Sensitivity of commuter cyclists to changes in weather in two Australian cities

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ABSTRACT

Policy makers are promoting bicycling as a mode of transportation since it offers sustainable economic, environmental and social benefits. However, user data collected from automated counting stations shows a considerable day-to-day variability in bicycle ridership. This study seeks to identify the role of a range of factors in helping to explain the variability in bicycle counts. Melbourne and Brisbane, the two cities which are the focus of this research, are two Australian cities which have been active over many years in encouraging the use of the bicycle for transportation. This research uses data from automated bicycle counters in an aggregate demand modelling approach to examine the impact of key weather and other parameters on bicycle ridership. Temperature and precipitation are found to have significant influence on ridership in both Melbourne and Brisbane but with different degrees. The results have implications for government strategies that seek to increase the role of bicycle in urban areas in order to enhance the sustainability of the transportation system. Directions for further research are identified including examination of commuter cyclist's travel behavior specifically focusing on their decision making process to response to changes in weather.

Keywords: Commuter cycling, weather, travel behaviour

INTRODUCTION

The recognition of the earth's geophysical limits and the impact of human activity on global systems is intensifying the focus on sustainability. Therefore bicycling is being encouraged as a mode of transportation since it reduces traffic congestion, energy consumption and greenhouse gas emissions and enhances health outcomes (Garrard et al, 2006, Dill and Voros, 2007 and Moreno and Nosal, 2011) and therefore offers sustainable economic, environmental and social benefits (Seneinejad et al, 2010). In line with global initiatives, the State, Federal and Local Governments of Australia have been promoting cycling (Austroads, 2005). Australia's 'National Cycling Strategy '2011–16' aims to double the number of people riding by 2016 (Minister for Infrastructure and Transport, Australia, 2012). In Melbourne and Brisbane, the State and Local Governments are supporting public bike hire schemes (Department of Transport, 2008 and Fishman et al, 2012) and the development of world-class end-of-trip facilities to promote commuter cycling (Australian Bicycle Council, 2009). However, to gain the maximum benefit from the investments and policies it is important that appropriate consideration be given to understand cyclist's travel behavior.

There are many factors that affect demand for bicycling although research consistently highlights the importance of adequate infrastructure (Dill, 2009). Cyclists are directly exposed to weather and thus the usage of this mode is sensitive to changes in weather. Seasonal variations in ridership (Rose and Murfart, 2007, Ahmed et al, 2010) suggest that there are many fair weather utilitarian cyclists and this presents a challenge from the perspective of gaining the maximum benefit from the investments in bicycle infrastructure targeted on promoting this mode of transport. Policies could be undermined by the influence of weather; particularly where the target is to increase women's cycling (Dill and Voros, 2007), if women are more likely to be deterred from riding in adverse weather.

Thus, this paper seeks to quantify the influence of weather on bicyclist volume particularly in Melbourne and Brisbane whose base climatic conditions are different. The results could also have implications for the development of factors which could be useful in adjusting counts made at one point in time (e.g. census journey to work data is collected in August in Australia which is in winter) to account for annual variations and regional differences in weather/climate.

The structure of this paper is as follows. Section two provides a review of the relevant literature. The review focuses on cyclist's travel behavior and explores the factors which contribute into cyclist's decision to ride. The following section describes the basic climatic conditions in the two cities chose for this study. It also explores the ridership data used for the analysis. Aggregate demand models incorporating a range of explanatory variables including weather data are then calibrated using the data from Melbourne and Brisbane. The final section presents the conclusions of the research and identifies future research needs and directions.

INSIGHT FROM THE LITERATURE

Bicycle riders are directly exposed to changing weather conditions. Moreno and Nosal (2011) investigated how bicycle usage in Montreal, Canada is impacted by various weather conditions. Their analyses found that precipitation (which refers to snow, rainfall, hail etc), temperature and humidity influenced bicycle ridership. When other factors were controlled, a 100% increase in temperature increased the ridership by 43-50%. However, temperature greater than 28^{0}C and humidity greater than 60% reduced the ridership which confirms a non- linear effect. Precipitation was also found to have both a direct and a lagged effect on ridership. As a result, bicyclist volume in a particular hour is not only affected by the presence of precipitation in that hour but also affected if there is precipitation in previous hours. Similarly, in the investigation of mode share in case of travel to work, Parkin et al (2008) found that an increase in annual rainfall corresponded to a decreased proportion of people cycling to work. Heinen et al (2011) found that commuter cyclists in Netherlands are influenced with both the quantity and the duration of rain. Moreover, increased wind speed discourages cyclists to ride to work. Again, temperature was identified to cause the greatest variation and wind to cause the least variation in bicycling demand in Netherlands (Thomas et al, 2009). More recently, Lewin (2011) confirmed that the impact of temperature on daily bicyclist volume in Boulder, CO was non linear with the optimum riding temperature estimated to be 32.2^{0}C. Other research (Rose et al, 2011) examined ridership sensitivity to weather in Portland, Oregon, USA. Analyses of six months of data from Portland, Oregon indicated that a 1^0C rise in temperature increases the volume of daily bicyclists by between 3% to 6% whereas each 1mm increase of rainfall decreases the volume by around 4%.

Smith and Kauermann (2011), Nankervis (1999), Richardson (2000) and Phung and Rose (2008) examined how weather affects bicycle ridership in Melbourne, Australia. Smith and Kauermann (2011) found weather conditions to be the strongest determinants of bicycle ridership. Both Richardson (2000) and Phung and Rose (2008) identified rain as the most influential weather parameter which significantly decreased commuting cyclist volumes. Both of these studies found that rainfall has a non-linear effect. Richardson (2000) identified that daily rainfall of around 8 mm reduces cyclist volumes by about 50% compared to days when there is no rain. In contrast, Phung and Rose (2008) found that light rain (defined as daily rainfall less than 10 mm) deterred between 8 and 19% of all cyclists while heavy rain (defined as daily rainfall greater than 10 mm) deterred about one-third more (13 to 25%). Air temperature has been identified to have a non-linear and non-symmetrical relationship on commuter cyclist volume with the volume of riders decreasing beyond the ideal riding temperature (Richardson, 2000 and Phung and Rose, 2008). Phung and Rose (2008) identified the ideal riding air temperature to be about 28^0C whereas Richardson's (2000) analysis identified the optimal air temperature for riding to be 25^0C. Wind effects were detected for most of the sites in Melbourne studied by Phung and Rose (2008), but ridership on the Bay Trail, which runs along the exposed coast of Port Phillip Bay, was the most sensitive to wind change. Strong wind (defined as 40-62 kph) reduced the volume of commuter cyclist by between 11 and 23%. Nankervis (1999) investigated commuter's behavior and identified a decrease in cycling over the winter months. Heavy rain was the biggest deterrent for the cyclists to ride with 67% of the respondents indicating that they would be deterred from riding in heavy rain. Among these respondents who did not ride (67%), almost all of them (90%) indicated that they still made the trip but used an alternative mode.

Studies have also identified several other factors which stimulate cyclists to ride. Among the motivating factors, environment and health was frequently noted (Gatersleben and Appleton, 2007 and Ahmed et al, 2013). The other potential factor, fuel prices, has received little attention in relation to cyclist's travel behaviour. Smith and Kauermann (2011) examined the relationship of fuel price to bicyclist volume using a Poisson model. A positive elasticity (+1.25) of ridership to fuel price particularly during the peak periods was found.

DATA

This section begins with a brief introduction to the climatic conditions in the two cities chosen for this study. Melbourne, the capital of Victoria and Brisbane, the capital of Queensland, are located in the south and north of Australia respectively and are about 1,400 km apart. These cities were chosen because they experience different base climatic conditions and because the transport authorities in both states had installed automatic bicycle counting equipment on bike paths which provided extended time series volume data.

Melbourne, the capital of Victoria is located in on the South-eastern edge of Australia. It could be characterized as experiencing a temperate climate. It experiences mild to warm summers (up to 40^0C for brief periods) and cool winters (daily maximums round 10^0C). Usually the winter in Melbourne is wet and little precipitation during the summer. Brisbane falls in a sub tropical climatic zone. It experiences hot dry summers (maximums round 40^0C) and mild winters (daily maximums round 15^0C). Brisbane's precipitation is primarily in the summer while the winters are fairly dry.

Automatic bicycle counting equipment has been installed at a number of locations in each city. In this analysis we draw on data from two sites which had high data reliability and were predominantly used by commuters. For Melbourne, the site to the north of the city, on St Georges Road is used in this analysis. The State Road Authority (Vic Roads) has installed an inductive loop bicycle counter at this site which provides aggregate two way counts on an hourly basis. For Brisbane, data from Normanby East counter is used because it provides continuous, directional 15min counts. Both sites are predominantly used by commuter cyclists (the Ratios of volumes on Weekdays versus Weekend and public holidays are greater than one).

Bicycle count data were obtained for each site covering the 2006 to 2011 period. Hourly weather data for the two sites was obtained from Bureau of Meteorology, Australia. Temperature, precipitation, humidity and wind speed data were considered for this study.

MULTIVARIATE MODELLING

Model formulation

This section explains the methodology employed in this study to estimate the effect of potential factors into commuter bicyclist volume. A regression modelling approach is adopted in this study as this approach has previously provided valuable insight (Phung and Rose, 2008, Ahmed et al, 2010 and Rose et al, 2011). As the analysis reported here focuses on commuter cyclist behavior, Saturdays and Sundays are excluded from the analysis. Public holidays are included in order to estimate how much public holidays influence the weekday ridership.

To examine the variation in bicycle usage and the factors contributing to those variations, a log linear model is employed. The model focuses on daily peak period ridership.

Daily peak period ridership model

The ridership model is formulated as a log linear model with the peak period ridership as the dependent variable:

$$\begin{aligned} log_e\,(Q_{it}) = \; & \alpha_i + \sum_{n=1}^{4} \beta_{iDOW,n} DOW_n \; + \; \beta_{iTIME} TIME_t \\ & + \sum_{m=1}^{2} \beta_{iATEMP,m}\, ATEMP_t^m + \sum_{j=1}^{3} \beta_{iPRECIPITATION,j} PRECIPITATION_j^t \\ & + \beta_{iPUB} PUB_t + \varepsilon_{it} \forall_{i,t} \end{aligned} \quad (1)$$

where;

Q = Daily total morning peak period (6am-9am) bicycle volume
i = Site index
t = Time index
DOW = DOW variable is coded using four dummy variables (Monday through Thursday) with the base case corresponding to Friday

TIME = a variable which increments to reflect the day when the data was collected (incrementing from the start to the end of the series of data). This variable is used to capture any time based growth effect.

PUB = Public holiday, coded as a dummy variable (1 for a public holiday and 0 otherwise)

ATEMP = Average of maximum, 9am and 3pm daily apparent temperatures (in degree Celsius). It is treated as continuous variable.

Here, the variable ‘apparent temperature’ is considered to relate people’s perception of the temperature rather the measured air temperature.

Apparent temperature is calculated as:

$$ATEMP = T + 0.33\,[6.105\, e^{(17.27\, T / 237.7 + T)} \times 0.01\, H] - 0.7\, W - 4.0 \qquad (2)$$

(Bureau of Meteorology)

where,

- T = Air temperature in degrees Celsius.
- H = Relative humidity (%)
- W = Wind speed (m/s)

PRECIPITATION = Daily total (6am-9am) precipitation (in mm).

‘PRECIPITATION’ variable is treated in two ways, as a categorical and as a continuous variable. Table 1 shows the two formulations.

Table 1 - Categorization of Variable ‘PRECIPITATION’

Parameter	**Type**	**Category**	**Melbourne**	**Brisbane**
Precipitation	Categorical variable	No precipitation	0 mm	0 mm
		Light precipitation (up to the third quartile)	Up to 1.6mm	Up to 3.8mm
		Heavy precipitation	>1.6 mm	>3.8mm
	Continuous variable		Previous day’s total daily precipitation (to examine whether there is any lag effect)	

The categorical representation is considered to reflect differences in the underlying climate of the two states. In this representation, the variable is coded using two dummy variables for ‘Light precipitation’ and ‘Heavy precipitation’ with the base case corresponding to ‘No precipitation’. The categorization shown in Table 1 is based on analysis of quartiles from the respective distributions. The fourth quartile i.e. the highest 25% of the daily total (6am-9am) precipitation is used for defining heavy precipitation days. The categorization corresponds to how each area experiences the variation in precipitation and so, therefore reflects differences in the base climatic conditions of the two locations.

Previous research identified that the bicyclist volume in a particular hour is not only affected by the presence of precipitation in that hour but is also affected by precipitation in previous hours (Moreno and Nosal, 2011 and Ahmed et al, 2012). To examine how precipitation during previous day affects the morning peak period ridership, the second continuous form is included in one of the models to test for the lag effect.

MODEL RESULTS

The estimation results are presented in Tables 2. The estimated coefficients and the Coefficient of Determination (R^2), a measure of 'Goodness of fit' for OLS regression, are also given in the table. The shaded boxes correspond to significant variables at a 95% confidence level.

Model results

R^2 values for Melbourne and Brisbane are .68 and .65 respectively. Thus, around 68% of the variation in morning peak period bicyclist volume has been explained by the models. All the explanatory variables are found to have statistically significant affect on ridership.

Alternative specifications for apparent temperature such as 'Average of 24 hr daily apparent temperature' and 'Average of (6am-9am) daily apparent temperature' were also examined but the 'Average of maximum, 9am and 3pm daily apparent temperatures' produced the best fit and so those results are presented here. In a similar way to temperature, an alternative specification for the precipitation variable (Total 24 hour or daily precipitation) was tested. However, the variable defined as 'total precipitation during the morning peak period (6am-9am)' was found to predict the morning ridership better and so only those results are presented here.

Table 2 - Regression model results

Explanatory variable		**Melbourne**	**Brisbane**
		Coefficient	Coefficient
Time based growth		0.0004 (26.85)	0.00097 (26.51)
Day of week	Mon	0.17 (6.48)	0.31 (7.27)
	Tue	0.28 (10.61)	0.46 (10.73)
	Wed	0.23 (8.77)	0.47 (10.82)
	Thu	0.19 (7.32)	0.31 (7.10)
Public holiday		-1.40 (-37.04)	-1.47 (-20.74)
Atemp		0.05 (9.13)	0.02 (3.36)
Atemp^2		-0.0013 (-7.62)	-0.00048 (-3.11)
Light precipitation		-0.24 (-6.98)	-0.32 (-7.21)
Heavy precipitation		-0.61 (-9.69)	-0.77 (-10.15)
Previous day's total daily precipitation		-0.01 (-2.01)	-0.01 (-6.37)
R^2		**0.68**	**0.65**

KEY: The associated t stats are presented in parenthesis. The critical values for t stats are for a 95% confidence interval. Variables which are significant at a 95%confidence level are lightly shaded.

Melbourne Results

The modelling result indicates that the site St. Georges Road experienced around 15% growth per annum during the analysis period. The annual growth has been calculated as Growth per annum = Coefficient* 365.

The morning peak period volume varies across different days of the week. The reference day in these models is Friday. Bicyclist volume reaches its peak in the middle of the week with Tuesday recording the highest volume that is around 33% [exp (.28) -1] higher than that on Friday. Volume declines as the week progresses with the lowest volume found on Friday. On Public holidays, the morning peak period bicyclist volume decreases by more than 75% [exp (-1.40) -1].

Temperature is found to have a non-linear effect on bicyclist volume. The non-linear effect is captured here by different signs on the coefficients of ATEMP and ATEMP^2. An optimum riding temperature of 20^{0}C is indicated by Figure 1. The result shows that when the temperature in Melbourne reaches to the optimum level, volume increases by more than 50% from that at 2^{0}C (the recorded minimum temperature).

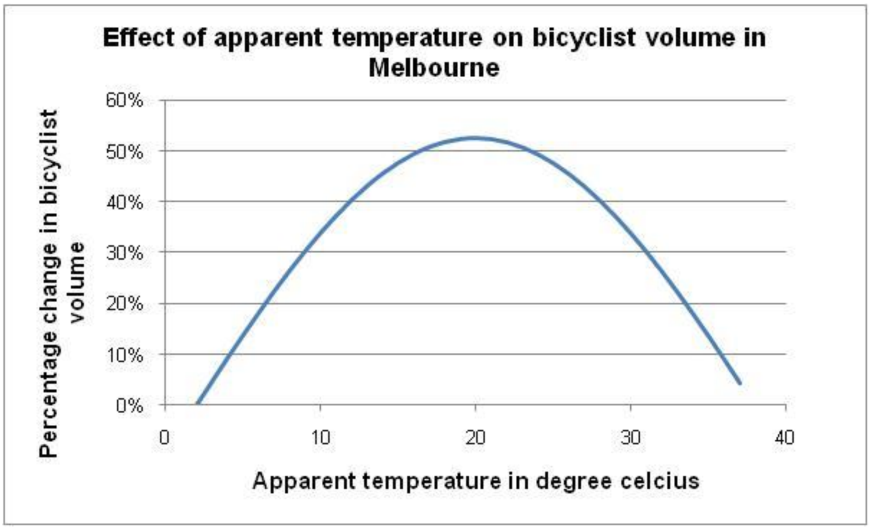

Figure 1 - Effect of temperature on bicyclist volume

Light precipitation (<=1.6mm) in Melbourne produces a 21% [exp (-.24)-1] decrease in morning bicycle ridership. Heavy precipitation (>1.6mm) has more than twice the effect of light precipitation (46% versus 21%). Commuter cyclists are also impacted by previous day's precipitation. Each 1 mm increase in previous day's precipitation decreases the current morning's volume by 1%.

Brisbane Results

During the analysis period, the Brisbane site has experienced around 35% growth per annum. Wednesday appears to have the highest morning bicyclist volume. Ridership decreases as the week progresses. On public holidays, the ridership decreases by 77%.

The optimum riding temperature is 25^0C in Brisbane (Figure 2). The volume increases by 23% at the optimum temperature from that at 4^0C which is the recorded minimum temperature. However, the effect of temperature drops off when it is greater than 25^0C.

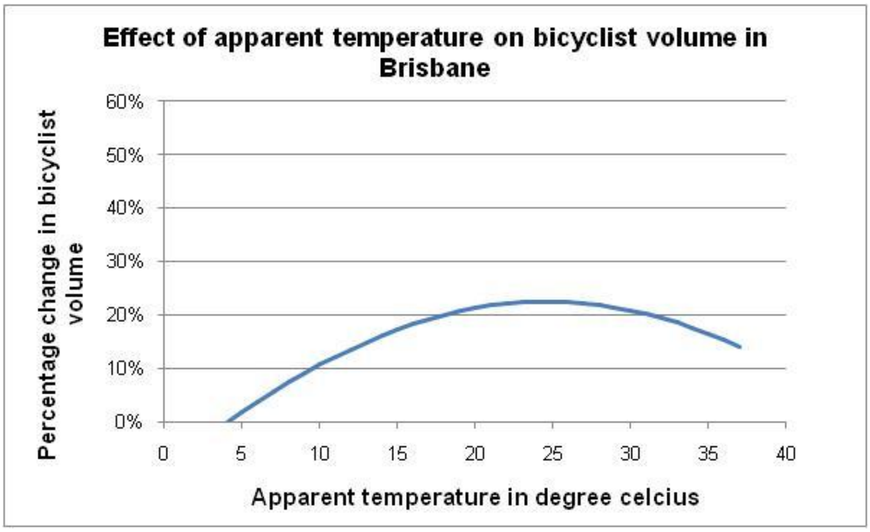

Figure 2 - Effect of temperature on bicyclist volume

Precipitation reduces morning ridership in Brisbane. The greatest impact comes from heavy precipitation which decreases volume by 53% about twice the impact of light precipitation. Previous day's precipitation decreases current morning ridership as well with the effect of the same magnitude as in Melbourne (each 1 mm increase in previous day's precipitation decreases the next morning's volume by 1%).

COMPARISON BETWEEN MELBOURNE AND BRISBANE

Day of the week

Comparing the modelling results of the two locations, it can be observed that both states experience a higher daily bicyclist volume during the week compared to Friday (Figure 3). However, it is noticeable that Friday gets much lower volume compared to other weekdays in Brisbane (coefficients of the days in Brisbane models are larger than that for Melbourne). The results indicate that commuters in Brisbane are less likely to ride to work in Friday compared to the commuters in Melbourne.

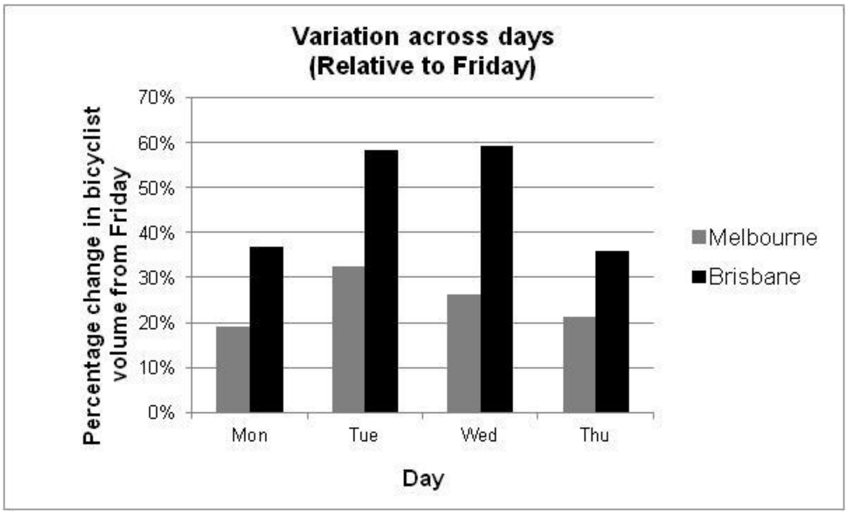

Figure 3 - Variation in bicyclist volume on different days

Effect of public holiday

Public holidays have similar impact on commuter bicyclists of Melbourne and Brisbane. On public holidays, morning bicyclist volume decreases by around 75%.

Weather effect

Cyclists at the two locations are found to have different sensitivities with respect to temperature. The effect of temperature is more pronounced in Melbourne than Brisbane. In Brisbane, the optimum riding temperature is 25^0C whereas it is 20^0C in Melbourne. On days with temperatures round the optimum, ridership in Melbourne is more stimulated than that in Brisbane (53% versus 23% for Brisbane).

The results also reveal that commuter cyclists from both states are impacted similarly by precipitation but with higher magnitudes for Brisbane. Light precipitation reduces morning ridership by around 21% in Melbourne whereas it is 27% in Brisbane. Likewise, the effect of heavy precipitation is more prominent in Brisbane (53% versus 45% in Melbourne).

CONCLUSIONS AND RESEARCH DIRECTIONS

This paper has investigated weather impacts on bicycle ridership in Melbourne and Brisbane using an aggregate regression modelling approach. The study confirms the sensitivity of ridership to weather although the sensitivity is different in the two locations. Ridership in both locations is sensitive to temperature but the impact is more pronounced in Melbourne. In contrast, precipitation deters commuter cyclists more in Brisbane than in Melbourne.

In the future, additional sites in both Melbourne and Brisbane will be analyzed to determine whether the effects identified here hold at other locations in the metropolitan area. Disaggregate travel data is also being collected through a survey of commuter cyclists. That data will be analyzed to examine commuter cyclist's travel planning behaviour and their adaptation to changes in weather. Exploring disaggregate panel data will facilitate an understanding of how commuters take their decisions to cycle to work and which factors contribute into their decisions across the seasons. From a travel behaviour perspective, future research will also explore fuel price data to identify any long term impact of fuel price on bicycle volume.

ACKNOWLEDGEMENT

The authors wish to thank Anthony Barton and Jas Bhatt, from VicRoads, Peter Berkeley, Mark Dorney and Michael Langdon from Department of Transport and Main Roads, Queensland and Doerte Jakob from the Bureau of Meteorology who provided invaluable data and support. Any opinions, findings and conclusions or views expressed here are those of the authors.

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