volumes around 65 per cent higher than in the winter months while for the recreational routes the summer time volumes are about 130 per cent higher than during the winter months. On the weekends, the ridership during the peak months is about twice the winter volumes. The weekend volumes begin to pick up noticeably from around August but the weekday volumes show a more gradual increase towards the end of the year. Knowledge about the variability in ridership by month of the year is important for adjusting counts to the appropriate month. That is particularly useful in the context of cycling estimates based on the ABS Census, which is conducted every 5 years in August.

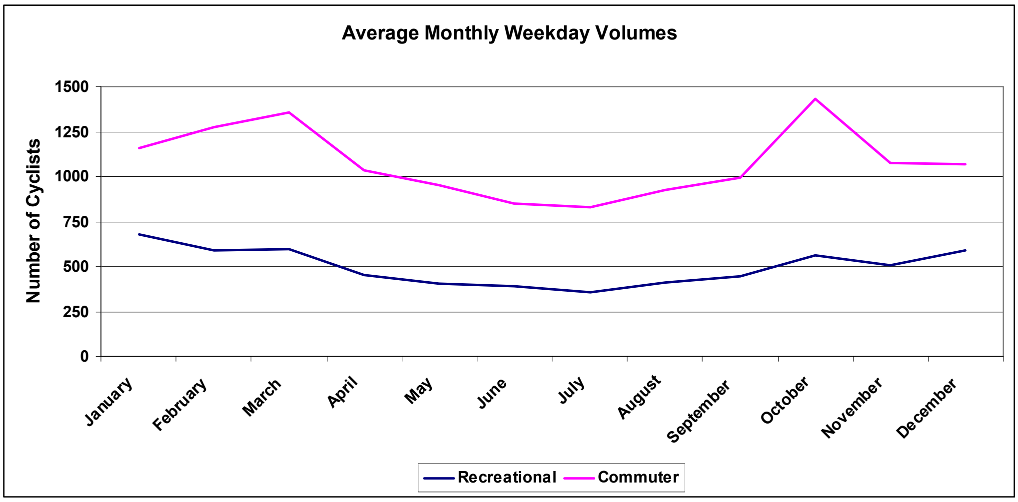


Figure 5: Average Weekday volumes over the year

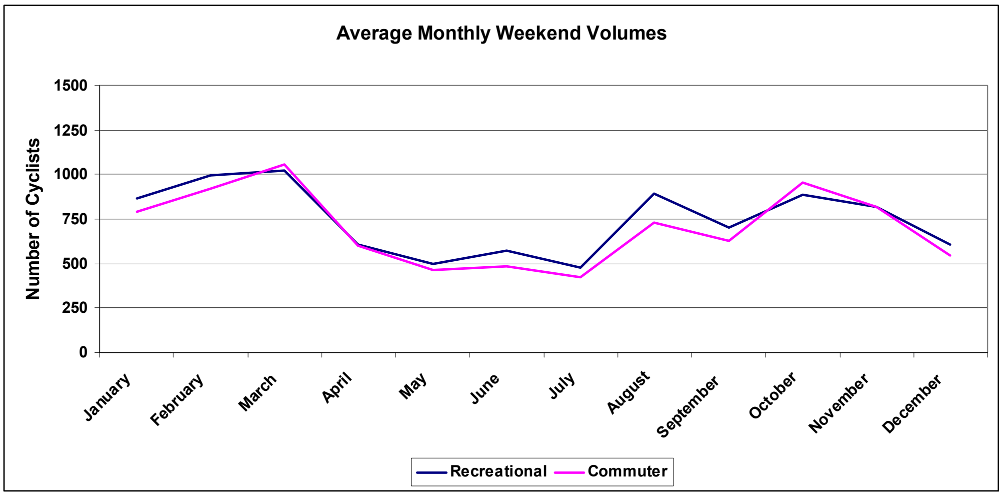


Figure 6: Average Weekend volumes over the year

4 Explaining differences in bike path usage

In this section we seek to identify factors contributing to variability in usage and also to assess the extent to which the usage of different paths is similar or different with respect to those factors.

4.1 Modelling Framework

To examine the factors contributing to the variations in bicycle path usage, a multivariate modelling approach is adopted. The model seeks to predict the daily bicycle volume at a particular location as a function of a range of explanatory variables. The inclusion of the explanatory variables provides insight into the effect of:

- time based growth
- public holidays
- rainfall
- the hours of sunlight over the day
- temperature
- humidity
- wind speed and
- the day of week.

The model comprises a set of 13 equations, each one predicting the daily bicycle volume for one of the 13 locations on the off-road paths where the automatic data collection equipment is installed. A log-linear formulation is used where the log of the daily bicycle volume is the dependent variable in a linear regression model which incorporates the explanatory variables. The system of equations is summarised as follows:

$$\log_e(Q_{it}) = \alpha_i + \beta_{iTIME}TIME_t + \beta_{iPUB}PUB_t + \sum_{j=1}^{2}\beta_{iRAIN,j}RAIN_{jt} + \beta_{iSUN}SUN_t + \sum_{m=1}^{2}\beta_{iATEMP,m}ATEMP_t^m + \sum_{k=1}^{3}\beta_{iWIND,k}WIND_{kt} + \sum_{n=1}^{6}\beta_{iDOW,n}DOW_n + \varepsilon_{it}\forall i,t \quad (1)$$

where;
Q = daily bicycle volume
i = site index
t = time index
TIME = time based growth, given in percent per day, easily translated into yearly growth by multiplying by 365 days.

PUB = public holiday coded as $\begin{cases} 0 & \text{not a public holiday} \\ 1 & \text{is a public holiday} \end{cases}$

RAIN = rainfall categorised as $\begin{cases} \text{no rain} < 0.2\text{mm} \\ \text{light rain} < 10.0\text{mm} \\ \text{heavy rain} \geq 10.0\text{mm} \end{cases}$

The Bureau of Meteorology (2007) defines a rain day to be one with at least 0.2mm of rainfall. The 10.0mm threshold value was chosen arbitrarily, based on the fact that that Bureau of Meteorology produces statistics on the number of rain days with falls greater than 1, 10 and 25mm. Over the time period considered by this analysis, Melbourne was in the grip of a drought and consequently there are fewer incidences of heavy rain. The RAIN variable is coded as two dummy variables for light and heavy rain with the base case (i.e. both RAIN dummies equal to zero) corresponding to "no rain". The reasoning behind the categorisation of the RAIN variable as opposed to using it as a continuous variable is that cyclists will not feel incremental changes in the amount of rainfall; rather the effect would be "stepped" as suggested by the results described earlier from Keay (1992) and Nankervis (1999).

SUN = hours of sunshine

ATEMP = apparent temperature in degrees Celsius (described in more detail below)

WIND = arithmetic mean of the 9am and 3pm wind speeds, categorised according to Bureau of Meteorology (2007) definitions:

WIND categorised as $\begin{cases} \text{light winds} \leq 19\text{ kph} \\ \text{moderate winds } 20\text{ - }29\text{ kph} \\ \text{fresh winds } 30\text{ - }39\text{ kph} \\ \text{strong winds } 40\text{ - }62\text{ kph} \end{cases}$

The WIND variable is coded as three dummy variables for moderate, fresh and strong wind with the base case (i.e. all WIND dummies equal to zero) corresponding to "light winds.

DOW = day of week, to allow for variations between different days of the week. The DOW variable is coded using six dummy variables (Monday through Saturday) with the base case (i.e. all DOW dummies equal to zero) corresponding to Sunday.

The advantage of the log-linear formulation (Equation 1) is that the coefficients of the continuous variables are directly interpretable as the percentage change in the dependent variable (daily bicycle volume) as a function of a change in the explanatory variable. For example, a coefficient of 0.05 on the hours of sunlight variable would imply that an additional hour of sunlight would increase daily bicycle volume by 5 per cent. However, interpretation of the categorical dummy variables is not straightforward. Halvorsen and Palmquist (1980, as cited by Gujariti, 2003) suggest taking the anti-log of the coefficient and subtracting one to obtain the percentage effect, i.e. $effect = e^{\hat{\beta}} - 1$. In addition, interpretation is relative to the base case. For example, coefficient of -0.50 for Monday would be interpreted as volumes on any given Monday are 39% less than that of Sunday and not simply 50% less.

The effect of temperature, humidity and wind cannot be isolated individually, as people will perceive temperature as the apparent temperature rather than the actual air temperature, (Bureau of Meteorology, 2007). Most common forms of apparent temperature only take into account the effects of humidity on air temperature, such as the HUMIDEX used in Canada and the Heat Index used in the United States. Burke et al (2006) used the Canadian HUMIDEX when examining the effect of climate on the propensity to walk in Brisbane. In Australia, the Bureau of Meteorology (2007) uses apparent temperature, which also takes into account the effects of wind speed (the wind chill factor), defined as follows:

$$ATEMP = T + 0.33\left[6.105e^{\left(\frac{17.27T}{237.7+T}\right)} \times 0.01H\right] - 0.7W - 4.0 \quad (2)$$

T = air temperature in degrees Celsius, in this modelling context, it is the arithmetic mean of the maximum, 9am and 3pm daily temperatures. This is to give a more overall estimate of the air temperature during the day when the majority of cycling trips occur. Note that air temperature is the reported temperature (Bureau of Meteorology, 2007).

H = relative humidity (%)

W = wind speed (m/s), it is derived using the arithmetic mean of the 9am and 3pm wind speeds.

Wind is likely to have two effects on bicyclists. The first, as discussed before, is an indirect effect on the perceived temperature. Wind effects are particularly significant at lower air temperatures and that is likely to discourage cyclists and be associated with lower volumes. The second is a direct effect, and in the context of cyclists, stronger winds will inevitably create a bigger challenge, particularly for those riding into the wind which may deter some less experienced or determined cyclists from riding.

4.2 Modelling Results

The modelling results are presented in Table 4, which identifies the estimated coefficients and the shading highlights coefficients which were insignificant at the 5% level. Goodness of fit for OLS regression is typically given by the Coefficient of Determination (R2), it measures the amount of variation in the response variable accounted for by the set of explanatory variables. Within the system of equations the associated R2 ranges from 0.528 (Anniversary Trail) to 0.866 (Canning Street). We now examine the effect of each of the explanatory variables.

4.2.1 Time based growth

Of the thirteen locations, only five experienced statistically significant growth during the period of analysis. The increase in the usage of these paths ranged from 10 to 20% per annum. These five paths in ascending order of growth are: Upfield Railway Trail (10.9% p.a.), Capital City Trail (13.2% p.a.), Main Yarra Trail (14.0% p.a.), Canning Street (16.2% p.a.) and St. George's Road (19.4% p.a.). St. George's Road may have experienced a greater growth because of its high connectivity with the on-road facilities, offering cyclists a higher degree of route flexibility.

4.2.2 Public Holidays

For sites classified as commuter trails, the public holiday variable was negative and statistically significant in all equations. For sites classified as recreational trails, the public holiday variable was generally positive and significant except in the case of the Main Yarra Trail and the Bay Trail. For sites classified as commuter trails, this variable was significant and negative across all trails, which implies that on public holidays, commuter trails recorded reductions in daily volumes ranging from 19 per cent to 52 per cent. In contrast, recreation trails typically experience higher volumes on public holidays particularly the Koonung trail where public holidays lift daily bicycle volumes by about 37 per cent.

4.2.3 Day of the week

Figures 7 and 8 show the change in volumes over the course of a week to that of Sunday (the reference day used in the models) for both recreational and commuter trails. Recreational trails and commuter trails exhibit very different usage patterns throughout the course of the week. Recreational routes experience higher volumes on weekends than weekdays with the highest on Sundays and lowest on Fridays. This would be expected as the majority of usage on recreational trails would be on the weekend. One trait which is shared by all trails is that Saturday volumes are lower than Sunday volumes.

Commuter trails exhibit the exact opposite with weekday volumes up to 200% higher than weekend volumes. Cyclist volumes peak on Tuesdays and decline throughout the week with a significant decline in cyclists on Fridays. As noted earlier, Nankervis (1999) speculate that this may be due to social activities after work which results in cyclists using an alternative mode of transport.

Table 4: Regression results

Trail $[R^2]$	Const	Time Growth	Public Holiday	Rain (Base: None, <0.2mm) Light <10mm	Rain Heavy ≥10mm	Sunshine (hours)	Apparent Temperature (C) Temp	Temp^2	Wind (kph) (Base: Light, ≤19kph) Moderate 20-29	Fresh 30-39	Strong 40-62	Day of Week (Base: Sunday) Mon	Tues	Wed	Thurs	Fri	Sat
RECREATIONAL TRAILS																	
Anniversary	5.040	2.7×10^{4}	0.166	-0.137	-0.149	0.036	0.093	-0.003	0.019	-0.047	-0.174	-0.607	-0.645	-0.740	-0.737	-0.732	-0.426
[0.528]	(0.000)	(0.146)	(0.014)	(0.001)	(0.128)	(0.000)	(0.000)	(0.000)	(0.639)	(0.354)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bay	6.145	-5.7×10^{-5}	0.042	-0.210	-0.286	0.050	0.095	-0.002	-0.081	-0.184	-0.345	-0.355	-0.332	-0.359	-0.452	-0.584	-0.271
[0.690]	(0.000)	(0.715)	(0.493)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Koonung	5.464	-1.8×10^{-4}	0.317	-0.141	-0.201	0.047	0.106	-0.003	-0.003	-0.016	-0.070	-0.604	-0.485	-0.588	-0.655	-0.713	-0.270
[0.673]	(0.000)	(0.308)	(0.000)	(0.000)	(0.031)	(0.000)	(0.000)	(0.000)	(0.928)	(0.738)	(0.261)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Main Yarra	5.270	3.8×10^{-4}	0.023	-0.113	0.174	0.038	0.124	-0.004	-0.041	-0.102	-0.242	-0.696	-0.596	-0.693	-0.722	-0.845	-0.325
[0.599]	(0.000)	(0.050)	(0.770)	(0.051)	(0.189)	(0.000)	(0.000)	(0.000)	(0.438)	(0.111)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COMMUTER TRAILS																	
Canning St.	5.725	4.4×10^{-4}	-0.728	-0.110	-0.225	0.016	0.052	-0.001	-0.012	-0.046	-0.116	1.082	1.130	1.121	1.090	0.955	0.197
[0.866]	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.648)	(0.153)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital City	5.462	3.6×10^{4}	-0.213	-0.153	-0.227	0.032	0.083	-0.003	-0.040	-0.100	-0.231	0.256	0.287	0.262	0.216	0.100	-0.223
[0.653]	(0.000)	(0.005)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.173)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.031)	(0.000)
Footscray	5.956	2.1×10^{-4}	-0.395	-0.155	-0.202	0.030	0.069	-0.002	-0.006	-0.065	-0.142	0.454	0.487	0.447	0.389	0.211	-0.262
[0.690]	(0.000)	(0.154)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.838)	(0.106)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gardiners	6.676	-5.3×10^{-5}	-0.437	-0.142	-0.008	0.019	0.062	-0.002	-0.030	-0.108	-0.149	0.192	0.290	0.258	0.209	0.051	-0.189
[0.589]	(0.000)	(0.734)	(0.000)	(0.003)	(0.943)	(0.001)	(0.000)	(0.000)	(0.515)	(0.046)	(0.025)	(0.005)	(0.000)	(0.000)	(0.003)	(0.448)	(0.005)
North Bank	6.438	-1.7×10^{-4}	-0.432	-0.176	-0.278	0.037	0.090	-0.002	0.011	-0.042	-0.071	0.281	0.314	0.225	0.190	0.027	-0.303
[0.599]	(0.000)	(0.342)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.769)	(0.403)	(0.283)	(0.000)	(0.000)	(0.000)	(0.002)	(0.654)	(0.000)
South Bank	5.469	9.5×10^{-5}	-0.413	-0.085	-0.242	0.033	0.097	-0.002	0.039	0.012	-0.053	0.372	0.372	0.346	0.321	0.096	-0.062
[0.631]	(0.000)	(0.537)	(0.000)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.249)	(0.780)	(0.368)	(0.000)	(0.000)	(0.000)	(0.000)	(0.071)	(0.247)
St. Georges	5.315	5.3×10^{-4}	-0.532	-0.123	-0.185	0.022	0.048	-0.001	-0.006	-0.048	-0.055	0.735	0.811	0.770	0.748	0.620	0.069
[0.812]	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.816)	(0.138)	(0.264)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.094)
Tram 109	5.592	-2.0×10^{-4}	-0.292	-0.139	-0.240	0.033	0.069	-0.002	-0.029	-0.072	-0.159	0.208	0.255	0.201	0.140	0.039	-0.177
[0.646]	(0.000)	(0.110)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.299)	(0.047)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.381)	(0.000)
Upfield	4.921	3.0×10^{-4}	-0.422	-0.119	-0.144	0.026	0.077	-0.002	-0.030	-0.061	-0.175	0.605	0.631	0.608	0.548	0.431	-0.056
[0.751]	(0.000)	(0.018)	(0.000)	(0.000)	(0.032)	(0.000)	(0.000)	(0.000)	(0.270)	(0.080)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.200)

KEY: Shaded boxes correspond to insignificant parameters at a 5% significance level, note that the associated p-values are presented in parenthesis and the model Coefficient of Determination (R^2) is given in brackets.

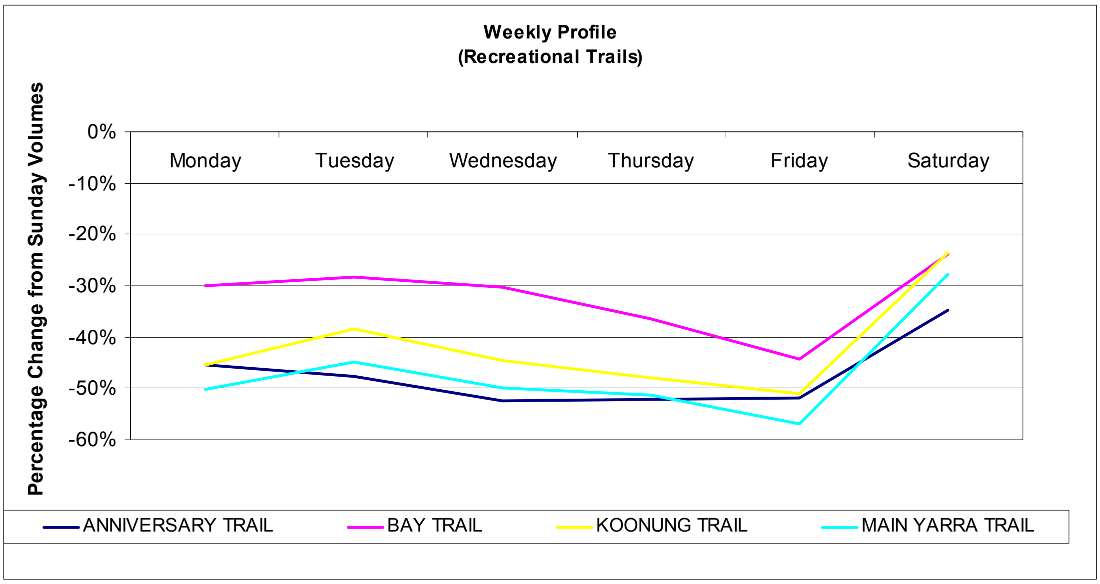


Figure 7: Change in cyclist volumes over the week (recreational trails)

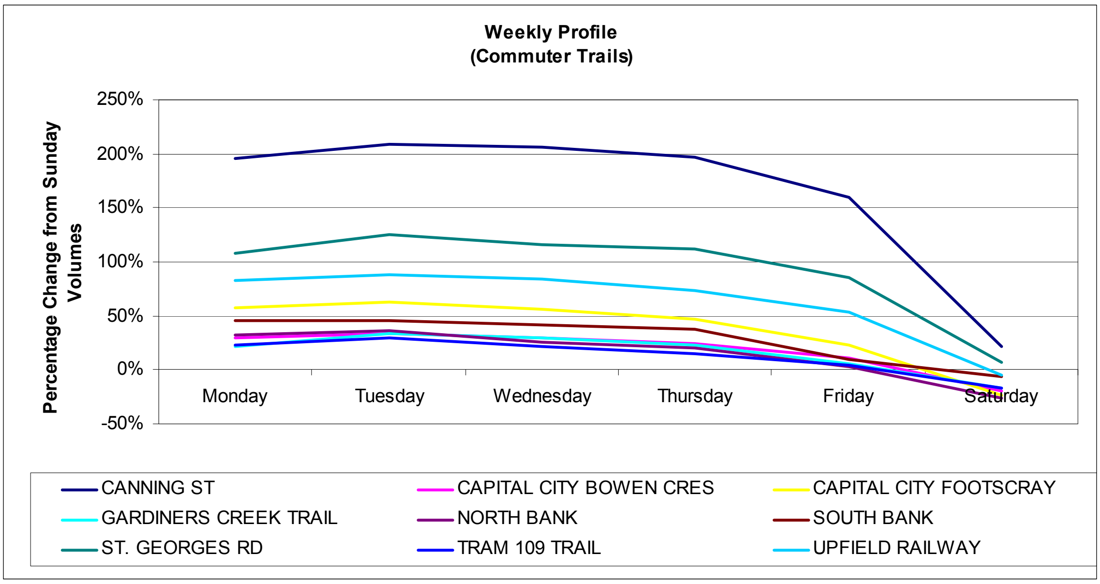


Figure 8: Change in cyclist volumes over the week (commuter trails)

4.2.4 Weather

The effects of weather varied widely across sites, particularly for wind and rain. Some sites, due to their physical location were more susceptible to weather effects, while at other sites, these effects were minimal. The effects of sunshine were minimal, ranging between 1.5 and 5% increases per additional hour of sunshine.

Rain was the biggest deterrent with all models reflecting reductions in cyclist volumes in response to light rain. Light rain deterred between 8 and 19% of all cyclists while heavy rain only one-third more (13 to 25%). This is consistent with Keay's (1992) findings that there is a sharp decline at the slightest hint of rain followed by much steadier reductions. These results differ from Nankervis' (1999) study where 67% of cyclists indicated they would not ride in heavy rain and with Burke et al's (2006) conclusion that rainfall does not affect non-motorised transport use.
The effect of wind is only felt at 9 of the 13 sites. Cyclist numbers at the majority of the 9 sites did not change under moderate or fresh winds, with decreases only under strong

winds, again confirming the results of Keay (1992). The Bay Trail, a site which has a clear recreational usage profile, was particularly sensitive to both wind and rain, with significant decreases under moderate winds and light rain. Figure 9 summarises the combined effects of wind and rain on each site. Light rain has been chosen to highlight likely conditions in Melbourne. It can be seen that the Bay Trail is most sensitive to changes in the weather, under strong wind and light rain, cyclist numbers on the Bay Trail reduce by 48%.

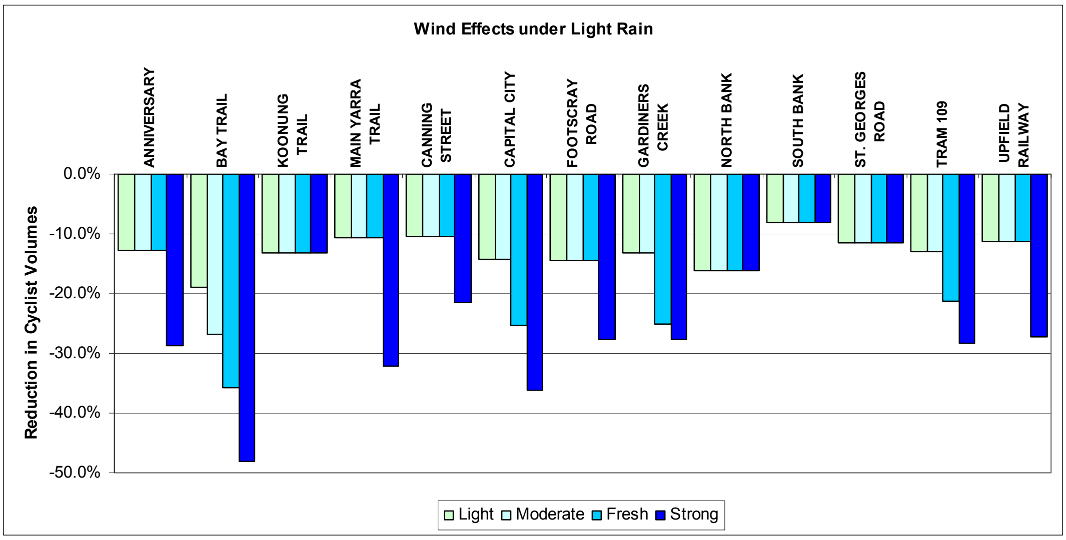


Figure 9: Wind effects under light rain

4.2.5 Temperature

The functional form allows for a non-linear effect to capture the different impact of low and high temperatures. The parabolic term for temperature in the regression model is as follows:

$$\sum_{m=1}^{2} \beta_{iATEMP,m} ATEMP_t^m = \beta_{iATEMP,1} ATEMP_t + \beta_{iATEMP,2} ATEMP_t^2 + constant \qquad (3)$$

Using this equation it is possible to identify the point at which a one degree rise in air temperature would result in the biggest increase in cyclist volumes, i.e. the turning point of the parabola. This temperature is coined the ideal riding temperature. It is calculated by setting the partial derivate of daily volumes with respect to temperature to zero, i.e. solving $\frac{\partial \log_e(Q_{it})}{\partial ATEMP_t} = 0$, yields: $ATEMP_{iMAX} = -\frac{\beta_{iATEMP,1}}{2\beta_{iATEMP,2}}$.

A comfortable riding range was also calculated. It was calculated by solving $\beta_{iATEMP,1} ATEMP_t + \beta_{iATEMP,2} ATEMP_t^2 + constant = 0$ and then converting the solution back into air temperature using Equation 1, where the constant is given by the combination of the other weather effects, with substitutions made for a typical day in Melbourne, that is values used for relative humidity (63.5%), wind speed (20.4 km/h, i.e. moderate winds), hours of sunshine (8.0 hours) and light rain conditions (Bureau of Meteorology, 2007). Figure 10 summarises temperature effects on cyclists for a typical day in Melbourne for both recreational (excluding the Bay Trail) and commuter routes. Note that a separate curve has been produced for the Bay Trail as this trail was more sensitive to weather effects than other sites. The comfortable riding temperature range is given by the range of temperatures with which the effect is positive, i.e. between 14 and 41 degrees Celsius, with the ideal riding temperature approximately 28 degrees Celsius. It should be noted that the effect is not symmetric; the effect diminishes more quickly after the ideal riding temperature.

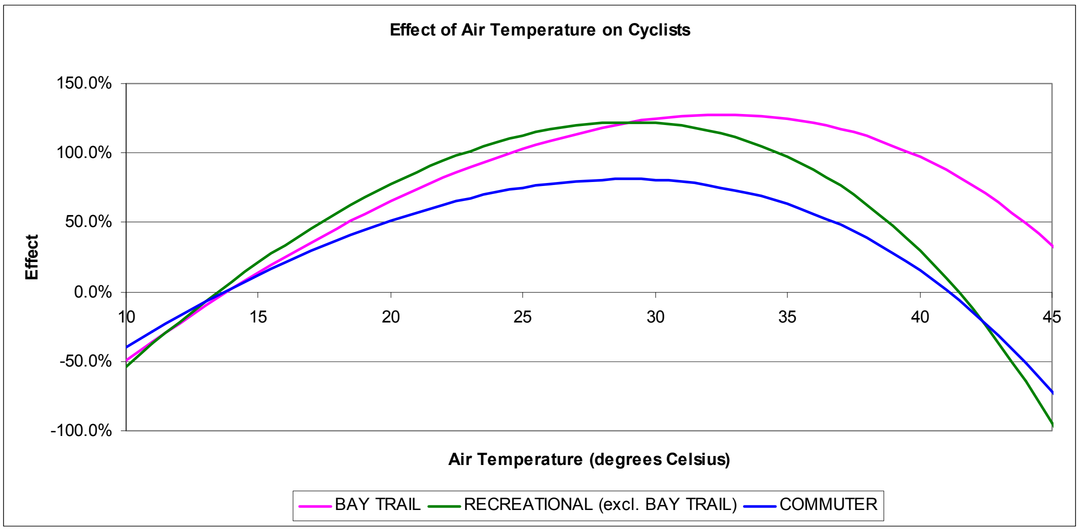


Figure 10: Percentage change in cyclist volume as a function of temperature

5 Conclusions and Research Directions

This paper has quantified the temporal variability in usage of Melbourne's bicycle paths. It is clear from the usage data that on weekdays the paths could be classified into two groups, one with a stronger commuter profile and the other more characteristics of a recreational character. A range of climatic variables were found explain the variability in usage of the bicycle paths. Rain and wind were found to suppress ridership volumes with light rain and strong winds the greatest deterrents. Temperature was found to have a non-linear effect, reflecting lower bicycle volumes at low and high temperatures.

It would be useful to undertake further testing of the model described in this paper by examining its predictive ability by drawing on more recent ridership and climatic data. Use of more sophisticated models such as time series cross section models may be useful in overcoming the limitations the method used, in which, issues such as panel heteroskedasiticity, serial autocorrelation and contemporaneous correlation can be accounted for. There would also be scope to include other variables into the model such as fuel prices and measures of network connectivity to either other bicycle routes or train stations (which vary by location).

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