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The impact of weather conditions on bikeshare trips in Washington, DC

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Abstract Bicycle usage can be affected by colder weather, precipitation, and excessive heat. The research presented here analyzes the effect of weather on the use of the Washington, DC, bikeshare system, exploiting a dataset of all trips made on the system. Hourly weather data, including temperature, rainfall, snow, wind, fog, and humidity levels are linked to hourly usage data. Statistical models linking both number of users and duration of use are estimated. Further, we evaluate trips from bikeshare stations within one quarter mile of Metro (subway) stations at times when Metro is operating. This allows us to determine whether Metro serves as a back-up option when weather conditions are unfavorable for bicycling. Results show that cold temperatures, rain, and high humidity levels reduce both the likelihood of using bikeshare and the duration of trips. Trips taken from bikeshare stations proximate to Metro stations are affected more by rain than trips not proximate to Metro stations and less likely when it is dark. This information is useful for understanding bicycling behavior and also for those planning bikeshare systems in other cities.

Keywords Bicycle sharing · Weather · Transit · Multivariate analysis

Introduction

Bikesharing systems have grown rapidly over the last few years throughout the world, following on the success of their implementation in Lyon and Paris. These provide an

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alternative means of transportation in cities by making bicycling more convenient for users, as they do not need to worry about parking or theft of their own bicycle and can be more easily used for one-way trips as a part of a multimodal tour. Cities can benefit by providing a new sustainable transportation option that can increase access to transit, but also reduce crowding on overburdened transit systems, such as the Underground in London. Bikesharing allows users, through a membership fee, to checkout a bicycle at stations placed throughout the city, ride to their destination, and return the bicycle at a nearby station. Trips are typically free for a certain amount of time (often 30–60 min) to encourage short trips and continued use of each bicycle amongst users. A recent count of systems estimated 100 bikesharing programs in approximately 125 cities worldwide (Shaheen et al. 2010). In the United States, notable systems currently exist in New York, Chicago, Denver, Minneapolis, Boston, and Washington DC.

In Washington, DC, Capital Bikeshare (CaBi) is currently one of the larger systems in the nation with over 2,500 bicycles at 300 stations (Alta Bicycle Share, Inc. 2012). The system grew out of an early bikesharing pilot project, SmartBike D.C., launched in 2008 (Alta Bicycle Share, Inc. 2012). Capital Bikeshare opened in September of 2010 with 400 bicycles at 49 stations in both Washington, DC and Arlington, Virginia and has expanded gradually through both station additions and station expansions (Goodman 2010). A wealth of data on travel behavior is being collected by these systems and Capital Bikeshare has made the trip logs of every trip taken in the system publically available.

This analysis exploits the dataset of bicycle trips made using Capital Bikeshare in order to determine how bicycle usage varies under different weather conditions. Hourly data on weather conditions for Washington, DC, are matched with the usage data. This allows us to determine relationships between rainfall, snow, temperature (both hot and cold), humidity, wind speed, and various other weather conditions that may affect bicycle usage, measured as both the number of trips per hour and their average duration. We are also able to control for how patterns of daylight and darkness affect trip behavior. The impact of weather on bikeshare trips that are proximate to Metro stations and those further away are also examined, allowing us to determine whether Metro serves as a back-up option for bikeshare trips when weather is not conducive to bicycling. Our results have implications for understanding the sensitivity of bikeshare usage to weather conditions and how this can affect the usefulness of bikesharing as an alternative mode of travel. It is also informative for those planning or operating bikesharing systems.

Previous literature

A growing body of research has examined the impacts of weather and climate on cycling in different cities, usually in combination with other factors that may affect cycling. Results have varied as to how important weather is in affecting usage. Pucher et al. (1999) found cities with relatively high cycling rates to have mild winters and often little rain compared to areas of the U.S. with extreme heat and humidity that discourage cycling. Additionally, in Pucher and Buehler's (2006) analysis predicting percentage of bicycle trips to work in U.S. and Canadian cities, precipitation and temperature were found to be statistically significant variables correlated with lower cycling rates (Pucher and Buehler 2006). However, Buehler and Pucher (2012) found no statistical significance for annual number of days above 90 °F (32.2 °C), annual number of days below 32 °F (0 °C), and annual inches of precipitation on bicycle commuting amongst large American Cities. Dill and Carr (2003) found the number of days of rain to be negatively correlated with bicycle commuting rates, but not statistically significant. In an investigation of impacts of individual and city-level characteristics on bicycling in Canadian cities, it was found that more days of precipitation per year and more days with freezing temperatures per year are associated with lower levels of utilitarian cycling, but average summer maximum temperature and average wind speed had no influence on cycling (Winters et al. 2007).

Studies have been conducted to assess the relative impact of weather on cycling trips within a city. Cervero and Duncan (2003) developed a bicycle mode choice model based on Bay Area Travel Survey data to predict the probability that a trip will be made by bicycle. They found that rain did not deter individuals from bicycling. An analysis of commuting patterns of students in Melbourne, Australia found seasonal weather variation to not have a significant impact, while specific weather conditions of wind, rain, and temperature were statistically significant (Nankervis 1999). An analysis of the impacts of weather on cycling through parks in Vienna counted cycling levels through the park and related these to weather variables including rain, temperature, and thermal index, all of which were found to have a significant impact on both recreational and commuting cycling levels (Brandenburg et al. 2007). Of note in the Brandenburg study was the use of individual trip counts as they related to daily weather conditions. Using a survey methodology, a Swedish study found that bicycle trips decreased by 47 % from summer to winter, and that temperature and precipitation were among the most important factors of concern among seasonal cyclists (Bergström and Magnusson 2003). More recent research in the Netherlands examined relationships between various weather variables and daily fluctuations in bicycle flows on selected bicycle lanes. Precipitation, temperatures, amount of sunshine, and wind all influenced bicycle use, especially for recreation (Thomas et al. 2013).

As bikesharing systems have proliferated, research on bikesharing systems has begun to emerge. While some research utilizes survey methodology to determine factors leading to bikeshare use (Bachand-Marleau et al. 2011), the availability of trip-level data collected by the systems is an exciting new data source for transportation researchers. One prior study evaluated bikeshare data and linked this to weather patterns (Noland and Ishaque 2006). This study used data from the OYBike pilot scheme in the Borough of Hammersmith and Fulham, in the west of London. Monthly aggregates of trips and weather variables were graphically analyzed and showed that fewer trips occurred in colder months. Months with more rain also appeared to reduce usage and less daylight decreased usage. The data was insufficient for conducting a multivariate analysis to separate these factors. The analysis presented here provides a much richer dataset of both hourly usage and weather patterns, overcoming the data shortcomings of this previous work.

Of note for our analysis, a weblog (JDAntos) provides an analysis of daily temperatures recorded at National Airport merged with the CaBi dataset (JDAntos 2012). The analysis observed an expected trend of increased bikeshare trips per day as average temperature increased, but also noticed a decrease in July 2011 during weeks of extreme heat. After plotting daily high temperatures, it was found that trips were more scattered for temperatures between 50 and 70 °F (10 and 21.1 °C), indicating that more extreme temperatures played a larger role in the decision to bicycle (JDAntos 2012).

Before the public release of Capital Bikeshare trip history data, the system's operator, Alta Bicycle Share, provided a limited dataset to researchers who conducted an analysis of bicycle infrastructure and other determinants of average daily bikeshare trips. Bicycle usage was correlated with a variety of spatially derived variables calculated using a geographic information system (Buck and Buehler 2012). These included proximity of bicycle lanes, total resident population, percent of households with no motor vehicle access, and a proxy for retail store density (liquor licenses). All had a positive association with bikeshare usage. In 2010, Barclays Cycle Hire (aka Boris Bikes) was opened in London, a far more expansive system. Research was conducted on the impact of a transit strike on bikeshare trips (Fuller et al. 2012). A temporary increase in usage was found immediately after the strike, suggesting experimentation with the system, after which levels of usage slowly diminished back to pre-strike levels. The impact of a policy change allowing casual users to access the London system resulted in more weekend usage and also increased commuting usage (Lathia et al. 2012). Much of this research was made possible by Transport for London freely providing trip history data. Additional research using bikeshare trip data includes factors effecting trip generation and attraction in Barcelona and Seville (Hamphire and Marla 2011) and an analysis of bike speeds and flows in Lyon (Lathia et al. 2012).

The contribution of the research presented here is to use a much more temporally detailed weather dataset with information on bikeshare use. From a policy perspective there are many reasons to want to understand how weather patterns may affect bikesharing. The operators of these systems expend significant resources on repositioning bicycles to match travel patterns. If travel patterns differ based on weather patterns, then the repositioning of bicycles may need to be adjusted based as weather varies. As these systems are also in many cases linked to transit systems, mainly as an egress mode from transit, weather patterns may also affect the interaction between these modes; either increasing or decreasing the demand for transit. Again, from an operational perspective, understanding weather patterns and their effect on bikesharing use, is a contribution of this work, not previously addressed in the literature.

Data

Capital Bikeshare made their data publically available in January of 2012 containing anonymous individual trip data (http://www.capitalbikeshare.com/trip-history-data). The dataset downloaded for this analysis includes 1,361,074 trips from September 15, 2010 to December 31, 2011 with attributes for trip duration (seconds), start trip date and time, end trip date and time, start station, end station, bicycle number, and whether the user had a casual (1–5 day) or registered (monthly or annual) membership.[1] For analysis purposes, trips were removed that lasted longer than 24 h (287). Additionally, trips that started and ended at the same station and lasted less than 60 s were removed (these observations were likely results of someone checking out a bicycle only to immediately return it and not actually take a trip). The first month of operation, September 2010, was also removed (4,205 trips) as the system was not fully operational and start-up effects resulted in a low number of trips and some unusually lengthy trips.

Weather data from October 1, 2010 to December 31, 2011 were obtained from Weather Underground history data which offers historical weather data for download of both daily and hourly observations, including temperature, humidity, wind speed, precipitation, and the observation of fog, rain, thunderstorms, and snow. Typically the dataset provided observations for each hour every 52 min after the hour. However, when additional observations were given, they were removed to maintain equal 1-h intervals. Observations which did not occur 52 min after the hour were assumed to occur at 52 min after the hour.

[1] At system opening, a 1-day, 5-day, monthly, or yearly membership was available. In the fall of 2011, a 3-day membership option replaced the 5-day membership option.

Table 1 Descriptive statistics

Variable	Mean or count[a]	SD	Min.	Max.
Dependent variables				
Trips per hour	122.236	125.58	0	807
Average trip duration per hour	18.32	16.31	2.03	644.62
Independent variables (weather)				
Temperature (°F)[b]	57.315	17.68	17.1	102.9
Temperature—10 s (°F)	28			
Temperature—20 s (°F)	386			
Temperature—30 s (°F)	1,848			
Temperature—40 s (°F)	1,790			
Temperature—50 s (°F)	2,058			
Temperature—60 s (°F)	1,693			
Temperature—70 s (°F)	1,818			
Temperature—80 s (°F)	1,064			
Temperature—90 s (°F)	267			
Temperature—100 s (°F)	16			
Relative humidity (%)	63.859	19.04	9	100
Wind speed (MPH)	8.236	5.202	0	41.4
Fog	18			
Rain	754			
Thunderstorm	69			
Snow	100			
Independent variables (control)				
Darkness	5,102			
Number of stations in system	40.531	6.215	19	54
Peak travel hours	3,200			
Weekends/holidays	3,480			

[a] Means are shown for continuous variables and counts for dummy variables

[b] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin

Missing observations were imputed by averaging conditions from the preceding and following hour; these constituted less than 30 records out of 10,968 total hourly observations.

Data for the measure of darkness were obtained from sunrise and sunset tables of the Astronomical Applications Department of the U.S. Naval Observatory (U.S. Navy 2012). The variable was coded as “dark” one-half-hour before sunrise and after sunset.

All variables and descriptive statistics are in Table 1. For the dependent variables analyzed, there was an average of 122.2 trips per hour with a standard deviation of 125.6. The average trip duration was 18.3 min ranging from as short as 2.0 to 644.6 min (10.7 h—represents a single trip beginning at 3:38 a.m. on October 7, 2010).

Independent variables included both weather variables and non-weather related control variables. Washington, DC recorded a wide-range of temperatures throughout the dataset spanning from 17.1 °F (−8.3 °C) to 102.9 °F (39.4 °C). Washington can be fairly humid with an average relative humidity of 63.9 % and a standard deviation of 19.0. The average wind speed was 8.2 MPH; this is defined as a “gentle breeze” according to the Beaufort wind force scale (Met Office 2010). Fog and thunderstorms were rare events in the recorded data (0.2 and 0.6 %), but rain (6.9 %) and snow (0.9 %) were observed more often. The correlation between our dummy variables for thunderstorms and rain was low (R = 0.206). For control variables, it was interpreted to be "dark" 46.5 % percent of the time. System growth is represented by 19 stations at opening in Washington, DC growing to 54 by December 2011, with a mean of 40.5 stations across all hourly observations. This variable only includes stations in Washington, DC, and does not include Arlington, VA. Therefore, it does not precisely measure total system growth. However, the general trend of an increasing number of stations is represented.

Preliminary analysis

A relationship between daily number of trips and average daily temperature can be seen in Fig. 1. This graph is based on aggregating trips for each day and joining daily weather observations from Weather Underground, an alternate weather dataset than was used for the hourly graphs and regression analysis. System growth early on in 2010 is visible even as temperatures begin to fall. By January 2011, a clear relationship is visible between the number of trips per day and average temperature. A few outlier days can be explained by adverse weather impacts that day. August 27, 2011, for example, saw only 1,106 trips, due to 3.3 inches of precipitation that day. Between July 18, 2011 and August 2, 2011, the high temperature was 93 °F (33.9 °C) or higher, with 4 days of temperatures over 100 °F (37.8 °C). A drop of ridership is visible throughout these days of extreme heat. Days with low ridership are also explained for reasons other than the weather, such as only 189 and 743 trips on Christmas Day in 2010 and 2011.

As humidity increases, fewer bikeshare trips are made. Figure 2 shows mean trips per hour of both casual and registered users plotted against relative humidity. The relationship is fairly linear. However, the low number of trips taken in very low humidity is likely a result of colder temperatures during these times.

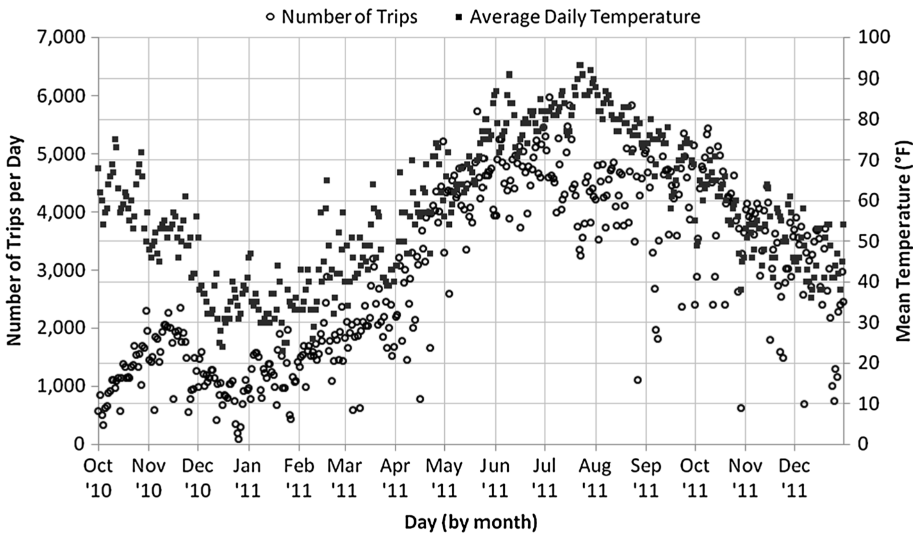

Fig. 1 Number of trips per day versus average temperature each day

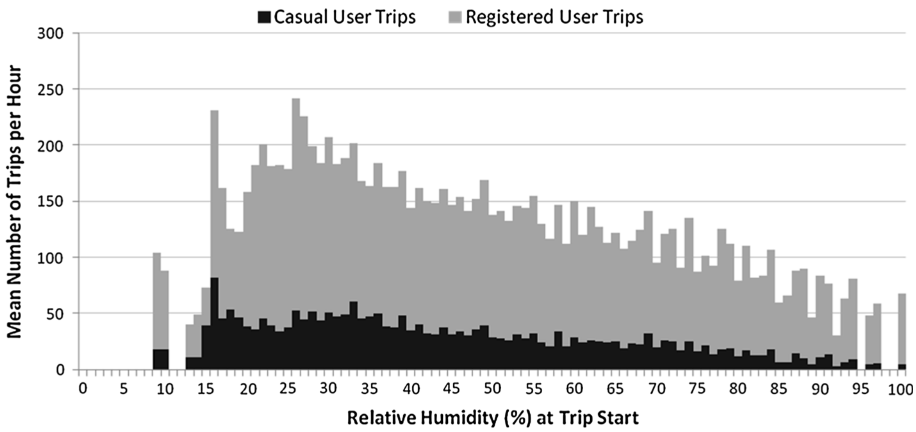

Fig. 2 Mean number of trips per hour by humidity level for registered users and casual users

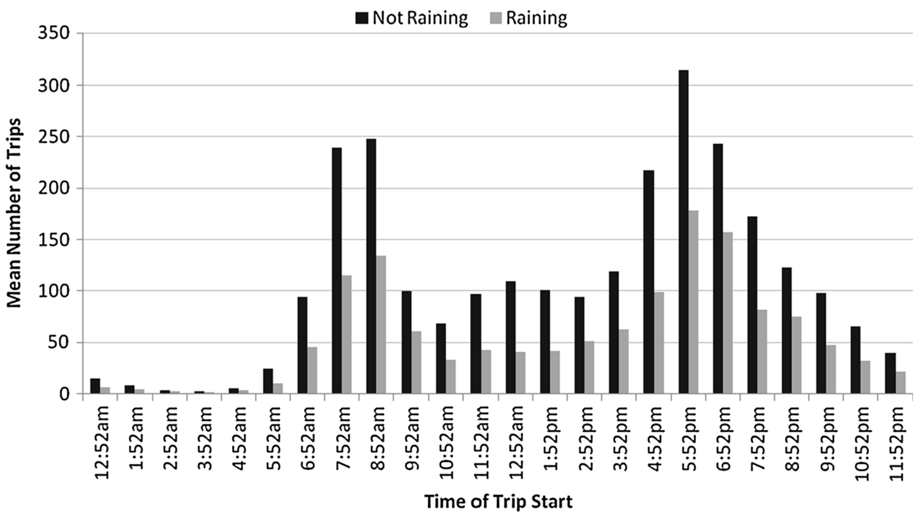

Fig. 3 Mean number of trips for registered users when raining versus not raining on weekdays

The number of trips made per hour is 122.2 across the whole system. Of this total, registered users make 97.6 trips per hour and casual users make 24.6 trips per hour. As would be expected, in the rain, the average number of trips for both groups drops to 58.1 per hour. However, registered users are far more likely to still use bikeshare in the rain with 50.3 trips per hour (48.5 % decrease) compared to 7.8 casual user trips per hour (68.3 % decrease). The differences throughout an average weekday, by hour, can be seen in Figs. 3 and 4. In addition to a pattern of decreased ridership due to rain, a clear commuting pattern (of morning and afternoon peaks) is seen amongst registered users, while casual users exemplify a pattern of continually increasing use throughout the day, peaking at 5:52 p.m., and then decreasing thereafter.

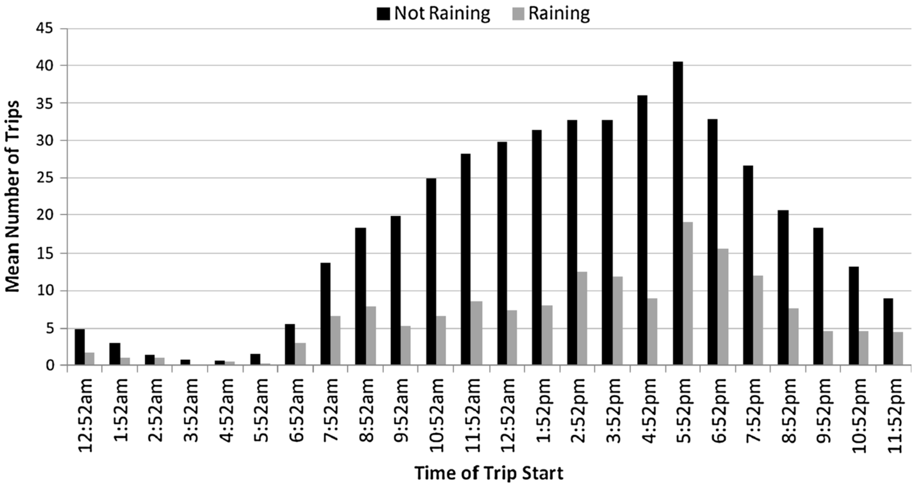

Fig. 4 Mean number of trips for casual users when raining versus not raining on weekdays

The average trip durations vary significantly between registered (12.5 min) and casual (39.0 min) users. This is likely due to the more utilitarian nature of trips for registered users versus the recreational nature of trips for casual users. Additionally, the impact of various weather events affects each group's trip duration differently. For registered users, trip durations decrease by 10.1 % in the rain and 9.4 % in the snow. Trip duration decreases are much larger for casual users in these weather conditions—22.4 % in the rain and 12.1 % in the snow. Additionally, fog and thunderstorms slightly increase trip durations for registered users (0.2 and 4.4 % respectively) yet considerably decrease trip durations for casual users (36.1 and 29.3 % respectively).

Modeling methodology

Weather observations for each trip start date and time were merged with the trip records based on the date and time. Trips were collapsed by hour, summing the number of trips and total duration of all trips attached to each hourly observation. Mean trip time per hour was calculated by dividing hourly duration by hourly trips.

Dummy variables were created for each weather "event" (fog, rain, thunderstorm, snow). Temperature was also recoded into ten-degree Fahrenheit bins and converted to dummy variables, as the relationship between temperature and bicycling behavior is not expected to be linear. Temperature and time-of-day are not correlated, so our estimates pick up the temperature effect and not an effect associated with variations in travel throughout the day. We include a peak/off-peak dummy variable to capture any daily variation in trips. Wind speed values were set to 0 for "Calm". If no wind data was recorded this was treated as a missing value. Dummy variables were created for each of the 15 months for which we had data, weekend and federal holidays, and peak travel times. The peak was defined as weekday observations at 6:52 a.m., 7:52 a.m., 8:52 a.m., 3:52 p.m., 4:52 p.m., 5:52 p.m., and 6:52 p.m. (as trip starts were rounded to the nearest weather observation, this captures actual trip start times between 6:22 a.m. to 9:22 a.m.

and 3:22 p.m. to 7:22 p.m.). As the system has grown over the years, a variable was also created for the number of stations in the system in Washington, DC at the time the trip was taken.[2]

Two dependent variables were analyzed: number of trips and average trip duration. To analyze the impacts of weather on the number of trips taken each hour, a negative binomial model was used. This count model was more appropriate than a Poisson regression as the variance of the dependent variable (trips) far exceeded the mean, leading to over-dispersion (which our models indicate is statistically significant). To analyze average trip time, an ordinary least squares regression was performed. We also examined if the weather an hour before the trip started influenced either the number of trips or the duration. For this we lagged all of the weather variables by 1 h. We also tested for serial correlation in our trip duration model; while the data appears to be serially correlated there was no substantive difference in results.[3] Interpretation of parameter estimates in the trip duration models allows us to determine the change in trip duration in minutes associated with each parameter. In the negative binomial estimates one must calculate a point elasticity estimate, due to the functional form of the estimated equation (Washington et al. 2003). Both are discussed in the results that follow.

The model was also tested using two truncated datasets, one consisting only of trips beginning and ending at CaBi stations within a quarter-mile of a Metro station (270,080 trips) and another of trips beginning and ending with no Metro station within a quarter-mile (399,452 trips). GIS was used to determine if a bikeshare station was within 0.25 miles of a Metro station entrance based on aerial distances and utilizing point datasets for CaBi stations and Metro stations found on DC's Data Catalog website (District Department of Transportation 2012; Washington Metropolitan Area Transit Authority (WMATA) 2007). For Metro stations in Arlington, VA, station entrances were first plotted in GIS using entrances/evacuation maps and then spatially compared to the location of CaBi stations (Washington Metropolitan Area Transit Authority 2012). Trips with a Metro station within 0.25 miles of only one end of the trip, were not included in either dataset. Both datasets also removed all trips beginning at times when the Metro was not running—Saturday and Sunday 3:00 a.m. to 7:00 a.m., Monday through Friday midnight to 5:00 a.m., and appropriate holidays between 5:00 a.m. to 6:00 a.m. (Washington Metropolitan Area Transit Authority 2006)[4]. By creating these two datasets, it was possible to effectively compare weather impacts on bikeshare trips when Metro is presumed to be an option to when it is not an option; allowing us to consider whether Metro serves as a back-up option when weather conditions are unfavorable for bicycling. These models did not include lags or any serial correlation adjustments as we found little effect from controlling for these in our other models.

To test whether our models produce different coefficient estimates, we compare these for various regressions. Z scores were calculated using the following formula (Paternoster et al. 1998):

[2] This was determined from the "install date" attribute of the Capital Bikeshare GIS point dataset (District Department of Transportation 2012). Stations outside of Washington, DC, in neighboring jurisdictions were not included in the dataset.

[3] Count models assume that each event is independent. We are not aware of any tractable methods to estimate a count model with serial correlation. The lags that we use are, in our opinion, sufficient.

[4] Metro opens at 7:00 a.m. instead of 5:00 a.m. on the following holidays that also fall on a weekday: New Year's Day, Memorial Day, July 4th, Labor Day, Thanksgiving Day, and Christmas Day (Washington Metropolitan Area Transit Authority 2006).

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{SE\beta_1^2 + SE\beta_2^2}}$$

Analysis of results

Results for models of the number of trips taken are shown in Tables 2 and 3. Models of trip duration are shown in Tables 4 and 5. The number of observations represents the total number of hours throughout the 15 months being analyzed from October 2010 to December 2011 (less 1 h for the lagged models). Tables 3 and 5 are models for trips proximate to Metro stations and have fewer hourly observations as these do not include times when Metro is not running. We tested all independent variables for multi-collinearity and all had a very low level of correlation.

Temperature was included as a dummy variable in 10 °F ranges (equivalent to 5.55 °C ranges). Coefficients show that trips decrease as temperatures decrease, but also decrease above 90 °F (32.2 °C) [relative to the reference category, 50–59 °F (10–15 °C)]. The most trips appear to be made when temperatures are in the 80–89 °F (26.7–31.7 °C) range. The Z test for comparing the coefficient values between the level and lagged weather variables are all uniformly statistically insignificant below the 95 % level. Elasticity estimates shown in Table 6 represent the incremental change in trip frequency associated with each temperature range. These are largest for the lowest temperature categories. Elasticities for dummy variables from a count model are calculated as $E = \frac{e^{\beta}-1}{e^{\beta}}$ and for continuous variables as $E = \beta\overline{X}$ (Washington et al. 2003).

While the comparison of coefficient estimates for trip count models suggest that the weather coefficients are not statistically different, the snow dummy variable while not significant in the level model does become statistically significant in the lag model. The Z score is 1.52, below the standard criteria for statistical significance. The change in coefficient size and the corresponding elasticity (changing from −0.0.07 to −0.31) suggest that foresight of a coming snowstorm slightly discourages bikeshare use.

Temperatures between 10 and 49 °F (−12.2 to 9.4 °C) are all significantly correlated ($p < 0.05$) with shorter average trip duration, as opposed to when the temperature is in the 50–59 °F (10–15 °C) range, *ceteris paribus,* for both the level and lagged model (Table 4). When temperatures range between 10 and 19 °F (−12.2 and −7.2 °C), average trip times are 9.9 min as opposed to 18.3 min, holding all other variables constant. Temperatures in the 70–89 °F range (21.1–31.7 °C) were significantly associated with increased trip durations, while temperatures above that were not significantly different than temperatures in the 50–59 °F range (10–15 °C). There are no significantly different coefficient estimates between the level (5) and lag (6) models; likewise there is no difference when serial correlation is controlled for using the Cochrane–Orcutt method (model 7). There is a degree of serial correlation in the level model (5) with a Durbin–Watson statistic of 1.569, but this is 1.804 in the Cochrane–Orcutt model, which also has a ρ of 0.0887, not too far from zero, suggesting serial correlation has been largely controlled for. The bottom line is there is no statistically significant difference in the coefficient estimates. Thus, it is clear that there is variation in both the amount of usage and the length of trips dependent on temperature with both decreasing as it gets colder and generally increasing as it gets warmer, but not when it is excessively hot.

Table 2 Negative binomial regression models for weather impacts on number of trips

Variable	(1)		(2)		Z value difference between β(1) and β(2)
	Trips		Trips, model with lagged weather variables		
	Coefficients	z statistic	Coefficients	z statistic	
Temp—10 s (°F)[a]	−1.89	(−10.68)	−1.75	(−10.00)	−0.54
Temp—20 s (°F)	−1.07	(−18.04)	−0.97	(−16.52)	−1.19
Temp—30 s (°F)	−0.71	(−18.68)	−0.67	(−17.83)	−0.75
Temp—40 s (°F)	−0.27	(−9.16)	−0.25	(−8.35)	−0.57
Temp—60 s (°F)	0.20	(6.58)	0.19	(6.16)	0.27
Temp—70 s (°F)	0.46	(11.70)	0.40	(10.18)	1.14
Temp—80 s (°F)	0.67	(13.38)	0.59	(11.80)	1.20
Temp—90 s (°F)	0.44	(6.05)	0.39	(5.41)	0.47
Temp—100 s (°F)	−0.02	(−0.08)	−0.05	(−0.21)	0.09
Relative humidity (%)	−0.01	(−27.19)	−0.01	(−26.58)	−0.65
Wind speed (MPH)	−0.01	(−3.93)	−0.01	(−3.62)	−0.19
Fog	−0.07	(−0.35)	−0.11	(−0.56)	0.15
Rain	−0.56	(−15.55)	−0.49	(−13.43)	−1.39
Thunderstorm	0.07	(0.64)	0.15	(1.41)	−0.55
Snow	−0.07	(−0.73)	−0.27	(−2.87)	1.52
Dark	−0.70	(−37.21)	−0.81	(−44.88)	4.54
November 2010[b]	0.25	(4.11)	0.23	(3.77)	0.22
December 2010	0.20	(2.75)	0.13	(1.85)	0.63
January 2011	0.56	(7.71)	0.49	(6.84)	0.61
February 2011	0.59	(8.51)	0.53	(7.71)	0.55
March 2011	0.51	(7.70)	0.45	(6.87)	0.57
April 2011	0.55	(8.05)	0.52	(7.57)	0.31
May 2011	0.43	(4.66)	0.40	(4.36)	0.21
June 2011	0.00	(−0.02)	0.01	(0.08)	−0.07
July 2011	−0.05	(−0.46)	−0.03	(−0.29)	−0.12
August 2011	0.02	(0.16)	0.03	(0.30)	−0.10
September 2011	0.39	(3.78)	0.38	(3.71)	0.04
October 2011	0.50	(4.82)	0.46	(4.40)	0.29
November 2011	0.44	(3.95)	0.39	(3.49)	0.31
December 2011	0.08	(0.56)	0.02	(0.16)	0.29
No. of stations	0.06	(10.37)	0.06	(10.63)	−0.22
Peak travel hours	0.65	(33.42)	0.61	(31.28)	1.49
Weekends/holidays	−0.01	(−0.80)	−0.02	(−1.00)	0.14
Constant	2.30	(13.82)	3.00	(18.02)	−0.02
Overdispersion	0.72	(74.89)	0.73	(75.02)	
Observations	10,968		10,967		
Pseudo R-squared	0.064		0.063		
Chi2	8059.1		7959.2		

[a] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin. "Temp – 50 s (°F)" served as a reference group for temperature bin dummy variables. For model 2 these variables are lagged by 1 h

[b] "October 2010" served as a reference group for month dummy variables

Table 3 Negative binomial regression models for weather impacts on number of trips to and from Metro stations

Variable	(3) Trips to/from Metro		(4) Trips to/from no Metro		Z value difference between β(3) and β(4)
	Coefficients	t statistic	Coefficients	t statistic	
Temp—10 s (°F)[a]	−1.76	(−9.22)	−1.37	(−7.48)	−1.47
Temp—20 s (°F)	−0.89	(−17.54)	−0.74	(−14.88)	−2.02
Temp—30 s (°F)	−0.60	(−19.68)	−0.54	(−18.07)	−1.58
Temp—40 s (°F)	−0.27	(−11.41)	−0.24	(−10.69)	−0.76
Temp—60 s (°F)	0.19	(8.10)	0.17	(7.50)	0.62
Temp—70 s (°F)	0.36	(12.15)	0.34	(11.80)	0.59
Temp—80 s (°F)	0.50	(13.33)	0.48	(13.48)	0.29
Temp—90 s (°F)	0.25	(4.76)	0.27	(5.48)	−0.35
Temp—100 s (°F)	−0.26	(−1.71)	−0.19	(−1.33)	−0.31
Relative humidity (%)	−0.01	(−27.18)	−0.01	(−26.38)	−1.21
Wind speed (MPH)	−0.01	(−6.35)	−0.01	(−4.20)	−1.65
Fog	0.17	(0.95)	0.26	(1.49)	−0.36
Rain	−0.71	(−24.33)	−0.54	(−18.73)	−4.20
Thunderstorm	−0.03	(−0.41)	0.05	(0.63)	−0.74
Snow	−0.36	(−4.47)	−0.31	(−3.83)	−0.48
Dark	−0.57	(−38.09)	−0.20	(−13.38)	−17.87
November 2010[b]	0.15	(3.08)	0.25	(5.34)	−1.54
December 2010	−0.06	(−1.13)	0.04	(0.66)	−1.27
January 2011	0.32	(5.54)	0.33	(5.84)	−0.12
February 2011	0.38	(7.02)	0.44	(8.23)	−0.73
March 2011	0.42	(8.13)	0.49	(9.53)	−0.85
April 2011	0.56	(10.25)	0.63	(11.88)	−1.00
May 2011	0.56	(7.58)	0.53	(7.35)	0.30
June 2011	0.23	(2.89)	0.28	(3.53)	−0.40
July 2011	0.22	(2.63)	0.26	(3.22)	−0.36
August 2011	0.24	(2.97)	0.24	(3.06)	−0.01
September 2011	0.49	(6.01)	0.43	(5.42)	0.52
October 2011	0.56	(6.75)	0.47	(5.79)	0.78
November 2011	0.47	(5.34)	0.35	(4.06)	0.97
December 2011	0.04	(0.36)	0.10	(0.88)	−0.36
No. of stations	0.05	(11.30)	0.05	(10.86)	0.50
Peak travel hours	0.51	(36.07)	0.36	(26.44)	7.56
Weekends/holidays	−0.13	(−9.17)	0.22	(16.14)	−17.76
Constant	1.57	(11.59)	1.19	(9.07)	1.97
Overdispersion	0.32	(−66.94)	0.28	(−69.13)	
Observations	8,806		8,806		
Pseudo R-squared	0.105		0.096		
Chi2	9137.1		7142.3		

[a] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin. "Temp – 50 s (°F)" served as a reference group for temperature bin dummy variables

[b] "October 2010" served as a reference group for month dummy variables

Table 4 Regression models for weather impacts on hourly average trip duration

Variable	(5) Trip duration		(6) Trip duration with lagged weather variables		Z value difference between β(5) and β(6)	(7) Trip duration, Cochrane–Orcutt model		Z value difference between β(5) and β(7)
	Coefficients	t statistic	Coefficients	t statistic		Coefficients	t statistic	
Temp—10 s (°F)[a]	−8.47	(−2.69)	−9.34	(−2.91)	0.19	−8.05	(−2.49)	−0.09
Temp—20 s (°F)	−4.56	(−4.26)	−4.17	(−3.91)	−0.26	−4.63	(−4.25)	0.04
Temp—30 s (°F)	−3.45	(−5.23)	−3.27	(−4.96)	−0.20	−3.19	(−4.81)	−0.28
Temp—40 s (°F)	−1.19	(−2.20)	−1.33	(−2.46)	0.19	−0.99	(−1.86)	−0.25
Temp—60 s (°F)	1.04	(1.85)	0.74	(1.32)	0.38	1.29	(2.32)	−0.32
Temp—70 s (°F)	3.68	(5.29)	2.95	(4.25)	0.74	3.83	(5.53)	−0.16
Temp—80 s (°F)	3.99	(4.52)	2.99	(3.40)	0.80	4.10	(4.67)	−0.09
Temp—90 s (°F)	2.18	(1.69)	1.04	(0.80)	0.63	2.26	(1.76)	−0.04
Temp—100 s (°F)	−0.81	(−0.20)	−0.88	(−0.22)	0.01	−0.72	(−0.19)	−0.01
Relative humidity (%)	−0.06	(−5.77)	−0.04	(−4.45)	−0.98	−0.06	(−6.14)	0.27
Wind speed (MPH)	−0.13	(−4.18)	−0.10	(−3.13)	−0.75	−0.13	(−4.18)	−0.04
Fog	2.17	(0.59)	0.94	(0.26)	0.24	2.32	(0.66)	−0.03
Rain	−2.77	(−4.19)	−3.08	(−4.65)	0.33	−2.31	(−3.60)	−0.50
Thunderstorm	0.46	(0.24)	0.84	(0.44)	−0.14	0.23	(0.12)	0.09
Snow	2.68	(1.55)	−0.15	(−0.09)	1.18	3.25	(1.91)	−0.23
Dark	−3.13	(−8.74)	−3.63	(−10.50)	1.00	−3.06	(−8.66)	−0.14
November 2010[b]	−3.86	(−3.39)	−4.01	(−3.52)	0.09	−4.44	(−3.82)	0.36
December 2010	−6.95	(−5.25)	−7.27	(−5.49)	0.17	−7.88	(−5.84)	0.50
January 2011	−7.71	(−5.82)	−7.94	(−5.99)	0.12	−8.72	(−6.46)	0.54
February 2011	−8.01	(−6.33)	−8.28	(−6.54)	0.16	−8.93	(−6.93)	0.51
March 2011	−4.23	(−3.46)	−4.50	(−3.67)	0.15	−5.13	(−4.11)	0.51
April 2011	−2.58	(−2.02)	−2.79	(−2.19)	0.12	−3.71	(−2.85)	0.62
May 2011	−1.15	(−0.68)	−1.21	(−0.71)	0.02	−3.27	(−1.87)	0.87

Table 4 continued

Variable	(5) Trip duration		(6) Trip duration with lagged weather variables		Z value difference between β(5) and β(6)	(7) Trip duration, Cochrane–Orcutt model		Z value difference between β(5) and β(7)
	Coefficients	t statistic	Coefficients	t statistic		Coefficients	t statistic	
June 2011	−4.95	(−2.68)	−4.53	(−2.45)	−0.16	−7.29	(−3.86)	0.89
July 2011	−5.10	(−2.71)	−4.55	(−2.41)	−0.21	−7.42	(−3.86)	0.86
August 2011	−5.73	(−3.09)	−5.31	(−2.86)	−0.16	−8.08	(−4.27)	0.89
September 2011	−5.95	(−3.16)	−5.91	(−3.13)	−0.02	−8.38	(−4.36)	0.90
October 2011	−4.92	(−2.57)	−5.15	(−2.69)	0.09	−7.45	(−3.81)	0.93
November 2011	−5.57	(−2.71)	−5.86	(−2.84)	0.10	−8.32	(−3.96)	0.94
December 2011	−5.50	(−2.06)	−5.86	(−2.19)	0.10	−9.45	(−3.46)	1.04
No. of stations	−0.18	(−1.82)	−0.18	(−1.72)	−0.06	0.00	(0.00)	0.00
Peak travel hours	−3.13	(−8.67)	−3.31	(−9.15)	0.34	−2.90	(−8.33)	−0.46
Weekends/holidays	5.43	(16.82)	5.45	(16.83)	−0.03	5.48	(16.78)	−0.10
Constant	32.63	(10.96)	34.92	(11.73)	0.20	–	–	–
Observations	10,737		10,736			10,737		
R-squared	0.108		0.105			0.105		
Adjusted R-squared	0.106		0.103			0.102		
F	39.38		38.23					
ρ						0.0887		
Durbin–Watson	1.569					1.804		

Coefficients represent the change in mean trip duration for each unit of increase of that variable, holding all other variables constant. As most variables are dummies, the coefficient is the effect on the mean when the variable is true (i.e. equals 1). For example, average trips in the rain are 2.77 min shorter, *ceteris paribus*

[a] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin. “Temp – 50 s (°F)” served as a reference group for temperature bin dummy variables. For model 6 these variables are lagged by 1 h

[b] “October 2010” served as a reference group for month dummy variables

Table 5 Ordinary least squares regression model for weather impacts on hourly average trip duration for trips to and from Metro stations

Variable	(8) Avg trip duration to/from Metro		(9) Avg trip duration to/from no Metro		Z value difference between β(8) and β(9)
	Coefficients	t statistic	Coefficients	t statistic	
Temp—10 s (°F)[a]	−10.49	(−2.55)	−9.79	(−1.81)	−0.10
Temp—20 s (°F)	−5.03	(−4.01)	−5.90	(−3.56)	0.42
Temp—30 s (°F)	−2.55	(−3.34)	−4.67	(−4.64)	1.68
Temp—40 s (°F)	−1.60	(−2.67)	−2.79	(−3.53)	1.20
Temp—60 s (°F)	1.69	(2.70)	3.05	(3.71)	−1.32
Temp—70 s (°F)	4.47	(5.75)	5.20	(5.09)	−0.57
Temp—80 s (°F)	5.54	(5.70)	3.91	(3.05)	1.02
Temp—90 s (°F)	3.48	(2.54)	0.52	(0.29)	1.31
Temp—100 s (°F)	−2.05	(−0.51)	−3.64	(−0.68)	0.24
Relative humidity (%)	−0.09	(−8.45)	−0.09	(−6.34)	−0.06
Wind speed (MPH)	−0.12	(−3.49)	−0.07	(−1.60)	−0.84
Fog	−1.83	(−0.39)	−0.15	(−0.02)	−0.21
Rain	−2.50	(−3.29)	−2.50	(−2.50)	0.00
Thunderstorm	−3.11	(−1.45)	−1.61	(−0.57)	−0.42
Snow	0.97	(0.47)	7.14	(2.57)	−1.79
Dark	−5.40	(−13.63)	−5.88	(−11.25)	0.73
November 2010[b]	−8.72	(−6.93)	−0.31	(−0.19)	−4.04
December 2010	−11.73	(−7.95)	−1.98	(−1.02)	−3.99
January 2011	−12.68	(−8.60)	−2.95	(−1.52)	−3.99
February 2011	−13.53	(−9.66)	−1.72	(−0.93)	−5.10
March 2011	−6.82	(−5.03)	1.36	(0.76)	−3.65
April 2011	−6.56	(−4.63)	4.83	(2.59)	−4.86
May 2011	−9.65	(−5.06)	8.74	(3.49)	−5.84
June 2011	−13.68	(−6.62)	4.26	(1.57)	−5.26
July 2011	−12.16	(−5.77)	6.57	(2.37)	−5.39
August 2011	−13.48	(−6.50)	6.51	(2.39)	−5.84
September 2011	−12.99	(−6.19)	5.29	(1.92)	−5.28
October 2011	−13.79	(−6.47)	7.77	(2.78)	−6.13
November 2011	−14.60	(−6.36)	7.56	(2.51)	−5.86
December 2011	−16.87	(−5.66)	12.08	(3.09)	−5.89
No. of stations	0.27	(2.33)	−0.91	(−6.13)	6.28
Peak travel hours	−3.87	(−10.42)	−3.47	(−7.08)	−0.66
Weekends/holidays	9.71	(26.99)	5.70	(12.02)	6.74
Constant	22.39	(6.67)	53.67	(12.30)	−5.68
Observations	8,693		8,661		
R-squared	0.190		0.104		
Adjusted R-squared	0.187		0.101		
F	61.52		30.34		

[a] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin. "Temp – 50 s (°F)" served as a reference group for temperature bin dummy variables

[b] "October 2010" served as a reference group for month dummy variables

Table 6 Elasticity estimates—trip counts, negative binomial model estimates

Variable	(1) Trips Elasticity	(2) Trips, weather lags Elasticity	(3) Trips to/from Metro Elasticity	(4) Trips no Metro Elasticity
Temp—10 s (F)[a]	−5.60	−4.77	−4.80	−2.94
Temp—20 s (F)	−1.92	−1.65	−1.43	−1.10
Temp—30 s (F)	−1.04	−0.96	−0.83	−0.71
Temp—40 s (F)	−0.32	−0.28	−0.31	−0.27
Temp—60 s (F)	0.18	0.17	0.18	0.16
Temp—70 s (F)	0.37	0.33	0.30	0.29
Temp—80 s (F)	0.49	0.45	0.39	0.38
Temp—90 s (F)	0.36	0.32	0.22	0.24
Temp—100 s (F)	−0.02	−0.05	−0.30	−0.21
Relative humidity (%) (mean elasticity)	−0.95	−0.91	−0.73	−0.68
Wind speed (MPH) (mean elasticity)	−0.06	−0.05	−0.01	−0.01
Fog	−0.07	−0.12	0.16	0.23
Rain	−0.75	−0.63	−1.04	−0.72
Thunderstorm	0.07	0.14	−0.04	0.05
Snow	−0.07	−0.31	−0.44	−0.36
Dark	−1.00	−1.26	−0.77	−0.22
Peak travel hours	0.48	0.46	0.40	0.30
Weekends/holidays	−0.02	−0.02	−0.14	0.19

[a] Equivalent temperature ranges in Celsius begin at about −12.2 °C and ranges are about 5.55 °C for each bin

Controls for month of year are included in both models, thus the temperature effect is independent of any seasonal pattern. Darkness is also controlled for and there is both less usage and shorter durations when it is dark and this is independent of any temperature effects. The lagged model results in a significant difference in only the darkness dummy variable in the trip model. Darkness results in a reduction in trip frequency of about 1 in the level and 1.25 in the lagged model (see Table 6); this is the only statistically significant difference between these two models. The trip duration model shows a 3.1 min decrease in trip length when it is dark, which is highly significant ($p < 0.001$).

Other weather variables also show an association with bicycle usage and trip duration. Parameter estimates for humidity show that it is statistically significant and negative in both models. Thus, increasing humidity levels decrease usage and duration of trips, independent of temperature (see also Fig. 2). The elasticity for relative humidity changes is a point elasticity estimate (−0.94) calculated at the mean value in the data (63.86 %) and implies a 0.94 % reduction in frequency of trips for a 1 % change at the mean value, 0.91 % in the lagged model (Table 6). The magnitude of the reduction in duration is small, only about 0.056 min per trip. We also estimated models using the heat index, which combines the effect of temperature and relative humidity. This was statistically significant and positive when temperature dummies were excluded, suggesting it was just picking up the effect of temperature, not humidity. When temperature dummies are included, the results do not match expectations, likely due to the fact that the heat index is a function of temperature. Interaction variables create similar inference issues.

Rainfall also is statistically significant in both models, being associated with reductions in usage and trip duration. Trip frequency is about 0.75 % less when it is raining, so less of a percent reduction than when it is dark or temperatures are very cold. Trip durations are about 2.8 min shorter when it is raining, also less of a reduction than in very cold temperatures. Higher wind speed is also significantly correlated with fewer trips and shorter average trip durations, although actual impacts are much smaller than for other weather conditions.

The effects of fog and thunderstorms are not statistically significant for either the number of trips taken or their duration (both have low correlations with rain and temperature, so this is not a result of multi-collinearity). As previously noted, snow is not statistically significant in model 1, but becomes statistically significant in our trip model with lagged weather variables (2); snow is not statistically associated with trip durations at a 95 % level. Snow is significant and positive at the 90 % level in the Cochrane–Orcutt model (7) suggesting that snow lengthens trip duration. While the number of stations in the system had an impact on the number of trips taken, it has no statistically significant impact on the average trip length.[5] This variable mainly controls for growth of the system over time. Another control is a dummy for peak travel times which shows that there is more usage in peak hours but trips are shorter than at off-peak times. Usage on weekends and holidays is not significantly different than on weekdays, however trips are over 5 min longer in duration, suggesting perhaps more recreational use of the bicycles.

The models in Tables 3 and 5 include only trips that begin and end proximate to a Metro station when the station is within a quarter-mile of the bikeshare station (models 3 and 8), and also trips that are not proximate to a Metro station (models 4 and 9). Both sub-samples contain trips that occurred only when the Metro is operating. Thus, this provides a way to compare the weather impacts on bikeshare trips when Metro is an option versus when it is not. The resulting impacts of weather variables are similar in terms of direction and significance, save for the negative correlation between snow and number of trips which is highly significant.

We evaluate these models based on the difference in coefficients between models 3 and 4 (Table 3). For the lower temperature ranges, 30 to 39 °F (−1.1 to 3.9 °C) and below, the coefficients are generally more negative for bikeshare stations proximate to Metro. Most of the differences between the coefficients are not statistically significant, except for the 20 to 29 °F (−6.7 to −1.7 °C) range. The decrease in number of bikeshare trips when Metro is an option is statistically significant in the rain with fewer trips occurring from bikeshare stations proximate to Metro (1.04 vs. 0.72 fewer trips, Table 6). The differences in the coefficient for the darkness variable are also statistically significant, as lack of daylight results in far fewer bikeshare trips when Metro is likely an option compared to when Metro is not an option (−0.77 vs. −0.22, Table 6). The other major differences are that more peak hour trips occur at bikeshare stations proximate to Metro stations, while the trips on weekends and holidays are less likely from bikeshare stations near Metro and more likely from those bikeshare stations that are not near Metro. The magnitude of these trips is, however, small as shown in Table 6.

[5] All coefficients for the month dummy variables in model 4 (Table 3) are negative. This is a result of October 2010 serving as the reference month, which reported particularly longer trips. This is likely a result of a novelty effect due to the newness, and therefore novelty, of the system.

When looking at the differences between coefficients of trip duration when Metro was an option versus when Metro was not an option, no statistically significant relationships were found between most weather variables. The main exception is when it snows; while the coefficient difference is significant at the 90 % level, trip duration is over 6 min longer for those trips from stations not near Metro compared to those that are, suggesting that Metro users may be more likely to walk to and from stations when it is snowing. Interestingly though, trip duration on weekends and holidays increases significantly in each regression, and more when Metro is an option.

The adjusted R^2 and pseudo R^2 for all the models are relatively low, suggesting various unexplained factors also affect both the number of trips taken and their duration. It is likely that socio-economic characteristics of the users likely influences when and how the bicycles are used, but this information was not available.

Discussion of results

The results found here are not surprising and confirm what would theoretically be assumed as the likely impact of weather on bikeshare trips. Adverse weather such as very cold temperatures, rain, high humidity, and increased wind speeds decreases the number of bikeshare trips in Washington, DC. However, it was surprising to find that the number of trips significantly increased for temperatures in the 90 °F range (32.2–37.2 °C) as compared to the 50 °F range (10–15 °C), as one might expect temperatures in the 90 °F range (32.2–37.2 °C) to be uncomfortably hot for cycling. As these temperature impacts hold while other variables are held constant, including humidity, one can infer that while increased humidity decreases trips, high temperatures do not have as much impact.

While the CaBi dataset does not provide us with other modes chosen instead of bikeshare, the regressions on trips at and to locations where Metro stations exist compared to trips where Metro stations do not exist provided one way to analyze the differing weather impacts when an alternative transit option is more likely to exist. Indeed, the significant coefficient differences between the two regressions on the rain variable is evidence that more people will choose to bike in the rain if transit is a less likely option. The large difference in the darkness variable suggests that people much prefer to take the Metro, if possible, after nightfall. However, a Metro station simply existing at the beginning and end of a person's trip is only one aspect travelers must consider when choosing a mode of travel. Modal choice also includes the number of transfers and overall transit trip time, compared to the attributes of using a bicycle for the trip which would include factors such as bicycle infrastructure (lanes), topography, and general safety and ease of the trip. As these details are not included, the models are fairly coarse in their ability to consider if Metro is an option and how weather affects the choice of mode.

The results for average trip durations suggest that in certain conditions (rain, darkness, cold temperatures, increased wind speeds, and higher humidity), people use bikeshare for shorter trips and may either take another mode or forego longer trips in such conditions. There is some evidence that trip durations may be longer in snowy weather for those trips that do occur, most likely because people are riding more cautiously. The impact of more recreational riding (which tends to be longer) during nice weather is also likely to have an impact. Further research analyzing trip durations at selected origin and destination pairs in different weather conditions could be conducted to address with more precision the impact of trip durations for specific trips.

Conclusions

In the world of bicycle research, data collection is often both challenging and expensive. Since the number of trips made by cycling is relatively small compared with alternative modes, it can be difficult to deduce trends and analyze behavior from existing surveys. Additionally, research regarding the relationship between weather and cycling is typically conducted based on daily averages and not necessarily at the precise time that the trip was taken. The latter is more meaningful as weather can vary throughout the day. Through data collection technology embedded within bikeshare systems, the ability to understand different impacts on bikeshare trips is possible, if not for all bicycle trips. The weather of Washington, DC contains almost all variations. It rains and snows, has very cold days and very hot days (especially in 2011) and can be especially humid at times and windy. This analysis helps to better document the relative impact of various weather conditions on bikesharing trips in Washington, DC, considering the weather observation at the time the trip was taken. The results of this analysis show that fewer trips are made in the rain, high humidity, high wind speeds, and low temperatures. Trips increase with higher temperatures up through temperatures in the 90 °F range (32.2–37.2 °C). The availability of Metro may also cause a larger decrease in cycling trips in the rain and during cold temperatures.

While many of these effects are not surprising, the impact may be less pronounced than many would assume. The sentiment that "no one bikes in the rain" is simply not true. While these results are directly related to bikeshare usage in Washington, DC, the results would be expected to be fairly applicable to general cycling as well. Of course, one should be cautious in generalizations, as different types of cyclists may be wont to use bikeshare versus a personal bicycle, and therefore, may respond differently to various weather conditions. Additionally, some cyclists may decide to use bikeshare instead of a personal bicycle or vice versa depending on weather conditions. Bikeshare bicycles tend to be sturdier and have fenders, which many personal bicycles may not have. Also, people may prefer not to expose their personal bicycle to rainy or snowy weather, which can damage the bicycle. Capital Bikeshare has proven to be immensely successful in providing an additional mode of transportation to either complete a full trip or better access existing transit. The system is useful to people during fair-weather conditions, but also, still useful to many during adverse weather conditions as well.

References

Alta Bicycle Share, Inc.: P Capital Bikeshare. http://www.capitalbikeshare.com (2012). Accessed 29 Apr 2012

Bachand-Marleau, J., Lee, B.H.Y., El-Geneidy, A.M.: Towards a better understanding of the factors influencing the likelihood of using shared bicycle systems and frequency of use. In: Transportation Research Board 91st Annual Meeting, Washington, DC (2011)

Bergström, A., Magnusson, R.: Potential of transferring car trips to bicycle during winter. Transp. Res. A Policy Pract. **37**(8), 649–666 (2003)

Brandenburg, C., Matzarakis, A., Arnberger, A.: Weather and cycling—a first approach to the effects of weather conditions on cycling. Meteorol. Appl. **14**, 61–67 (2007)

Buck, D., Buehler, R.: Bike lanes and other determinants of capital bikeshare trips. In: TRB 2012 Annual Meeting, Washington, DC (2012)
Buehler, R., Pucher, J.: Cycling to work in 90 large American cities: new evidence on the role of bike paths and lanes. Transportation **1**(39), 409–432 (2012)
Cervero, R., Duncan, M.: Walking, bicycling, and urban landscapes: evidence from the San Francisco Bay Area. Am. J. Public Health **93**(9), 1478–1483 (2003)
Dill, J., Carr, T.: Bicycle commuting and facilities in major U.S. Cities: if you build them, commuters will use them—another look. Transp. Res. Rec. **1828**, 116–123 (2003)
District Department of Transportation: DCGIS.CapitalBikeSharePt, Washington, DC. http://data.dc.gov (2012)
Fuller, D., Sahlqvist, S., Cummins, S., Ogilvie, D.: The impact of public transportation strikes on use of a bicycle share program in London: interrupted time series design. Prev. Med. **54**, 74–76 (2012)
Goodman, J.D.: Bike Sharing Expands in Washington (September 20, 2010). http://green.blogs.nytimes.com/2010/09/20/bike-sharing-expands-in-washington/ (2012). Accessed 29 Apr
Hamphire, R.C., Marla, L.: An analysis of bike sharing usage: explaining trip generation and attraction from observed demand. In: TRB 2012 Annual Meeting, Washington, DC (2011)
JDAntos: Capital Bikeshare: Usage and Weather. http://jdantos.wordpress.com/2012/03/01/capital-bikeshare-usage-and-weather/ (2012). Accessed 2 Mar 2012
Lathia, N., Ahmed, S., Capra, L.: Measuring the impact of opening the London shared bicycle scheme to casual users. Transp. Res. C **22**, 88–102 (2012)
Met Office: National Meteorological Library and Archive: Fact Sheet 6—The Beaufort Scale (version 01). http://www.metoffice.gov.uk/media/pdf/4/4/Fact_Sheet_No._6_-_Beaufort_Scale.pdf (2010). Accessed 27 Apr 2012
Nankervis, M.: The effect of weather and climate on bicycle commuting. Transp. Res. A **33**, 417–431 (1999)
Noland, R.B., Ishaque, M.M.: Smart bicycles in an urban area: evaluation of a pilot scheme in London. J. Public Transp. **9**(5), 71–95 (2006)
Paternoster, R., Brame, R., Mazerolle, P., Piquero, A.: Using the correct statistical test for the equality of regression coefficients. Criminology **36**(4), 859–866 (1998)
Pucher, J., Buehler, R.: Why Canadians cycle more than Americans: a comparative analysis of bicycling trends and policies. Transp. Policy **13**(3), 265–279 (2006)
Pucher, J., Komanoff, C., Schimek, P.: Bicycling renaissance in North America? Recent trends and alternative policies to promote bicycling. Transp. Res. A **33**, 625–654 (1999)
Shaheen, S.A., Guzman, S., Zhang, H.: Bikesharing in Europe, the Americas, and Asia. Transp. Res. Rec. J. Transp. Res. Board **2143**, 159–167 (2010)
Thomas, T., Jaarsma, R., Tutert, B.: Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: the influence of weather on cycling. Transportation **40**, 1–22 (2013)
U.S. Navy: Astronomical Applications Department of the U.S. Naval Observatory. http://aa.usno.navy.mil/data/docs/RS_OneYear.php (2012). Accessed 2 Apr
Washington Metropolitan Area Transit Authority (WMATA): Metro Station Entrances (MetroEntPt) 21 Mar 2007. http://data.dc.gov/Metadata.aspx?id=97 (2012). Accessed 15 Apr
Washington Metropolitan Area Transit Authority: "Metrorail Timetable." http://www.wmata.com/pdfs/rail/Midday.pdf (7 Sep 2006). Accessed 25 Apr 2012
Washington Metropolitan Area Transit Authority: Stations. http://www.wmata.com/rail/stations.cfm (2012). Accessed 18 Apr 2012
Washington, S.P., Karlaftis, M.G., Mannering, F.L.: Statistical and Econometric Methods for Transportation Data Analysis. Chapman & Hall/CRC, Boca Raton (2003)
Weather Underground. http://www.weatherunderground.com (2012). Accessed 10 Feb 2012
Winters, M., Friesen, M.C., Koehoorn, M., Teschke, K.: Utilitarian bicycling: a multilevel analysis of climate and personal influences. Am. J. Prev. Med. **32**(1), 52–58 (2007)

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