THE IMPACT OF WEATHER ON TRANSIT RIDERSHIP IN CHICAGO

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Abstract
This paper explores the weather-ridership relationship and its potential applications in transit operations and planning. Using the Chicago Transit Authority (CTA) as a case, the paper investigates the impact of five weather elements (temperature, rain, snow, wind, and fog) on daily bus and rail ridership, and its variation across modes, day types, and seasons. The resulting relationships are applied to the CTA ridership trend analysis, showing how preliminary findings may change after controlling for weather. The paper emphasizes the importance of having a theoretical framework encompassing weather and travel.

Keywords: Weather, Transit, Ridership, Chicago

INTRODUCTION
Weather influences almost every aspect of transit service. Bad weather can reduce transit ridership, lengthen vehicle running time and dwell time, reduce service reliability, and increase the cost of operation. Better understanding of the weather impact on transit performance can not only improve transit service, but also help to assess investments related to weather protection such as bus shelter construction, or air conditioning. Given its potential importance, it is surprising that there has been little research on the impact of weather on transit systems. Prior studies that deal with weather and travel have focused on driving, traffic volumes (1, 2, 3), vehicle speed (4, 5, 6, 7, 8), or accidents (9, 10, 11, 12, 13, 14).

There are three plausible reasons why the weather-transit relationship has been rarely investigated. The first one is lack of data. Traditionally, transit authorities have used manual methods, conventionally point or ride checks, to collect information on vehicle
trip time, passenger load, and boardings per trip (15, 16). Data collection is usually spread across different time periods and days to obtain a representative sample in order to estimate typical performance. Therefore, each time period or day usually has only a few observations. However, to investigate the relationship between weather and transit performance, we need to control for the impact of time of day or day of week on performance, and thus need large amounts of data within each period of interest.

Traditional manual data collection simply can not support such analysis. In contrast, data collected on the weather-auto relationship is straightforward: automatic traffic counters installed on highways can generate a large amount of data on traffic volumes and speeds within a short period of time. Similar types of automatic data collection for transit systems have become available only recently with the installation of Automatic Fare Collection (AFC) systems. For example, in New York City, the Metropolitan Transit Authority (MTA) became the first major multi-modal US transit agency to install an AFC system in January 1994. AFC was accepted system wide at the end of 1995 for bus, and in May 1997 for subway. In Chicago, an AFC system was installed on the subway in 1998, and on bus in 2001. In Boston, an AFC system is now being commissioned.

Secondly, the weather impact on transit performance is more complex than on driving. Drivers are affected by weather through its effect on the operation of vehicles (17). For transit riders, they are often directly subject to weather while waiting or walking to and from the system as well as indirectly affected by the deterioration in transit service in the in-vehicle portion of the trip. Both direct and indirect effects influence the travel demand for transit as well as riders’ behavior for those who still travel by transit.
The third and maybe the most important reason is that the importance of the weather-transit relationship has not been well recognized. A common misunderstanding is that since we can not control weather, such an investigation would not be beneficial. However, this paper argues that a better understanding of the impact of weather on transit performance could provide benefit in at least two areas. First, it can help improve transit service quality. For example, knowing how weather affects service reliability, we may redesign stations or vehicles accordingly. Knowing how good or bad weather may increase or decrease ridership on particular routes, we may change schedules beforehand if large ridership changes are expected based on forecast weather. Second, such research can help in project appraisal related to weather protection. For example, bus shelters improve customer protection from bad weather, and likely attract new riders. A weather-ridership model may be able to quantify the benefit of such projects in terms of ridership gain. Given the potential benefits, we expect more weather-transit studies will follow this, given the great availability of AFC data. This paper starts this exploration.

Clearly, transit is more complicated than driving in terms of the weather impact. Accordingly, there is little theory on the relationship between weather and transit use. The few prior studies in the area are strictly empirical following ad hoc research designs and methodologies and producing inconsistent results. For example, one study found higher transit ridership during adverse weather because of the diversion from other modes including auto, walk and bike (18), while others found no appreciable change or a slight decrease in transit ridership in bad weather (19, 20). However, the real reason behind the difference in these observed impacts is that the first study only looked at a blizzard in Chicago that affected the afternoon commute, when road service was disrupted, and rail...
remained one of the few operational urban transport modes, while the other study targeted more moderate adverse weather.

This research investigates the weather impact on transit ridership at the system level. We focus on transit ridership because it is perhaps the single most important dimension of system performance, and on the system level impact because the relationship is likely to be more evident at this level than at the route level. Individual route level analysis is a logical follow-on topic. We target both bad and good weather conditions in order to have a more complete picture of the weather impact on transit ridership. We also analyze the variation of the impacts across mode and day type.

Section 2 categorizes the sources of weather impact on transit ridership. Section 3 defines the research design to link weather changes to ridership changes. Section 4 introduces the Chicago case study, and defines the weather variables. Section 5 develops a group of models, and presents and interprets estimation results. Section 6 applies the findings to a form of performance tracking used by most transit agencies. Section 7 concludes the analysis and proposes further research in this area.

POTENTIAL IMPACTS OF WEATHER

Weather can influence travel behavior in two ways. First, it affects the activities that drive travel demand. For example, hot dry weather may increase recreation activities at beaches and parks, while cold wet weather may depress outdoor sports, recreation, and even social events. Secondly, weather affects travel experience. Transit users are subject to direct physical impacts from weather when they wait or walk in exposed areas. When they are in a vehicle, they are affected indirectly by bad weather through deterioration in
transit service quality. In this paper the potential sources of weather impact are categorized into four types: infrastructure, service, trip, and passenger characteristics. However, the purpose of this investigation is to explore the impact of weather on ridership, not to model these potential sources of weather impact individually.

Infrastructure refers to the physical routes, buildings, and vehicles that involve long term capital investment by transit agencies. The technology used for the physical routes, e.g. pavement vs. track or shared vs. full separation, affects the movement of vehicles under various weather conditions. The different types of station/stop facility (all-weather protection, simple shelter, or just a stop) affect travelers’ waiting and transfer experience. The distance between stations (stops) influences the access and egress walking distance, and thus the time exposed to weather. Vehicle attributes such as air conditioning directly affect the comfort of travel. Therefore, different transit modes (bus, subway, light rail, or commuter rail) may be impacted differently by weather. Subway is least affected by weather due to its full separation from other traffic and full protection from weather. Bus is likely to be most affected because it shares roads with local traffic and offers less protection from weather at stops, compared to rail systems.

Service characteristics primarily refer to frequency and travel time. Service frequency determines passenger waiting times, and thus the time exposed to weather if the waiting environment is not protected. Total travel time in adverse weather might be lengthened due to slower speed and longer dwell time at stations. For example, rainy weather may cause longer dwell time because passengers need to open or close umbrellas when they get on and off the vehicle. Service reliability may deteriorate due to longer and more variable run times and dwell times, thus increasing passenger waiting times. In
general, high frequency service should be less affected by weather than low frequency service. Accordingly, bus is likely to be more sensitive to weather than rail because the latter normally has higher service frequencies. A transit system using effective real time operation control should be less affected by weather than a system based only on a static operations plan.

Trip characteristics which may affect the weather impact include trip length, time flexibility, and trip purpose. A longer trip might be more sensitive to weather because the period of exposure is higher. If a trip has time constraints such as latest arrival time or earliest departure time, it might be less sensitive to weather because it is less flexible. If the trip purpose is discretionary such as personal business rather than mandatory such as work, it might be more sensitive to the weather. If the trip purpose is susceptible to weather, it will be more sensitive. In summary, long, time-flexible, and non-commuting trips are likely to be affected more by weather than short, time-constrained commuting trips.

Personal characteristics can influence the weather-transit relationship in two ways. First, different people may respond differently to identical weather. A teenager may view a snowfall differently from an elderly person. A professional in a suit may respond differently to rain than a runner in shorts. Second, people may have different travel options, and their response to weather may vary accordingly. The transit travel of people who don’t own a car may be less affected by weather compared to people who can easily switch to auto.
The above discussion suggests that the weather impact may vary across transit modes, routes, trips, and passengers. Bus may be more sensitive to weather than rail. Routes serving shopping centers may be more sensitive to weather than routes serving employment centers. A passenger who just takes transit occasionally might be more sensitive to weather than a rider who takes transit every day. The same passenger might be more sensitive to weather in off-peak hours than peak hours, and on weekends than weekdays, because off-peak and weekend service frequencies are typically lower.

**RESEARCH DESIGN: LINKING WEATHER TO RIDERSHIP**

Both weather and transit ridership are changeable from hour to hour and from day to day, so a critical issue in investigating the weather-ridership relationship is how to control for these inherent fluctuations when examining their interrelationship. Three aspects of the research design are discussed below: absolute level vs. relative change, unit of analysis, and method of comparison.

**Absolute Level or Relative Change**

The weather-ridership relationship can be structured in two ways. First, we can compare the absolute levels of weather and ridership, with the underlying rationale that the current weather conditions affect the current level of transit ridership. For example, cold weather may lead to low transit ridership. Secondly, we can relate the changes in weather conditions and ridership. The underlying rationale is that changes in weather can lead to changes in travel. The absolute-level method captures the true impact of weather (cold, heat, rain, etc.), while the relative-change method ignores the absolute weather
conditions. For example, a 5 degree temperature rise in a cold winter still represents cold weather, but the relative-change method will treat it as relatively warm weather and ignore the fact that it is still cold in an absolute sense. However, the disadvantage of the absolute-level method is that it brings in systematic seasonal impacts, which are not based solely on weather. For example, the lowest ridership months (typically January and December) are due to the holiday season, while low August ridership is due to vacations. In contrast, the highest ridership months (typically September and October) are due to the start of school and college years. These fluctuations are not due to seasonal changes in weather. The relative-comparison method can avoid this problem by focusing on the pure impact of short-term weather variation.

This research uses the relative-comparison method because it is less problematic in statistical estimation and more likely to reflect the short-term impact of weather on travel.

**Unit of Analysis**

Because weather and ridership can change all the time, they should be compared based on the same unit of analysis, for example, ridership and weather in the same hour, or on the same day. The unit of analysis is selected based on four criteria. First, it should allow sufficient variation between units in both weather and ridership to make for a statistically meaningful analysis, e.g. daily ridership should be different. Secondly, there should be little intrinsic fluctuation between units in terms of both weather and ridership. A month is a bad unit of analysis because there is systematic change in monthly ridership from January to December. Third, the weather condition(s) should be easy to represent by a specific variable. Fourth, the unit of analysis should reflect the real decision-making
context. Based on these criteria, a year or month is not an appropriate unit of analysis because people don’t make travel decisions on an annual, or monthly basis. An hour is also inappropriate because hourly ridership will have tremendous intrinsic variability, not related to weather.

The day is chosen as the unit of analysis because it meets the four criteria. Daily weather conditions are quite variable. Ridership for the same type of day (weekday, Saturday, or Sunday) has small intrinsic variability. Although, ridership can also change from Monday to Friday in a systematic way, such differences are relatively small. It is easy to define variables to represent daily weather conditions, and people do make travel decisions on a daily basis.

**Methods of Comparison**

Applying the relative-comparison method, we need to compare the daily weather and ridership to some “benchmark” weather and ridership to assess the changes. Two methods can be used to define the benchmark: adjacent-day comparison, and normal-extreme comparison. In the first approach, the benchmark is the weather and ridership on the immediately preceding day of the same type (e.g. weekday, Saturday, Sunday). The rationale for this is that people may adjust their travel behavior by comparing today’s weather with the forecast for tomorrow: for similar weather, travel should also be similar. This is a reasonable argument especially for non-work trips, which is likely to be the major part of weekday ridership variation. In the second approach, the benchmark is defined as “normal” weather and ridership for that time of year, recognizing the seasonal fluctuations in both weather and ridership. The underlying assumption is that a deviation
from “normal” weather will result in a corresponding deviation from “normal” ridership. In this paper, normal weather is defined as having a temperature within a 6 degree range around the 30 year historical average (1971 to 2000) for that particular day, and no precipitation. Correspondingly, normal ridership is the average ridership on all normal weather days.

Each method has advantages and disadvantages. The advantage of the adjacent-day method is that it has both theoretical and empirical supporting evidence, and better controls for exogenous variables by narrowing the comparison to today and the previous day. The disadvantage is that it assumes a constant impact of a unit change of weather variable. In reality, an 0.1 inch rainfall increase from zero to 0.1 inch probably has a different impact from the same increase but from 1 inch to 1.1 inches. However, this method treats expected impact as being equal, and averages them to get the final result. The normal-extreme method partially resolves the problem by setting up a benchmark based on a threshold of weather impact. Changes in weather conditions within the normal range will have little impact on transit ridership. But the disadvantage of this method is the loss of information. By setting up a normal weather range and averaging ridership within that range, some information is lost, and there is less variation in both weather and ridership variables. This may reduce the explanatory power of the estimated models.

Because of these advantages and disadvantages, this research explores both methods to investigate the weather-ridership relationship. If the two methods lead to consistent results, the weather impact on ridership will be more strongly supported and better understood.
CHICAGO TRANSIT AUTHORITY CASE STUDY

Chicago Transit Authority (CTA) is the nation's second largest public transportation system serving the City of Chicago and 40 surrounding suburbs. The CTA bus system has about 2,000 buses operating on 152 routes serving more than 12,000 bus stops, while the rail system has 7 lines and 145 stations. On an average weekday, nearly 1 million rides are taken on the bus system, and a half million rides on the rail system. Ridership has been recorded by an AFC system since March 1998 for the rail system, and January 2001 for the bus system. The large resulting AFC database is well suited to support this type of research and is used in this study.

Chicago has dense lakefront development with beaches and recreational areas and a large lower density area away from the lakefront and the “Loop”. Lake Michigan has a moderating influence on the local weather, but also frequently causes overcast skies. Chicago averages 126 days annually with precipitation and 176 with clouds. The weather can also change rapidly as successions of air masses pass generally from west to east. Winters are not always consistently cold while summers are not always consistently hot, making Chicago particularly attractive for this research.

Meteorological data for O’Hare Airport was chosen to represent the weather conditions throughout the region (http://www.crh.noaa.gov/lot/climate/ordmonthly.php). Five weather elements are examined in this research: temperature, wind, rain, snow, and fog.

The highest daily temperature is used to represent temperature because it typically occurs during daylight hours, and so probably best represents people’s perceptions of
temperature for that day. Three types of temperature variables are defined: temperature change, and two dummy variables: warm and cool. For the adjacent-day approach, temperature change is the difference in the highest temperature between that day and the previous day. Warm weather is defined as an increase of at least 12 degrees (Fahrenheit) from the previous day, while cool weather is defined as a decrease of at least 12 degrees. For the normal-extreme approach, temperature change is the temperature departure from a 30-year average on that particular date. Warm weather is defined as a temperature at least 12 degrees above the average, while cool weather is defined as a temperature at least 12 degrees below the average.

Two types of wind variables are defined: the daily highest wind speed that lasts for at least two minutes, and windy weather defined as a speed exceeding 25 miles/hour. This threshold is chosen because this type of wind can blow dust and paper from the ground, and may indicate a threshold at which wind begins negatively to affect walking. Strong wind may be especially unpleasant for pedestrians on chilly winter days in Chicago. For the adjacent-day approach, the wind speed variable is the difference between that day and the previous day. For the normal-extreme approach, it is defined as the highest wind speed. The dummy variable for windy weather is the same for both approaches.

For variables such as rain and snow, the total amount of daily precipitation is used as the variable. The two precipitation variables are defined as differences between that day and the previous day for the adjacent-day approach, and between that day and normal weather (no precipitation) for the normal-extreme approach. Dummy variables are also defined to capture the effect of significant precipitation. For rain, it is defined as greater than 0.6 inches (80 percentile for all rainy days), and for snow, it is greater than 0.5
Inches (50 percentile for all snowy days). Different percentiles are chosen because there are fewer snow observations, and snow is likely to have a larger impact than rain on vehicle movement.

Fog might affect driving because of reduced road visibility, and it may also influence transit use. The intensity of fog probably makes a difference, but the meteorological data only records the occurrence of fog, and does not indicate intensity. Therefore, fog is treated as a single trinary variable in this analysis. For the adjacent-day approach, it is 0 if both that day and the previous day are identical with respect to fog, 1 if that day has fog while the previous day did not, and -1 if the previous day had fog while that day does not. For the normal-extreme approach, it is a two-value dummy, 1 if there is fog, and 0 otherwise.

MODEL ESTIMATION AND ANALYSIS
Because the impact of weather on transit ridership is highly dependent on mode, time, and trip purpose, it is unlikely that a single model will apply in all situations. A balance between in-depth analysis for a particular situation and comparison among situations is required. We chose an Ordinary Least Square (OLS) model structure because it is simple, and can be easily applied to various situations. A total of 12 OLS models are estimated. These models are for mode and day type with seasons included as dummy variables. The goodness-of-fit statistics reflect the daily ridership variations explained by weather. Each model is estimated based on both the adjacent-day and the normal-extreme specifications.
The basic OLS equation and the notation for the two specifications are explained below. The models are calibrated using the backward-delete method. Estimations with the highest adjusted R square are accepted. The results of the twelve estimations are summarized in Tables 1 and 2 for bus and rail respectively.

\[ \Delta Y = \alpha + (\beta_1 \Delta R + \beta_2 \text{Heavy} \ast \Delta R) + (\beta_3 \Delta S + \beta_4 \text{Big} \ast \Delta S) + (\beta_5 \Delta W + \beta_6 \text{Windy} \ast \Delta W) + \beta_7 \Delta F + (\beta_8 \Delta T + \beta_9 \text{Cool} \ast \Delta T + \beta_{10} \text{Warm} \ast \Delta T) + \beta_j \text{Season}_j \]  

(1)

Adjacent-Day Specification

\( \Delta Y \) : Ridership change from the previous day
\( \Delta R, \Delta S, \Delta W, \Delta T \) : Changes in rain, snow, wind, and temperature from the previous day.
\( \Delta F \) : 1 from no fog to fog, -1 from fog to no fog, 0 otherwise
\( \text{Heavy} \) : rain dummy variables, 1 if change of rainfall \( \geq 0.6 \) inch/day, 0 otherwise
\( \text{Big} \) : snow dummy variables, 1 if change of snow fall \( \geq 0.5 \) inch/day, 0 otherwise
\( \text{Windy} \) : dummy variable, 1 if highest wind speed (2 minutes) \( \geq 25 \) miles/hour, 0 otherwise
\( \text{Warm} \) : dummy variable, 1 if temperature increases \( \geq 12 \) degrees from the previous day, 0 otherwise
\( \text{Cool} \) : dummy variable, 1 if temperature decreases \( > -12 \) degrees from the previous day, 0 otherwise
\( \text{Season}_j \) : dummy variables for seasons, \( j=1,2,3 \). Which season is the base varies by model
\( \alpha, \beta_1 - \beta_{10}, \beta_j \) : parameters for estimation, note \( \beta_2, \beta_4, \beta_6, \beta_8, \beta_{10} \) capture extreme weather event (heavy rain or snow, strong wind, warm and cool temperature) effects additional to rainfall, snowfall, wind speed, and temperature impact on ridership.

Normal-Extreme Specification

\( \Delta Y \) : Ridership change from the normal weather ridership
\( \Delta R, \Delta S, \Delta W, \Delta T \) : Deviations of rain, snow, wind, and temperature from normal.
ΔF : 1 if there is fog, 0 otherwise

Heavy : rain dummy variables, 1 if rainfall >= 0.6 inch/day for rain, 0 otherwise

Big : snow dummy variables, 1 if snowfall >= 0.5 inch/day for snow, 0 otherwise

Windy: dummy variable, 1 if highest wind speed (2 minutes) >= 25 miles/hour, 0 otherwise

Warm: dummy variable, 1 if temperature >= 12 degrees above the historical average, 0 otherwise

Cool: dummy variable, 1 if temperature >= 12 degrees below the historical average, 0 otherwise

**Temperature**

In most cases, temperature variables are significant and have a positive sign, which means that warmer weather tends to lead to higher transit ridership in all seasons. A one degree increase of temperature results in a system-wide daily ridership increase of between 652 and 1,087 for bus, and between 240 and 663 for rail depending on day type. The Cool and Warm weather variables are not significant in most cases, and when significant they have inconsistent signs. One possible reason for this is the variable definition: a sharp decrease (increase) in temperature might not be a good indicator of cold (hot) weather. Their impacts might depend on the current temperature: a sharp temperature decrease may be a pleasant relief in a hot summer, but painful in a cold winter. A better definition which combines both temperature changes and human perceptions is necessary to explore the possible effects of extreme temperature on transit ridership.

**Precipitation**

In most cases, rainfall variables are significant, and have negative coefficients, which means that rain tends to reduce ridership in all seasons for both bus and rail. Such an
impact is stronger on weekends than on weekdays, and stronger for bus than for rail. One more inch of daily rainfall will reduce typical system-wide daily ridership by between 16,283 and 88,335 for bus, and between 5,220 and 44,557 for rail depending on day type. Snow, similarly to rain, tends to reduce bus ridership. One more inch of daily snowfall will reduce daily bus ridership by between 9,650 and 188,080 depending on day type. This effect is less evident for rail. As with temperature, heavy rain or snow are either insignificant or have inconsistent signs. However, the explanation might be different from that for temperature. Rain or snow may reduce rail ridership but heavy rain or snow, particularly blizzards, may shift travelers from auto and bus to rail especially on weekdays, thus increasing rail ridership.

**Wind**

Wind speed is also significant in most cases, and has a consistent negative sign. One mile/hour increase of highest wind speed typically reduces system-wide daily ridership by between 723 and 2,747 for bus, and between 506 and 996 for rail. Strong wind (>=25 miles/hour) has a negative sign but is not significant in most cases, which means that very windy weather does not cause additional loss of transit ridership. As with other weather elements, wind affects bus more than rail, and weekends more than weekdays.

**Fog**

Fog shows consistent positive signs, and in several situations is significant at the 10 percent level. This might suggest that foggy weather tends to increase transit ridership and has a stronger effect on rail than bus. Fog is a contributing variable in all rail models
(two are significant), but only in two bus models (both insignificant). A foggy day will typically increase system-wide daily rail ridership between 8,140 and 10,411. The explanation is intuitive: fog increases the difficulty and risk of driving, and may shift travelers to transit, especially rail, which has its own right-of-way.

In most cases, the adjacent-day method yields higher R squares than the normal-extreme method, which is our expectation. Therefore, the adjacent-day method is chosen for the planning implication in Section 6. In general, continuous variables such as rainfall, snowfall, temperature, and wind speed are significant with expected signs. Extreme weather variables such as warm, cool, windy, heavy rain or snow are either insignificant or have inconsistent signs. This indicates that the extreme weather events either do not have additional impact on ridership, or the additional impact is in the opposite direction, which the OLS model is unable to detect. It is also likely that the extreme weather variables have small variation compared to the continuous variables in the dataset, which causes inconsistent estimation results. More observations and other statistical models such as nonparametric techniques are necessary to investigate the impact of extreme weather events (21).

The composite impact of weather conditions may well be as important as the impact of individual weather elements in the weather-ridership relationship. The adjusted R square is the goodness-of-fit of a model, indicating how much of the variation in the dependent variable data is explained by the independent variables. It is a reasonable indicator of the composite effect of weather since all independent variables are weather
variables. The higher the adjusted R square, the more variation of ridership is explained by weather.

Models for bus have higher adjusted R square values than models for rail across all day types. The average R squares from the two specifications are 0.32 and 0.24 for bus, but only 0.09 and 0.04 for rail. Based on the discussion in Section 2, possible explanations include:

(1) bus stops are typically more exposed to weather than rail stations, especially underground stations,

(2) a much larger share of rail trips are work trips, and

(3) rail usually has a higher service frequency than bus.

Both specifications show the consistent result that weekend trips are more likely to be affected by weather than weekday trips. The average R squares for both bus and rail from the two specifications are 0.29 and 0.19 for weekend, but only 0.04 for weekdays. This is our expectation since many more weekday riders are commuters, and weekdays have higher service frequencies than weekends. Work trips are less affected by weather because they are inelastic and have inflexible schedules. Within weekends, Saturday trips seem more likely to be affected by weather than Sunday, but the difference is less clear. The R squares from Saturday models are higher than those from the Sunday models for rail (both methods) and bus (adjacent-day method), but lower for bus using the normal-extreme method. One explanation is the potential interaction between the two days. For example, if Saturday has bad weather, travelers may postpone their trips to Sunday.
IMPLICATION OF THE WEATHER-RIDERSHIP RELATIONSHIP

The weather-transit ridership relationship revealed through this research has policy implications in transit operations and planning as we demonstrate here with an application to ridership trend analysis. In any transit authority, an important dimension of performance tracking is to analyze system-level ridership trends. This is usually done at a monthly level by comparing the monthly ridership with the same period of the previous year. Although transit authorities acknowledge that ridership fluctuates, misinterpretation of underlying ridership trends can occur due to various exogenous factors such as major events or unexpected weather conditions. Weather can be viewed as a random element but it can have a systematic impact on transit ridership. Therefore, an important question in the month-to-month comparison is what the true ridership trend is after controlling for weather impacts.

The weather models developed in this research can be used to correct for the weather impact in ridership trend analysis. Suppose that the actual monthly ridership in a year $t$ is $R_t$, which consists of a weather-affected portion $W_t$, and a portion determined by all other factors $E_t$, including economic cycle, population growth, service change, fare increase, etc. It is safe to assume that $W_t$ and $E_t$ are not correlated, so not including $E_t$ in the weather model does not affect the estimation of the weather impact. Therefore, the analysis is not to develop a general ridership model, but rather look at the accumulative effect of weather on ridership. The following equations illustrate the process, where $P_t$ is the ridership predicted by the weather model.

Actual Ridership Change:

$$\Delta R = R_t - R_{t-1} = (W_t + E_t) - (W_{t-1} + E_{t-1}) = \Delta W + \Delta E$$  \hspace{1cm} (2)
Predicted Ridership Change:
\[ \Delta P = P_t - P_{t-1} = W_t - W_{t-1} = \Delta W \]  \hspace{1cm} (3)

Ridership Change Controlling for Weather Effect:
\[ \Delta R - \Delta P = \Delta E \]  \hspace{1cm} (4)

Because the model is developed for daily ridership, we need to calculate the ridership for every day in a month and sum them for the monthly ridership comparison. There is a question on whether the sum overlooks the potential of ridership changes to cancel each other out because of the possible interaction between different days. We believe it is not a concern because the model is built based on the observed daily ridership that already includes the canceling-out effect. Another issue is that the number of days in the compared months should be adjusted because there might be different numbers of weekdays and weekends in the same month in different years. To account for this, the average weekday and weekend day ridership is estimated and summed across the normal mix of weekdays and weekend days in that month (See Table 3).

Another concern is whether service changes during this period of analysis is controlled for. We believe service change and fare increase may have influence, but not significantly. Bus service changes infrequently, maybe once or twice a year. This only affects one observation on the service-changing day in the adjacent-day method, or less than one percents of total observations used in model estimation. This might be a greater concern for the normal-extreme method because it affects all observations in the service-changing month, which represent about three percent of total observations.

We use the summer bus ridership based on the adjacent-day model for this application with the results summarized in Table 3. Clearly, the result shows a noticeable difference
in ridership trends if the weather influence is controlled for. For example, the July ridership decreased by about 1 million from 2002 to 2003, but after controlling for weather, there was a small underlying ridership increase of 93,000. In August from 2001 to 2002, monthly ridership increased by almost 900,000, but our calculation indicated an adjusted ridership decrease of 330,000 after controlling for the weather. For months with unusual weather, the weather model can help transit agencies identify the true ridership trends and thus avoid mis-interpretation of the data.

Application in transit service improvement is more complicated than in service monitoring case demonstrated above. The timetable cannot be changed frequently in anticipation of weather changes. Even if a ridership drop is predicted due to bad weather, it is still generally necessary to operate the planned service rather than reduce it. One possible application is at the route level to add extra service if good weather is predicted and a corresponding ridership jump is expected. For example, extra service might be necessary for the several bus routes that serve lakefront in Chicago when buses are normally crowded on hot summer Saturdays.

CONCLUSIONS

This paper explored the impact of weather on a particular transit performance measure: transit ridership, using the Chicago Transit Authority (CTA) as a case. The research confirms that temperature, rain, snow, and wind all affect transit ridership in the expected direction, although to different extents depending on the mode, season, and day of week. In general, good weather tends to increase ridership, while bad weather tends to reduce it. But it is still possible that extremely bad weather such as fog or a blizzard may increase
ridership because some drivers are likely to switch to transit in these situations. The analyses also show that bus ridership is usually more sensitive to weather than is rail, and weekend ridership is more sensitive to weather than is weekday ridership. This suggests that any policies targeting the weather-ridership relationship should be mode- and day-specific, otherwise policy intervention might be ineffective or lead to unexpected outcomes.

The paper illustrates the potential of the findings to improve monitoring of transit system ridership. By adjusting for weather in monthly ridership comparisons for the CTA bus system in summer 2001 to 2003, it reveals quite different ridership trends if the weather influence is controlled for. This helps transit authorities diagnose how the system is performing, and when problems may be developing.

In terms of further research, four issues arise. First is the theoretical framework of the impact of weather on ridership. As illustrated by this paper, the analysis structure (unit of analysis, aggregation method, definition of change etc.) can affect the final results. A good understanding of the nature of the weather-travel relationship is the foundation of a sound research design. In this paper, we established a simple framework by identifying four potential sources of weather impact: infrastructure, transit service, trip, and traveler characteristics, but a more comprehensive framework could be developed.

Second is the apparent complexity of the weather-ridership relationship. For example, some weather conditions may be positively correlated with each other such as snow and low temperature, while others may have synergistic effects such as wind and rain. Weather might have a lagged effect. For example a blizzard might affect the travel on the following days even if those days have good weather. Weather might be associated
with the preparation effect-- its impact depending on people’s preparation for the weather. More advanced statistical models might be necessary in future research rather than the simple OLS models developed in this paper.

Third is a similar analysis at the route level. This topic is interesting because individual services may respond to weather differently due to differences in population served, trip purposes, relationship with other modes, spatial attributes, topography of the route, etc. Preliminary analysis of this in the case of CTA indicates that bus routes parallel to rail lines are more sensitive to weather because of the substitution effect. Routes along the lake front in Chicago are more sensitive to weather on summer weekends because they are heavily used to access recreation opportunities.

Fourth, it would be helpful to apply a similar analysis to other cities to see if the weather factors are significantly different from those at work in Chicago. (End)

ACKNOWLEDGEMENTS
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Table 2 Weather Impact on CTA Rail Ridership
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<table>
<thead>
<tr>
<th>Bus System</th>
<th>Saturday</th>
<th></th>
<th>Sunday</th>
<th></th>
<th>Weekday</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjacent Day</td>
<td>Normal-Extreme</td>
<td>Adjacent Day</td>
<td>Normal-Extreme</td>
<td>Adjacent Day</td>
<td>Normal-Extreme</td>
</tr>
<tr>
<td>Intercept</td>
<td>--</td>
<td>15271 (1.4)</td>
<td>--</td>
<td>10077 (1.5)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Rainfall</td>
<td>-40477 (-6.0)</td>
<td>-88335 (-2.6)</td>
<td>-11930 (-1.4)</td>
<td>--</td>
<td>-16283 (-1.9)</td>
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<td>Heavy Rainfall</td>
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<td>45065 (1.3)</td>
<td>--</td>
<td>33617 (1.8)</td>
<td>-18969 (-1.0)</td>
<td>--</td>
</tr>
<tr>
<td>Snowfall</td>
<td>--</td>
<td>-68896 (-1.8)</td>
<td>-10287 (-2.8)</td>
<td>-9650 (-2.2)</td>
<td>-11202 (-2.0)</td>
<td>-188080 (-4.0)</td>
</tr>
<tr>
<td>Big Snow</td>
<td>--</td>
<td>61441 (1.6)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>-2747 (-4.9)</td>
<td>-1204 (-2.0)</td>
<td>-1148 (-3.1)</td>
<td>-786 (-2.2)</td>
<td>-1229 (-2.4)</td>
<td>-723 (-3.8)</td>
</tr>
<tr>
<td>Strong Wind (&gt;25miles/hour)</td>
<td>-17921 (-1.3)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Fog</td>
<td>--</td>
<td>11286 (1.6)</td>
<td>--</td>
<td>17784 (1.2)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Departure of Temperature</td>
<td>962 (3.4)</td>
<td>1087 (2.4)</td>
<td>--</td>
<td>652 (2.5)</td>
<td>692 (2.4)</td>
<td>370 (1.1)</td>
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<tr>
<td>Cold</td>
<td>--</td>
<td>--</td>
<td>1299 (4.4)</td>
<td>1214 (2.0)</td>
<td>--</td>
<td>1114 (1.3)</td>
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<tr>
<td>Hot</td>
<td>--</td>
<td>-862 (-1.1)</td>
<td>1025 (3.7)</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Spring</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Summer</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Fall</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Winter</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>7151 (1.5)</td>
<td>17725 (2.2)</td>
<td>19293 (3.0)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.536</td>
<td>0.319</td>
<td>0.363</td>
<td>0.338</td>
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<td>0.055</td>
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<td># of Observations</td>
<td>110</td>
<td>138</td>
<td>123</td>
<td>148</td>
<td>567</td>
<td>709</td>
</tr>
</tbody>
</table>

Note: Numbers in parentheses are t statistics; put in bold indicate a significance level of at least 10 percent

Table 1 Weather Impact on CTA Bus Ridership
<table>
<thead>
<tr>
<th>Rail System (03/1998 ~ 05/2004)</th>
<th>Saturday</th>
<th>Sunday</th>
<th>Weekday</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjacent Day</td>
<td>Normal- Extreme</td>
<td>Adjacent Day</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3589 (-1.4)</td>
<td>--</td>
<td>-2376 (-1.3)</td>
</tr>
<tr>
<td>Rainfall</td>
<td>-12630 (-4.0)</td>
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<td>--</td>
</tr>
<tr>
<td>Heavy Rainfall</td>
<td>--</td>
<td>-9919 (-2.1)</td>
<td>--</td>
</tr>
<tr>
<td>Snowfall</td>
<td>--</td>
<td>--</td>
<td>-3481 (-1.5)</td>
</tr>
<tr>
<td>Big Snow</td>
<td>--</td>
<td>-5057 (-3.6)</td>
<td>--</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>-933 (-3.2)</td>
<td>-93 (-1.0)</td>
<td>-506 (-2.7)</td>
</tr>
<tr>
<td>Strong Wind (&gt;25miles/hour)</td>
<td>-9739 (-1.2)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Fog</td>
<td>7238 (1.0)</td>
<td>14228 (1.4)</td>
<td>8140 (1.7)</td>
</tr>
<tr>
<td>Departure of Temperature</td>
<td>663 (3.4)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Cold</td>
<td>-586 (-1.7)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Hot</td>
<td>--</td>
<td>--</td>
<td>490 (2.8)</td>
</tr>
<tr>
<td>Spring</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Summer</td>
<td>6934 (1.7)</td>
<td>--</td>
<td>5626 (1.7)</td>
</tr>
<tr>
<td>Fall</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Winter</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.169</td>
<td>0.079</td>
<td>0.081</td>
</tr>
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<td># of Observations</td>
<td>207</td>
<td>257</td>
<td>208</td>
</tr>
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</table>

Note: Numbers in parentheses are t statistics; put in bold indicate a significance level of at least 10 percent

Table 2 Weather Impact on CTA Rail Ridership
<table>
<thead>
<tr>
<th>Month</th>
<th>Actual Monthly Ridership</th>
<th>Day Type Mix Adjusted Monthly Ridership $R_i$</th>
<th>Weather Controlled Monthly Ridership $P_i$</th>
<th>Annual Ridership Change $\Delta R = (\Delta W + \Delta E)$</th>
<th>Weather Controlled Ridership Change $\Delta P = \Delta W$</th>
<th>Ridership Changes Controlling for Weather $\Delta R - \Delta P = \Delta E$</th>
<th>Number of Days Included</th>
</tr>
</thead>
<tbody>
<tr>
<td>8/03</td>
<td>23,476,981</td>
<td>23,873,017</td>
<td>23,752,527</td>
<td>-1,415,226 (-5.6%)</td>
<td>-1,302,801</td>
<td>-112,426</td>
<td>Saturdays: 5, Sundays: 4, Weekdays: 22</td>
</tr>
<tr>
<td>8/02</td>
<td>25,288,244</td>
<td>25,288,244</td>
<td>25,055,328</td>
<td>882,370 (3.6%)</td>
<td>1,227,038</td>
<td>-344,668</td>
<td></td>
</tr>
<tr>
<td>8/01</td>
<td>24,647,186</td>
<td>24,405,874</td>
<td>23,828,290</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7/03</td>
<td>24,125,081</td>
<td>24,125,081</td>
<td>23,904,576</td>
<td>-1,062,926 (-4.2%)</td>
<td>-1,155,638</td>
<td>92,712</td>
<td>Saturdays: 4, Sundays: 5, Weekdays: 22</td>
</tr>
<tr>
<td>7/02</td>
<td>25,188,007</td>
<td>25,188,007</td>
<td>25,060,214</td>
<td>1,591,85 (0.6%)</td>
<td>207,763</td>
<td>-48,577</td>
<td></td>
</tr>
<tr>
<td>7/01</td>
<td>24,537,095</td>
<td>25,028,822</td>
<td>24,852,451</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6/02</td>
<td>24,761,343</td>
<td>25,281,261</td>
<td>25,126,617</td>
<td>286,786 (1.1%)</td>
<td>244,906</td>
<td>41,880</td>
<td></td>
</tr>
<tr>
<td>6/01</td>
<td>24,994,475</td>
<td>24,994,475</td>
<td>24,881,711</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3  Controlling for Weather Impact in Analyzing Bus Ridership Trends