

The Impact of Weather on Bus Ridership in Pierce County, Washington

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Abstract

A factor that influences transit ridership but has not received much attention from researchers is weather. This paper examines the effects of weather on bus ridership in Pierce County, Washington, for the years 2006–2008. Separate ordinary least squares regression models were estimated for each season, as weather conditions may have different effects depending on the time of year. Four weather variables were considered: wind, temperature, rain, and snow. High winds negatively affected ridership in winter, spring, and autumn. Cold temperatures led to decreases in ridership in winter. Rain negatively affected ridership in all four seasons, and snow was associated with lower ridership in autumn and winter. These results suggest that adverse weather conditions can have a negative effect on transit ridership.

Introduction

Many factors influence transit ridership, including the quantity and quality of transit service provided, spatial factors, gasoline prices, the economy, and others. One factor that may affect ridership significantly on a day-to-day basis, but that has not received much attention from researchers, is weather. Adverse weather conditions such as rain, snow, fog, wind, or extreme temperatures may cause people to shift transportation modes or avoid traveling at all. The issue is important to transit

agencies. If weather was shown to have a significant impact on ridership, agencies could take steps to mitigate the effects of weather, such as installing more shelters at transit stations, in order to maximize passenger comfort and ridership.

This paper examines the impacts of weather on transit ridership in Pierce County, Washington. Three years of ridership data from Pierce Transit and weather data from Seattle-Tacoma International Airport were used to model the relationship with ordinary least squares (OLS) regression. The paper begins with an examination of the theoretical relationship between weather and transit and a review of the literature. Next, the study area, methodology, and data are described. A presentation of the results, the sensitivity analysis, and a discussion of the findings follow.

Theoretical Framework

The numerous factors that influence transit can be categorized into two general groups: internal and external (Taylor et al. 2009). Internal factors are those that the transit agency can control, including the quality and quantity of service provided and the cost of a ride. External factors are influences beyond the control of transit agencies, including spatial factors (land use, density, urban form design), socioeconomic factors (population, employment, rate of auto ownership, average income), pricing factors (price of gasoline, road cost, parking costs), and environmental factors (weather). Most of the factors tend to be constant or change gradually over time, but weather is an external factor that can change drastically from one day to the next and be measured on a daily basis. A city could be hit with major rain one day and have clear skies and no precipitation the next. Both conditions could have an effect on transit ridership.

Weather can affect transit use and other forms of travel in two ways (Guo et al. 2007). First, weather can affect the activities that cause people to travel. Weather is not likely to affect indoor activities, but it may affect outdoor activities. A person is more likely to participate in outdoor activities in pleasant weather, leading to more travel on nice days. Second, weather affects the travel experience. People may be less likely to ride transit if waiting for the bus in the rain makes them uncomfortable. In addition, inclement weather may slow down transit vehicles and reduce quality of service, making transit a less appealing option to travelers. Numerous studies have found that adverse weather conditions such as rain and snow affect traffic speeds (Lamm et al. 1990; Ibrahim and Hall 1994; Rakha et al. 2008), and it is likely that those conditions affect bus operating speeds, making transit service slower. Hofmann and O'Mahony

(2005) found bus travel times to be longer on rainy days than on non-rainy days, although they did not state whether the results were significant.

The extent to which weather affects travel decisions may be influenced by the sources that travelers use to receive weather information. Information can be obtained from secondary sources, such as weather forecasts provided by the media, or from direct observations. People who receive weather information from secondary sources may be more likely to change their travel modes because they have more time to plan alternate trips, although research on this issue has been inconclusive. Khattak and de Palma (1997) found that drivers were slightly more likely to change their travel modes if they received their weather information from secondary sources, but the result was not statistically significant. A survey of Geneva commuters found that 55 percent of respondents who changed their travel patterns because of weather received weather information from secondary sources (de Palma and Rochat 1998).

Previous Research

Little research has been conducted on the impacts of weather on transit ridership, although interest in the topic appears to have increased in recent years. In general, studies that have examined the impacts of weather on aggregate ridership data have found that ridership decreases in adverse weather conditions.

Kalstein et al. (2009) studied the extent to which different types of air masses affected ridership on rail systems in Chicago, the San Francisco Bay Area, and northern New Jersey. Air masses are parcels of air that affect entire regions and can be categorized on the basis of variables such as temperature, humidity, and cloud cover. The researchers found that ridership was significantly higher on dry, comfortable days and significantly lower on moist, cool ones.

A study in Chicago used OLS regression to explore the relationship between ridership on Chicago Transit Authority buses and trains and five weather variables (temperature, rain, snow, wind, and fog). All of the variables had significant impacts on ridership, although they affected bus and rail modes differently. In general, ridership was higher in good weather and lower in bad weather. The weather affected bus ridership more than rail ridership and weekend days more than weekdays (Guo et al. 2007).

Cravo and Cohen (2009) used OLS regression to assess the impacts of temperature, rain, and snow on transit ridership/revenue in New York City. Most of the variables were found to have a statistically significant impact on revenue. Cooler-than-nor-

mal temperatures increased subway revenue in the spring/fall and increased bus revenue in all seasons. Warmer-than-normal temperatures decreased subway revenue in the summer. Snow decreased revenue for both bus and subway, as did rain.

Changnon (1996) examined the effects of summer precipitation on transit systems in the Chicago area. The study found that ridership was significantly lower at the five percent level on rainy days when compared with non-rainy days. Rain that occurred during the midday hours had a stronger effect than rain that occurred in the morning or evening periods, which suggests that discretionary passengers were more affected by rain than commuters, who tend to ride in the mornings and evenings.

Related studies have used surveys to determine how weather influences travel behavior. Khattak and de Palma (1997) conducted a survey in Brussels to determine how weather caused commuters to change travel decisions. Fifty-four percent of automobile users stated that they changed their mode, departure time, and/or route choice because of weather conditions. Twenty-seven percent of those respondents stated that the influence of weather on travel mode change was either "very important" or "important." This result suggests that some drivers will shift modes to carpools or public transit in response to weather, although it is unclear whether this deviation would lead to an overall increase in transit ridership. In a survey of commuters in Geneva, 53 percent of respondents stated that the influence of weather conditions on mode choice was "very important" or "important" (de Palma and Rochat 1998).

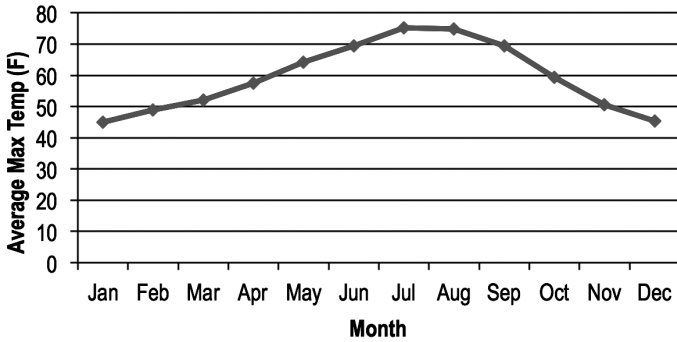
Study Area

Pierce County is located in the Puget Sound region of Washington and is the state's second most populous county, with approximately 786,000 residents in 2008. Its county seat and largest city is Tacoma, with an approximate population of 197,000 in 2006, according to the U.S. Census Bureau. The county is considered to be a part of the Seattle metropolitan area, as it is directly south of King County, where Seattle is located. Public transit in the county is provided by Pierce Transit, which serves all of the county's major jurisdictions and some unincorporated areas, but not the entire county. The agency operated 58 local, express, and dial-a-ride routes as of December 2008. For the years 2006 to 2008, the average weekday ridership was approximately 44,000. Including weekends, the average ridership was about 37,000.

The weather data for this study were observed at Seattle-Tacoma (Sea-Tac) International Airport, which is located in King County approximately 15 miles (24 km) northeast of Tacoma. The airport is close to Pierce County and is a station in the

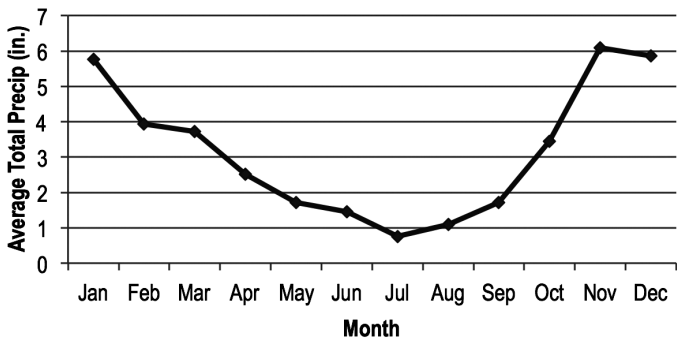
Automated Surface Observing Systems (ASOS) program, which is intended to be the “nation’s primary surface weather observation network” (National Weather Service 2009). The station provides quality-controlled data for the variables analyzed in this study. Pierce County does have an ASOS station at Tacoma Narrows Airport, but that particular station does not provide a 30-year historical average temperature. The Sea-Tac Airport station was chosen because it provides the necessary data and has weather that is similar to Pierce County because of its close proximity.

The Seattle area’s climate is classified as warm temperate with a dry warm summer (type Csb) on the Köppen-Geiger climate classification map (Kottek et al. 2006). Summer tends to be warm and dry, while winter is typically cold and wet. Temperatures seldom dip below freezing, and snow is rare. Figures 1 and 2 present the average monthly temperature and precipitation for Sea-Tac Airport.



Source: Western Regional Climate Center

Figure 1. Sea-Tac Airport average monthly temperature



Source: Western Regional Climate Center

Figure 2. Sea-Tac Airport average monthly precipitation

Methods and Data

The primary intent of this study was to measure the impacts of weather factors (the independent variables) on transit ridership (the dependent variable). Two general methods to measure these impacts have been identified in the literature: absolute level and relative change (Guo et al. 2007). The absolute method compares the absolute levels of weather and transit ridership to identify relationships between the two. For example, higher temperatures may lead to higher ridership and greater rainfall may lead to lower ridership. With the relative change method, weather is compared to a benchmark. The benchmark could be the weather conditions from the previous day or the historical average weather for the day. The rationale for the relative change method is that travelers may make decisions about which mode they will take on the basis of how the weather forecast compares to the previous day or the normal weather for that day.

For the temperature variable, this study took a departure from the normal (historical average) approach, and for the rainfall, wind speed, and snow variables, it used an absolute level approach. Daily temperatures were compared to the historical averages for each day, and a departure from the normal value was calculated to quantify the change. If, for example, on a given day the temperature was 60°F (16°C) and the normal temperature was 69°F (21°C), then the departure from normal was designated as -9 °F (-5°C). The hypothesis was that temperature would affect ridership only if it significantly departed from the historical average. An analysis of average ridership data determined that an 8°F departure in either direction might be the threshold at which temperature begins to impact ridership. Two dummy variables were created to test this: a variable for days when the departure temperature was 8°F above normal or higher, and a variable for days when it was 8°F below normal or lower.

The absolute level method was used for the rainfall and wind speed variables to determine what effects absolute changes in the variables have on ridership. A dummy variable for snow was included in the model rather than the actual amount of snowfall because the weather station at Sea-Tac Airport does not record the magnitude of snowfall, only total precipitation and a remark that snow occurred. Additionally, the amount of snowfall is often highly localized in the Puget Sound region, so a snowstorm might accumulate 4 inches (10 cm) of snow at Sea-Tac Airport but only 1 inch (2.5 cm) in downtown Tacoma. By using a dummy variable for snow, the model measured the impact that any amount of snow would have on ridership. To obtain an accurate measure for rain by itself, precipitation from all days with measured snow

was assumed to be snow, and precipitation was assumed to be rain when snow did not occur. Weather data were obtained from the National Climatic Data Center.

Although this study is concerned primarily with the effects of the weather variables, omitting other independent variables that affect the dependent variable would bias the estimated value of the regression coefficients. Additional independent variables were added to the models to account for non-weather factors that influence transit ridership and to help avoid omitted variable bias. Vehicle revenue hours and the adult fare price were obtained directly from Pierce Transit. The price of gasoline was defined as the price of a gallon of unleaded regular gasoline in dollars for the Seattle-Tacoma-Bremerton area. Unemployment rate was included to control for the state of the local economy, as the economy has an impact on how much people travel. The size of the labor force was used as a proxy for population. Data for all three variables were obtained from the Bureau of Labor Statistics.

The study period for the analysis was January 2006 to December 2008. Because the temperature variables could have different effects on ridership depending on the season, a separate model was estimated for each of the four seasons: winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November). Ordinary least squares was used to estimate the parameters of the multiple regression models. Each model took the following form at the outset:

$$\text{riders} = \beta_0 + \beta_1 \text{windspeed} + \beta_2 \text{departurewarm} + \beta_3 \text{departurecold} + \beta_4 \text{raintotal} + \beta_5 \text{snow} + \beta_6 \text{gasprice} + \beta_7 \text{laborforce} + \beta_8 \text{revenuehours} + \beta_9 \text{unemployment} + \beta_{10} \text{fare} + \beta_{11} \text{Monday} + \beta_{12} \text{Tuesday} + \beta_{13} \text{Wednesday} + \beta_{14} \text{Thursday} + \beta_{15} \text{Friday} + \beta_{16} \text{Saturday} + \beta_{17} \text{HolidaySaturday} + \beta_{18} \text{HolidaySunday} + u$$

where,

<i>riders</i>	= unlinked passenger trips on local routes
<i>windspeed</i>	= daily average measured wind speed (miles per hour)
<i>departurewarm</i>	= departure from normal temperature higher than 7°F
<i>departurecold</i>	= departure from normal temperature lower than -7°F
<i>raintotal</i>	= total rainfall (inches)
<i>snow</i>	= dummy variable for snow
<i>gasprice</i>	= price of gasoline (in dollars)
<i>laborforce</i>	= size of the labor force
<i>revenuehours</i>	= revenue hours of service provided on local routes
<i>unemployment</i>	= unemployment rate

<i>fare</i>	= price of basic adult fare (in dollars)
<i>Monday</i>	= dummy variable for Monday
<i>Tuesday</i>	= dummy variable for Tuesday
<i>Wednesday</i>	= dummy variable for Wednesday
<i>Thursday</i>	= dummy variable for Thursday
<i>Friday</i>	= dummy variable for Friday
<i>Saturday</i>	= dummy variable for Saturday
<i>HolidaySaturday</i>	= dummy variable for holidays when a Saturday schedule was used
<i>HolidaySunday</i>	= dummy variable for holidays when a Sunday schedule was used
<i>u</i>	= unobserved factors
β_0	= intercept parameter
β_{1-18}	= independent variable parameters

Estimation of each regression model was a multi-step process. Initially, an *unrestricted* model was estimated to include all possible relevant variables. Variables with p-values of 0.10 or greater were deemed insignificant and were removed from the model, except in some close cases. A Wald test was performed for the day-of-week dummy variables to determine whether they were jointly significant. If together they were significant, they remained in the model, even if some were insignificant individually. Finally, a *restricted* model was estimated by using all significant variables. After each step, a White test was used to detect heteroscedasticity, and an LM test was used to test for serial correlation. If necessary, heteroscedasticity-robust standard errors and autoregressive terms (which appear as AR(n) in the results tables) were used to correct for the conditions.

Results

Table 1 presents the unrestricted results from the four seasonal models. Restricted models were estimated after insignificant variables had been removed, and those results are displayed in Table 2. The coefficient for each independent variable represents the change in ridership given a 1-unit change in the independent variable, holding other variables constant. The results for the weather variables are given in absolute change (number of riders) and percentage change (compared to the mean daily ridership for the season in question). The daily ridership averages were 35,167 for winter, 37,497 for spring, 37,045 for summer, and 38,566 for autumn. Variables in the restricted model were significant at the 10 percent level or lower, or very close. P-values are included in Tables 1 and 2.

Table 1. Unrestricted Model Results

Dependent Variable: riders				
Independent Variable	Winter	Spring	Summer	Autumn
windspeed	-163.72 (0.0032)	-121.36 (0.0037)	-65.02 (0.2928)	-181.13 (0.0083)
departurewarm	2,361.29 (0.0786)	449.55 (0.2699)	161.46 (0.7407)	1,345.79 (0.1401)
departurecold	-4,076.37 (0.0016)	-1,374.58 (0.2606)	89.54 (0.8540)	-903.66 (0.5321)
raintotal	-1,832.24 (0.0569)	-3,473.40 (0.0000)	-2,655.13 (0.0857)	-2,467.43 (0.0001)
snow	-4,069.00 (0.0003)	932.72 (0.3870)	N/A	-4,316.57 (0.0553)
gasprice	41.33 (0.0018)	28.66 (0.0001)	22.03 (0.0232)	23.40 (0.0022)
laborforce	0.03 (0.7268)	-0.05 (0.1869)	-0.03 (0.3647)	-0.09 (0.0959)
revenuehours	4.96 (0.4533)	32.75 (0.0000)	48.00 (0.0000)	48.84 (0.0000)
unemployment	2,845.15 (0.0053)	-1,977.10 (0.0045)	-19.70 (0.9083)	2,424.04 (0.0001)
fare	1,933.27 (0.7716)	N/A	N/A	N/A
Monday	20,311.26 (0.0040)	-6,523.85 (0.1624)	-24,145.8 (0.0000)	23,309.60 (0.0104)
Tuesday	21,227.88 (0.0024)	-5,802.63 (0.2000)	-23,720.98 (0.0000)	-23,207.99 (0.0106)
Wednesday	21,080.47 (0.0025)	-6,113.30 (0.1776)	-24,255.02 (0.0000)	-22,645.37 (0.0125)
Thursday	20,817.44 (0.0029)	-6,344.06 (0.1623)	-24,461.67 (0.0000)	-23,613.83 (0.0092)
Friday	21,253.83 (0.0024)	-6,578.40 (0.1477)	-24,681.17 (0.0000)	-24,741.93 (0.0064)
Saturday	6,683.02 (0.0000)	1,594.52 (0.1089)	-2,221.18 (0.0295)	-2,828.48 (0.1548)
HolidaySaturday	-14,578.69 (0.0106)	N/A	N/A	N/A
HolidaySunday	-20,571.16 (0.0047)	6,214.94 (0.1792)	28,607.42 (0.0000)	25,491.72 (0.0053)
AR(1)	0.22 (0.0014)	0.38 (0.0000)	0.39 (0.0000)	0.35 (0.0000)
AR(2)	0.16 (0.0004)	0.15 (0.0179)	N/A	N/A
Intercept	-24,092.31 (0.1183)	12,622.35 (0.3293)	-14,964.75 (0.2854)	-2,902.04 (0.8545)
Observations	269	276	276	273
Adj R-squared	0.9237	0.9774	0.9726	0.9455

(): p-value

N/A: variable was omitted because there were no changes or occurrences of that variable during the study period, or AR(n) was unnecessary.

Table 2. Restricted Model Results

Dependent Variable: riders				
Independent Variable	Winter	Spring	Summer	Autumn
windspeed	-170.42 (0.0013)	-109.00 (0.0070)	---	-186.46 (0.0303)
departurewarm	1,988.95 (0.1130)	---	---	---
departurecold	-3,949.38 (0.0023)	---	---	---
raintotal	-1,776.88 (0.0724)	-3,649.76 (0.0000)	-2,726.26 (0.0066)	-2,304.98 (0.0000)
snow	-3,910.39 (0.0002)	---	---	-5,052.18 (0.1011)
gasprice	55.83 (0.0000)	24.11 (0.0000)	19.78 (0.0001)	22.51 (0.0061)
laborforce	---	---	---	-0.10 (0.0233)
revenuehours	---	26.82 (0.0000)	44.92 (0.0000)	48.93 (0.0000)
unemployment	3,594.10 (0.0000)	-2,017.17 (0.0035)	---	2,521.91 (0.0001)
fare	---	N/A	N/A	N/A
Monday	25,569.48 (0.0000)	---	-20,924.29 (0.0000)	-23,430.56 (0.0055)
Tuesday	26,443.65 (0.0000)	---	-20,519.80 (0.0000)	-23,337.41 (0.0060)
Wednesday	26,310.86 (0.0000)	---	-21,051.90 (0.0000)	-22,776.70 (0.0078)
Thursday	26,022.19 (0.0000)	---	-21,224.20 (0.0000)	-23,776.21 (0.0054)
Friday	26,495.89 (0.0000)	---	-21,468.33 (0.0000)	-24,850.88 (0.0038)
Saturday	7,805.53 (0.0000)	2,977.91 (0.0000)	-1,529.34 (0.1213)	-2,792.50 (0.1320)
HolidaySaturday	-18,866.12 (0.0000)	N/A	N/A	N/A
HolidaySunday	-25,642.01 (0.0000)	---	25,430.75 (0.0000)	25,419.08 (0.0026)
AR(1)	0.25 (0.0000)	0.38 (0.0000)	0.39 (0.0000)	0.33 (0.0003)
AR(2)	0.16 (0.0000)	0.15 (0.0133)	N/A	N/A
Intercept	-15,346.55 (0.0066)	-2,302.33 (0.5298)	-25,399.08 (0.0000)	-2,166.29 (0.8564)
Observations	269	276	276	273
Adj R-squared	0.9236	0.9775	0.9729	0.9454

(): p-value

N/A: Variable was omitted because there were no changes or occurrences of that variable during the study period, or AR(n) was unnecessary.

---: Variable was omitted because it was insignificant in the unrestricted model.

Average wind speed was significant in the winter, spring, and autumn models, but not summer. A 1-mph (1.6 kph) increase in average wind speed resulted in decreases in ridership of 170 in winter, or a 0.48 percent drop from the average ridership in that season. The decrease was 109 (0.29%), and 186 (0.48%) for spring and autumn, respectively. Assuming a linear relationship, a 10-mph (16 kph) increase

in wind speed would lead to a decrease of 1,865 riders in autumn, a drop of 4.84 percent. Although the model assumed a linear relationship between ridership and wind speed, this may not be true in reality, as wind speed may have a greater effect during strong wind events.

Temperature was found to affect ridership in the winter months only. The colder-than-normal variable was statistically significant, and the warmer-than-normal variable was on the border of being statistically significant. A temperature that was more than 7°F cooler than normal resulted in 3,949 (11.23%) fewer riders, while a temperature that was more than 7°F warmer than normal resulted in 1,989 (5.66%) more riders. This suggests that ridership decreases in cooler than normal temperatures and increases in warmer than normal temperatures during the winter months. This is logical, as cold temperatures make waiting for the bus outside more uncomfortable. The variables may be insignificant in the spring, summer, and autumn months because temperatures in those seasons are more comfortable than in winter, and departures from the normal temperature are still generally comfortable.

Rain was the only variable that was significant in all four seasons. One inch (2.5 cm) of rain resulted in decreases in ridership of 1,777 (5.05%) for winter, 3,650 (9.73%) for spring, 2,726 (7.36%) for summer, and 2,304 (5.97%) for autumn. These results are logical, as rainy weather makes waiting for a bus in the rain unpleasant if no shelter is provided. When it rains, many people likely switch to automobiles for transportation if that mode provides a more comfortable experience. Rain may also affect travel in general, reducing travel on all modes. In addition, rain may decrease bus operating speeds, making the mode less attractive to travelers.

The final weather variable, snow, was significant in winter and on the border of being significant in autumn. The occurrence of snowfall led to a decrease of 3,910 (11.12%) riders in winter and 5,052 (13.10%) riders in autumn. Snow may cause travelers to choose a different mode or to not travel at all. In addition, some Pierce Transit route alignments are modified when it snows, which likely reduces ridership.

Sensitivity Analysis

Sensitivity analysis was used to test the sensitivity of the regression models to modifications. The first sensitivity test dropped Saturdays and Sundays from the models and estimated them using weekdays only. Table 3 presents the results for the weather variables from the restricted models. In general, the coefficients are larger than in the original models due to higher average ridership on weekdays

than on all days, but the significant variables are largely the same. Rain became insignificant in the summer model, but warmer than normal temperatures became significant in the autumn model and had a positive impact on ridership.

Table 3. Weekday Model Results

Dependent Variable: riders				
Independent Variable	Winter	Spring	Summer	Autumn
windspeed	-190.88 (0.0045)	-108.93 (0.0562)	---	-188.97 (0.0905)
departurewarm	3,060.64 (0.0128)	---	---	1,925.41 (0.0668)
departurecold	-5,778.00 (0.0006)	---	---	---
raintotal	-2,308.68 (0.0186)	-4,733.23 (0.0002)	---	-3,114.87 (0.0001)
snow	-5,915.16 (0.0000)	---	---	-8,374.21 (0.0880)

(): p-value

---: Variable was omitted because it was insignificant in the unrestricted model.

In the second sensitivity test, outlying observations with at least 1 inch of daily rainfall (14 observations) and/or an average wind speed of 15 mph (32 observations) were excluded. Table 4 presents the results for the weather variables from the restricted models. The results are slightly different but mostly similar to the original results. Wind speed became insignificant in the winter and autumn models, snow became insignificant in the autumn model, and warmer-than-normal temperatures became significant in the autumn model. This suggests that wind may only have a significant impact in autumn and winter on very windy days. The significance of rain was not affected by removing outliers.

Table 4. Outliers-Removed Model Results

Dependent Variable: riders				
Independent Variable	Winter	Spring	Summer	Autumn
windspeed	---	-105.41 (0.0122)	---	---
departurewarm	2,885.43 (0.0300)	---	---	1,651.14 (0.0226)
departurecold	-4,767.64 (0.0005)	---	---	---
raintotal	-3,964.41 (0.0044)	-3,783.70 (0.0000)	-2,726.26 (0.0066)	-3,979.32 (0.0024)
snow	-4,195.79 (0.0009)	---	---	---

(): p-value

---: Variable was omitted because it was insignificant in the unrestricted model.

The sensitivity analysis yielded interesting findings. Wind speed may not have as strong an impact as the original results suggest, except when winds are very strong. In addition, warmer-than-normal temperatures may lead to increased ridership in autumn, which the original model did not show. The changes in results caused by modifying the models indicate that they are somewhat sensitive to removing weekend days and outliers. The choice of which data are included in the analysis can affect the results, but the overall conclusions of the analysis remain the same. Each weather variable had an effect on ridership in at least one season, and rain was the most significant variable throughout the year.

Discussion

The results of this study are consistent with others in suggesting that adverse weather conditions lead to lower transit ridership. Each of the four weather variables had a significant effect on ridership in at least one season. Winter was the season most affected by weather, while summer was the least affected. Puget Sound weather during the summer is generally less severe than in other seasons, so it is logical that weather affects transit less in that season than in others.

This study adds to the small body of research on the effects of weather on transit ridership by using different analysis methods as well as a new study area. The use of absolute level and relative change methods for different variables and the inclusion of independent variables other than weather distinguish this study from others on the topic. Examining the relationship between weather and transit ridership for different agencies in various geographic areas is important because the weather-transit relationship may vary in different locations.

The results are significant for Pierce Transit and other transit agencies. Some of the effects that weather has on ridership could be mitigated by making the transit experience more comfortable. A common belief in the transit industry is that people are more likely to ride transit when they are comfortable while waiting for transit and while on transit vehicles. One way to improve the comfort of waiting passengers is by placing shelters at stops, which provide weather protection and a place to sit (Law and Taylor 2001). Pierce Transit provides shelters at 21 percent of its stops (Sandy Johnson, Pierce Transit, unpublished data), and adding more shelters to highly-used stops could improve ridership, although there has been limited empirical study of the issue. A study on transit amenities found that a bus shelter with walls, a roof, and seating is an amenity that induces trips and that passengers

notice when weather protection is sufficient (Projects for Public Spaces, Inc. and Multisystems, Inc. 1999). In addition, providing a climate-controlled environment on buses can help mitigate the effects of weather.

This study had some limitations. The most significant was the combination of weather data from Sea-Tac Airport in King County with transit data from Pierce County. A more precise analysis would have used weather data from within the transit agency's service area. Although the airport is close to Pierce County, slightly different weather conditions in the two locations could have occurred, leading to less accurate results. In general, however, Sea-Tac Airport and the Pierce Transit service area have similar weather conditions during the same day, so the results can be used to make general observations about the weather-transit ridership relationship, such as rainfall leading to lower ridership. A second limitation was that the weather data were aggregated for 24-hour periods, but Pierce Transit buses only run during a portion of those hours. So, for example, rain included in the daily rainfall total may have occurred at night, when transit service was not running. It would likely have been more accurate to exclude weather data from the hours when buses were not running. Last, weather conditions such as snow and icy roads adversely affect transit operations and quality of service, which affects ridership. However, it is unknown which component affects ridership more on snowy days: the reduction in passenger comfort or the reductions in quality of service.

Additional research on the weather-transit relationship is necessary and should examine three issues. First, the specifics of the relationship may differ in other climates. Recent studies examined the issue in northern cities, but weather may have a different effect on ridership in cities with hotter climates, such as Phoenix or Houston. Second, further research should determine whether different types of bus routes are affected differently. For instance, routes that serve primarily park-and-ride lots with shelters may be affected differently than routes that serve areas where people walk to the closest bus stop. Last, a similar analysis could use forecast data for the weather variables as opposed to observed data because people may base their travel decisions on the forecast from the previous night rather than on actual conditions.

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