THE EFFECT OF WEATHER ON TRAVEL MODES: A CHICAGO CASE STUDY

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BY

SANGWOO PARK

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ABSTRACT

The last decade has been marked with the growth of new travel options such as bikeshare, e-scooters, and rideshare in major American cities. Given that some of these emerging transport modes are more exposed to the elements than other traditional modes of travel, it is important to understand how the current transportation landscape in urban areas is affected by adverse weather. This is of particular interest due to the possibility that climate change in the future could exacerbate any existing vulnerabilities that the urban transport sector has with respect to unfavorable weather conditions. Using daily-level weather data and trips data from various transport modes in Chicago, this study examines the effect of weather on the composition of bikeshare, public transit, and rideshare use, as well as on certain average trip characteristics. Specifically, I consider the effect of weather on average ridesharing trip distances, average rideshare trip speeds, and average bikeshare trip times.

This study reveals that the hottest days are linked to lower proportions of rail transit trips and higher proportional use of rideshare. The wettest days in terms of precipitation coincide with lower bikeshare trip proportions, higher proportional use of rideshare, lower average rideshare trip distances, and lower rideshare speeds. The coldest daily temperatures are associated with reduced proportions of bikeshare trips and average bikeshare trip times. Furthermore, the windiest days correspond to shorter and slower rideshare trips. While this study does not make any direct projections of how urban mobility will be impacted by climate change, my findings give insights into the sensitivities that travellers in Chicago have with respect to specific weather events. By considering a number of metrics that have not yet been widely considered in the literature, this study aims to give a more comprehensive picture of the ways in which weather can affect urban mobility.

BIOGRAPHICAL SKETCH

Sangwoo Park graduated from Brookfield Academy in Brookfield, Wisconsin in 2014. He completed a BA in Economics in 2018 at Northwestern University. After undergrad, he enrolled in the MS program in the Dyson School of Applied Economics and Management at Cornell University.

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Contents

1 Introduction

In recent years, innovative transportation modes such as bikeshare and rideshare have become widely embedded in major American cities. As of April 2016, there were 3,378 bikeshare stations in the United States spread across 104 cities (Firestine, 2016, p.1). Moreover, a 2018 Pew Research Center survey found that "36% of U.S. adults say they have ever used a ride-hailing service such as Uber or Lyft" (Jiang, 2019). Given the relatively recent emergence of these modes, one might consider the potential implications that these newer modes might have on mobility in urban areas.

Particularly in the face of climate change, local stakeholders would benefit in having insight into potential strains on parts of the transportation network that may arise if certain modes of travel are more sensitive to extreme weather than others. The primary question of this study focuses on the effect of weather on the relative utilization of different modes that have varying levels of exposure to the outdoors. In a similar vein, there is likely a benefit to understanding some of the potential costs at the trip-level as a result of extreme weather. For this reason, I also examine the effect of weather conditions on certain average trip characteristics, specifically average rideshare trip distances, average rideshare trip speeds, and average bikeshare trip times.

I rely on the likely exogeneity of weather events in order to identify the causal effects of weather conditions on these various transportation metrics of interest. This empirical strategy borrows from the existing "approach" that "use[s] longitudinal data to investigate the effects of weather shocks [italics in original removed]" (Dell et al., 2014, p.744). Although my study does not utilize panel data, I similarly rely on the assumption "that temperature, precipitation, windstorms, and other weather events vary plausibly randomly over time" (Dell et al., 2014, p.744). To further strengthen the case that my estimates represent the causal effects of weather, I aggregate data at the daily-level as opposed to longer units of time, such as "years,...months," or "seasons" (Dell et al., 2014, p.744).

Among the key findings, I conclude that the hottest days induce lower proportions of rail transit use and higher proportions of rideshare use. The highest precipitation levels are linked to lower proportional use of bikeshare and higher proportional use of rideshare. The coldest days correspond to reduced proportions of bikeshare trips and lower average bikeshare trip times. Lastly, both the highest levels of precipitation and wind speeds bring about reductions in average rideshare trip distances and average rideshare speeds.

This study undertakes a methodological approach that builds on the work done in two related areas of existing research. One of these research areas is the extensive literature on the impact of weather on the utilization of individual transport modes. For instance, studies that examine how weather affects public transit ridership include Singhal et al. (2014), Ngo (2019), Miao et al. (2019), and Wu and Liao (2020). Moreover, there are a number of studies (e.g., Gebhart and Noland. (2014), An et al. (2019), Kutela and Teng (2019), and Chan and Wichman (2020)) that consider the effect of weather on the quantity of bikeshare trips. Rather than focus on a single mode of transport, I take a broader view and explore the interaction of several modes in response to adverse weather.

By taking this approach, I draw influence from existing research (e.g., Liu et al. (2015), Hyland et al. (2018), and Wu and Liao (2020)) that examines the effect of weather on transport mode choice. These studies usually apply discrete choice models on survey data in order to determine how weather conditions affect the likelihood of taking certain travel modes versus others. In contrast, I focus on the proportion of usage of various modes to elicit information on residents' preferences during certain weather conditions. This overcomes some possible limitations that may be encountered by relying on data from survey responses. For instance, Hyland et al. (2018) ask survey participants to choose travel modes under hypothetical "weather scenarios" (p.47). Responses offered in this type of setting may not accurately reflect participants' behavior under real world circumstances. In contrast, I use travel data that is derived from information on observed trips, not hypothetical ones.

I also contribute to the scarce existing literature on the effect of weather on ridesharing activity. To the best of my knowledge, Ghaffar et al. (2020) and Shokoohyar et al. (2020)

are the only studies that address this research question. Ghaffar et al. (2020) use daily data at the census tract-level from the same data source as my study, and they include both daily precipitation and daily max temperature as regressors in models that either have trips “originating” or “terminating” from Chicago census tracts as the dependent variable (pp.14-5). Using data from Philadelphia in June 2018, Shokoohyar et al. (2020) estimate the effect of “extreme weather” on “pick-up” and “in vehicle” times for rideshare, as well as the effect on rideshare trip fares (p.6).

Unlike Ghaffar et al. (2020), I consider the effect of weather on average trip characteristics for rideshare. This allows for a more complete understanding of the various sensitivities that urban travellers display in response to weather, beyond just changes to the quantity of rideshare trips. In contrast to Shokoohyar et al. (2020), I apply my analyses on data that span more than a single month. This allows for month-of-year controls to be included in my models, and also makes it possible to study the effects of weather occurrences that are common in different parts of the year. I also examine the impact of weather on average trip characteristics that are in some cases similar, but not identical, to those considered in Shokoohyar et al. (2020).

2 Data

2.1 Travel data

I consider four transportation modes in the City of Chicago: bikeshare, rail transit, bus transit, and rideshare. Data for bikeshare, rail transit, and rideshare are used in my main analysis, while I use the bus transit data for a supplementary model I include in the appendix. Bikeshare in the context of this study refers to the use of shared bicycles that are available at docking stations for a payment or a subscription and that must be returned to a station by the cyclist after use. Ridesharing refers to services that enable travellers to hail and set up trips with company-affiliated vehicles using mobile devices.

Chicago Divvy currently operates 712 bikeshare stations that are "[i]n service" in the City of Chicago, as well as in some of the surrounding suburbs ("Divvy Bicycle Stations – In Service," 2021). Figure 1 shows the location of bikeshare stations from which trips originated during the time period of this study. The stations shown in Figure 1 are separated by an average distance of approximately 6.2 miles.

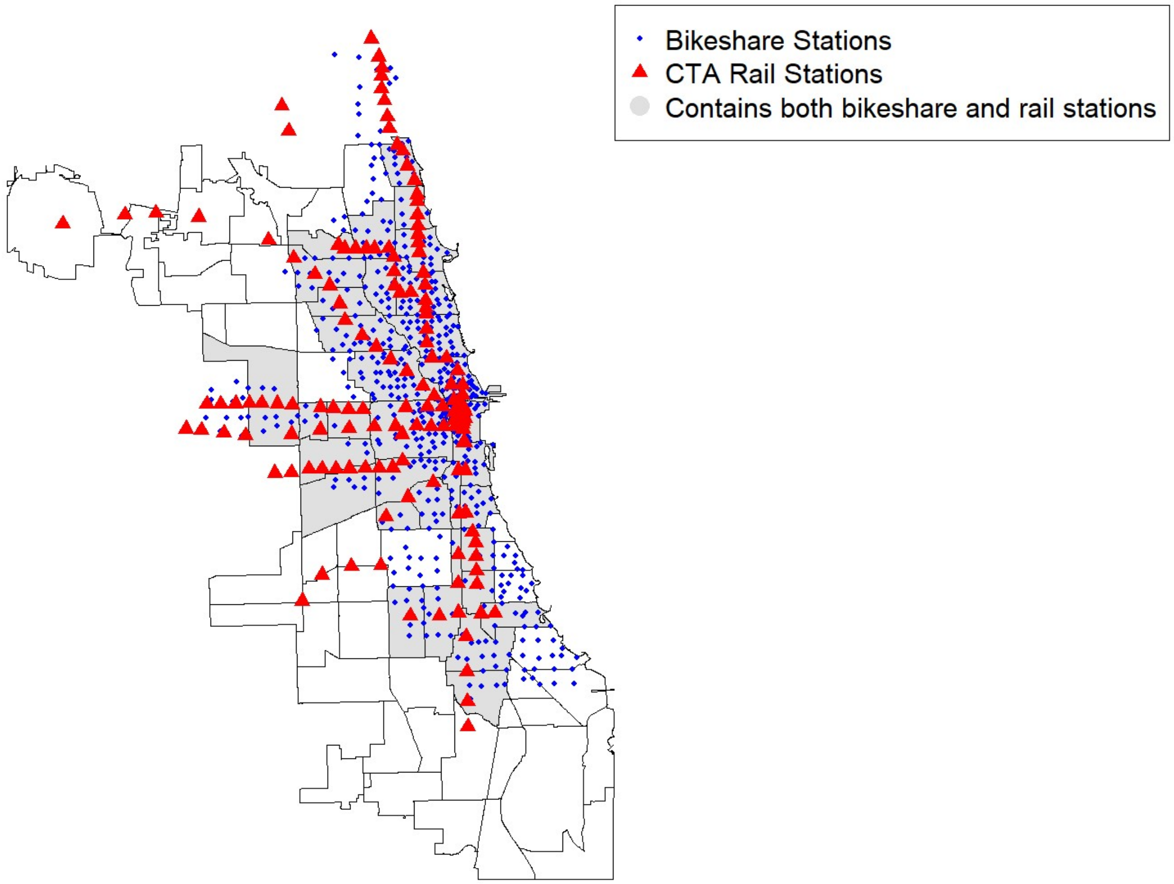

Figure 1: Map of Chicago Community Areas

The bikeshare data made available by Chicago Divvy is at the trip level and includes information such as the start and end time, the start and end station, and the duration in seconds of each trip. Data on the latitude and longitude coordinates of Divvy bikeshare stations comes from the Chicago Divvy website and the Chicago Data Portal. Each bikeshare trip is matched to the start day of the trip. Therefore, daily bikeshare trips in this study refer to the number of initiated trips per day.

The Chicago Transit Authority (CTA) provides public transit services to the City of Chicago as well as to 35 of its suburbs ("Facts at a Glance", 2017, paras. 1-3). As of fall 2017, CTA rail transit operates 145 stations, and the CTA bus network is comprised of 129 routes ("Facts at a Glance", 2017, paras. 2-3). Figure 1 displays the location of an updated list of CTA rail stations that correspond with this study's time frame. The rail stations displayed in Figure 1 are separated by an average distance of approximately 7 miles. The Chicago Data Portal provides daily-level ridership data for CTA rail by station and daily-level ridership data on CTA buses by route. The latitude and longitude coordinates of each CTA rail station are also available through the Chicago Data Portal. According to the Chicago Transit Authority, "[r]idership is primarily counted as boardings, that is, customers boarding a transit vehicle" ("Ridership Readme", 2011). Therefore, daily-level bus ridership in my analysis refers to the number of bus "boardings" per day, in accordance with the CTA definition above. However, the dataset I use for rail transit ridership is "CTA – Ridership – 'L' Station Entries – Daily Totals" from the Chicago Data Portal (2021). The Chicago Transit Authority clarifies that "[o]n the rail system, a customer is counted as an 'entry' each time he or she passes through a turnstile to enter a station" ("Ridership Readme", 2011). They further explain that "[c]ustomers are not counted as 'entries' when they make a 'cross-platform' transfer from one rail line to another" ("Ridership Readme", 2011). Therefore, daily-level rail transit ridership or the number of rail transit trips per day in my analysis refers specifically to the number of rail transit "entries" per day as described above.

Data on rideshare trips (or "Transportation Network Provider" trips) is available through the Chicago Data Portal. This data includes information on the start and end time of each reported trip, the time elapsed during each trip, and the distance covered by each trip. For most reported trips, the data also includes the pickup community area for the given trip. A community area is a Chicago-specific geographical unit, and the city is divided into 77 community areas. Figure 1 shows the borders of these 77 community areas delineated across the city. As with the bikeshare data, each rideshare trip is matched to the start day of the trip; therefore, the daily number of rideshare trips in this study refers to the number of initiated rideshare trips for a given day.

I remove certain types of trips from the raw data for bikeshare and rideshare before I perform my main analysis. In the case of bikeshare, the data used to produce my main results include all trips lasting greater than or equal to 5 minutes and less than 5 hours. This removes trips that are likely to be recreational or exercise trips. I also drop all rideshare trips that are greater than or equal to 40 miles in duration to perform my main analysis. This removes extremely long distance trips that are plausibly not substitutable with trips using the other modes in my study. The time-series plots that follow use the same data on which I perform my main regression analyses.

Figure 2 displays plots of daily trip counts for each mode considered in my analysis. The daily number of bikeshare trips shows clear seasonality, with a greater number of trips on average occuring in the warmer months. The mean of bikeshare trips per day is roughly 8,701, and the standard deviation of daily bikeshare trips is approximately 5,595. A clear seasonal pattern does not exist with the daily number of bus or rail transit trips over time. However, there are clear day-of-week differences in daily ridership over time. Namely, daily ridership for public transit generally declines during weekends as compared to weekdays.

There are roughly 498,927 rides per day on average taken on rail transit during the time frame of this study, and there is an average of roughly 652,298 rides taken daily on bus transit. The standard deviations of daily ridership on rail and bus transit are approximately 154,325 and 189,893, respectively. A time-series plot of the number of rideshare trips per day, as shown in the bottom panel of Figure 2, likewise does not indicate a seasonal pattern. Daily rideshare trips generally peak on Fridays and Saturdays. There are approximately 302,502 rideshare trips on average taken per day, and the standard deviation of the daily number of rideshare trips is roughly 55,015.

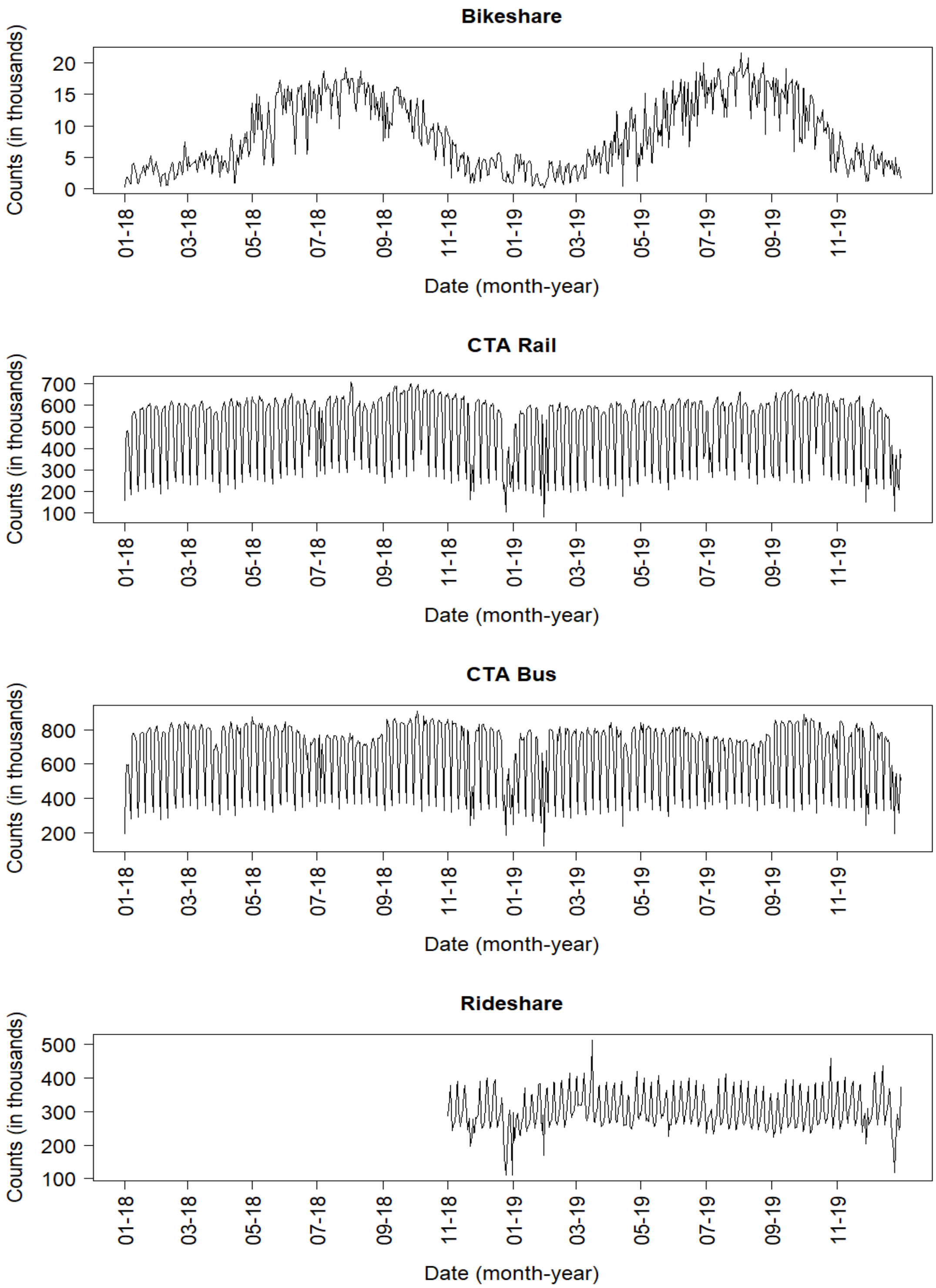

Figure 2: Daily Trip Counts

Figure 3 displays time-series plots of average bikeshare trip times, average rideshare trip distances, and average rideshare speeds. Average bikeshare trip times per day, as plotted in the top panel of Figure 3, indicate differences across seasons, with trip times being longer typically in the spring and summer. Average trip times for bikeshare also generally increase on weekends as compared to weekdays. Both average trip distances and average speeds for rideshare modestly trend upward over time. These measures for rideshare also show upticks on certain days (e.g., Christmas Day for both measures and Thanksgiving Day for average trip speeds).

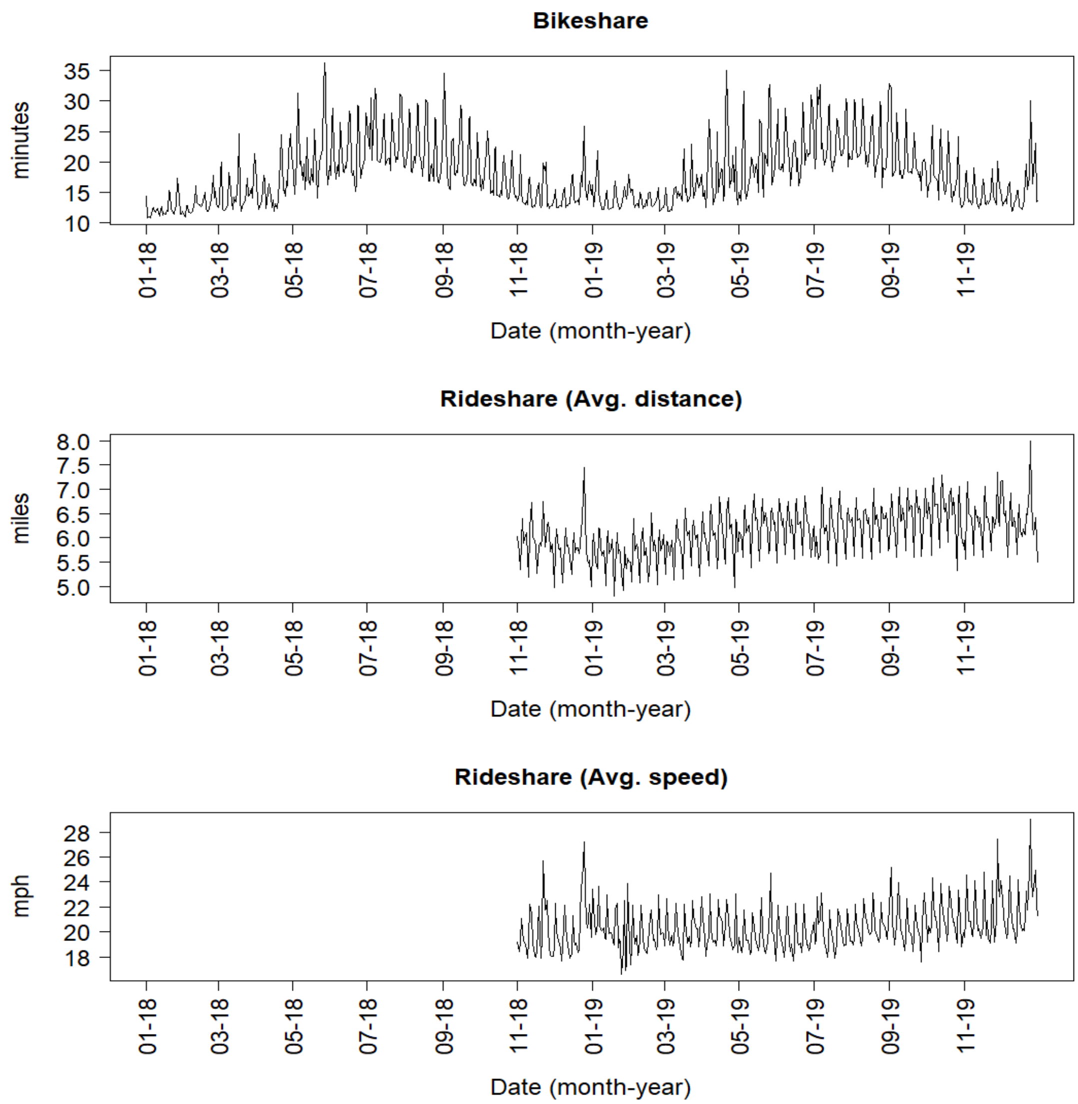

Figure 3: Daily Average Durations and Rideshare Speeds

I should note that the daily average speeds for rideshare that are plotted in the bottom panel of Figure 3 are computed after first removing trips that have missing trip times or trip distances in the raw data. This is necessary because there is one day (June 6, 2019) for which roughly 67.1% of all trips covering less than 40 miles have missing trip times. However, all other days have percentages of missing trip times or missing trip distances that are less than 1.2% of the total number of trips on any given day that are less than 40 miles in duration.

The models with daily trip proportions as the dependent variable use data exclusively from community areas in Chicago that contain both CTA rail stations and bikeshare stations from which trips originated during the time period of this study. Community areas that match this description are shown in Figure 1. For the models with daily trip proportions as the dependent variable, the trip proportion for each mode denotes the share of trips that are taken by the mode in question divided by the total number of trips taken by bikeshare, CTA rail transit, and rideshare in the shaded community areas in Figure 1. For the models with average trip duration as the dependent variable, average trip duration is computed as the total of the durations (measured in minutes or miles) of all relevant trips divided by the total number of trips. Average trip speed for rideshare is calculated as the total distance divided by the total time duration for all trips taken on a given day. The data for all modes except for rideshare span January 1, 2018 to December 31, 2019. The data for rideshare span a subset of this time frame: from November 1, 2018 to December 31, 2019.

2.2 Weather data

Daily weather data for Chicago comes from NOAA's Local Climatological Data (LCD) database. The weather variables included in this study are average wind speed, average dry bulb temperature, precipitation, and snowfall. Figure 4 shows histograms of each weather variable from January 1, 2018 to December 31, 2019. Daily average temperatures, as shown in the top-left panel of Figure 4, appear to follow a bimodal distribution with a long tail of days with extremely low temperatures. Average wind speeds display a unimodal distribution with a tail of days with high wind speeds. Both daily precipitation and snowfall follow heavily right-skewed distributions, with most days having little to none of either.

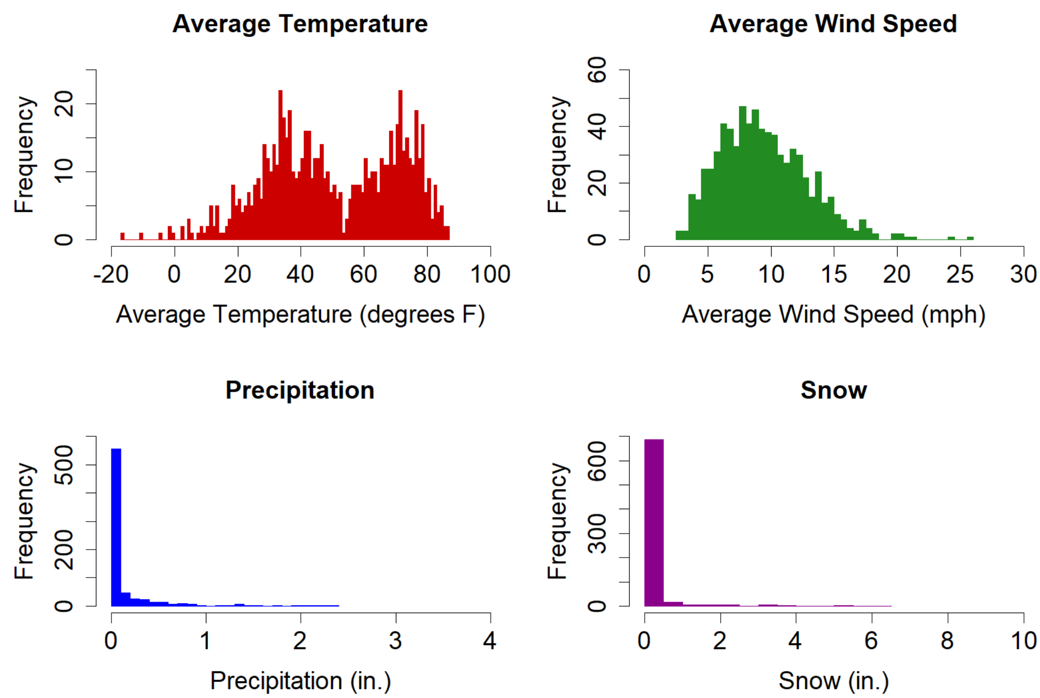

Figure 4: Histograms of weather variables

I use LCD weather data specifically from the Chicago O'Hare weather station. I keep only the rows in this data that are categorized as "SOD" ("Summary of day report from U.S. ASOS or AWOS station"). Figure 5 shows time-series plots for each of these weather variables from January 2018 to December 2019. "Trace" amounts of precipitation and snowfall are coded as 0 inches. "Trace" levels of precipitation occur for 102 days, and "trace" levels of snowfall occur for 53 days in the time period between January 1, 2018 and December 31, 2019 (a total of 730 days). The time-series of average wind speeds, as shown in the top panel of Figure 5, do not indicate an obvious pattern or trend. The mean of average wind speeds is approximately 9.5 mph. Roughly 7.5% of days have an average wind speed less than 5 mph, and roughly 6% of days have an average wind speed greater than 15 mph. Moreover, nearly 60% of days have zero or only "trace" levels of precipitation. For days with more than zero inches or "trace" levels of rainfall, the mean level of precipitation per day is about 0.33

inches.

Average daily temperatures, as displayed in the third panel of Figure 5, show a clear seasonality, with temperatures generally peaking from late spring to early fall. Average daily temperatures have a mean of roughly 30°F during the winter months (i.e., December to March), and have a mean of roughly 73°F in the summer months (i.e., June to September). Furthermore, the bottom panel of Figure 5 shows that snowfall events are generally concentrated during the winter months, with snowfall, sometimes heavy, also occuring in the spring and fall. From November to April, about 9.5% of days have greater than zero inches or "trace" levels of snowfall, and this subset of days during these months have an average snowfall of roughly 1.23 inches.

Furthermore, data that span 1963-2020 from the Chicago O'Hare LCD station is used in order to construct Figure 6, which is presented in the Discussion section. The counts from 2004-2020 for these plots were computed from the "Summary of Day" report types in the LCD. Because the fields for the "Summary of Day" report types are either non-existent or have substantial numbers of missing values from 1963 to 2003, the weather data from these years had to first be aggregated from the hourly level to the daily level. For the sake of consistency, hourly observations not recorded at the "00" minute mark for each hour are removed. I should note that any "suspect" values are retained and "trace" values of precipitation are set to zero inches. Moreover, due to the presence of many missing values, data for years 1965-1967 and 1969-1972 are omitted. Among the hourly observations from 1963-2003 that are kept in the data, 400 precipitation observations are missing out of 298,115 total observations.

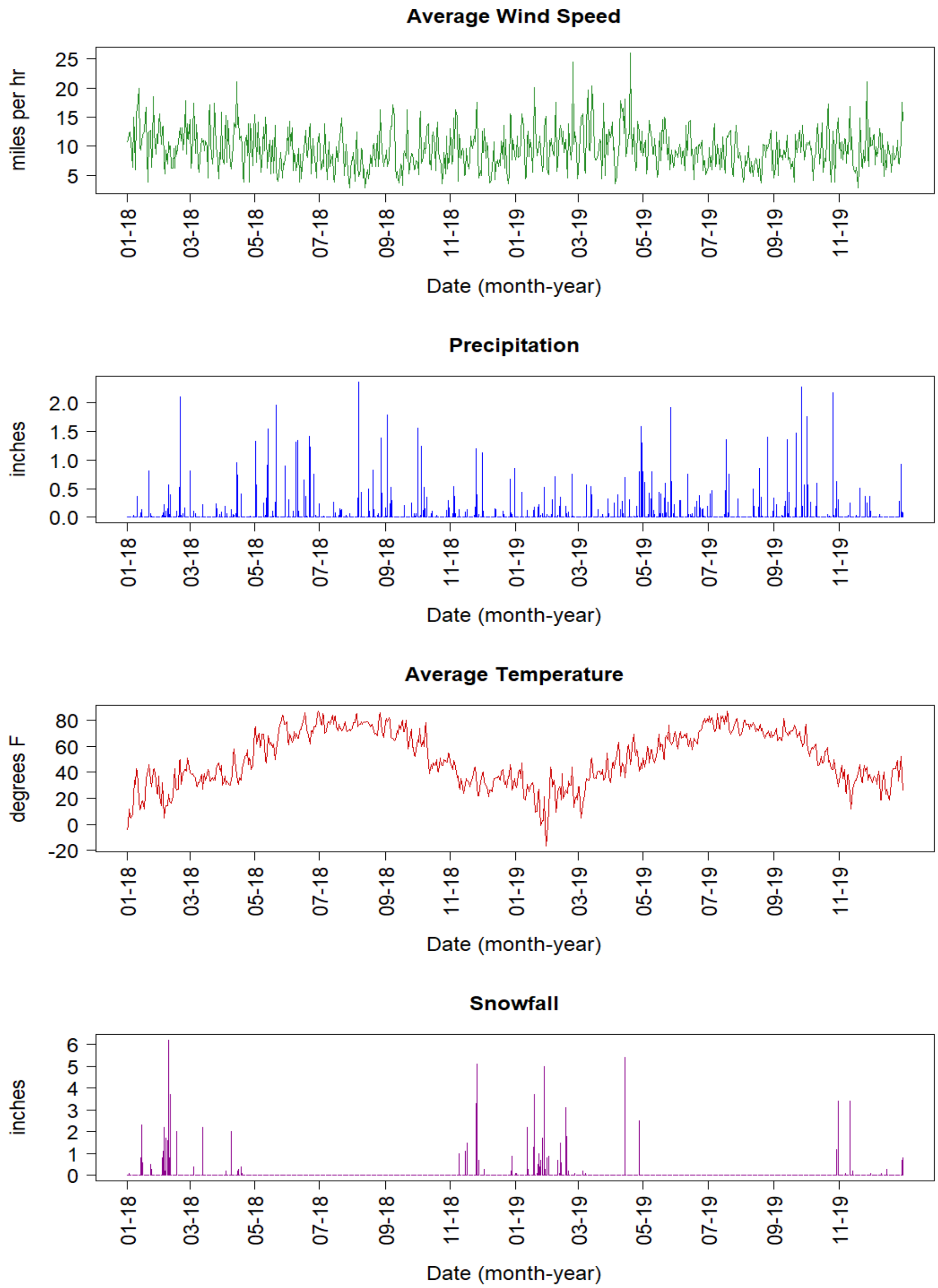

Figure 5: Weather Time-Series Plots

3 Conceptual Framework

I assume that travel composition is affected primarily through two channels. Firstly, travel composition is likely affected by individual decisions to shift modes based in part on the state of the weather. In particular, the occurrence of adverse weather would presumably make travellers with access to multiple transport options more inclined to shift away from modes with greater exposure to the outdoors (e.g., from bikeshare to public transit or from bikeshare to rideshare). The percentage of aggregate trips taken on a given mode is likely also affected by binary decisions to take or not take trips meant for specific modes. It is plausible, particularly for more discretionary trips, that travellers would choose to defer or cancel trips intended for modes with greater outdoor exposure (e.g., bicycling).

Furthermore, I assume that average bikeshare times and rideshare distances are affected by the decision of travellers to abstain from trips with greater distances or to reserve trips of this kind for other modes. These conjectures are informed by the potential mechanisms offered by Gebhart and Noland (2014), who find evidence to "suggest that...people use bikeshare for shorter trips and may either take another mode or forego longer trips" under specific weather events (p.1222). As an example, regular users of bikeshare and rideshare, when faced with severe weather conditions, might be more likely to switch to personal vehicles for long distance trips. In addition, it could be possible in some cases that travellers do not shift modes in response to adverse weather, but instead choose to shorten their trips. For instance, it is imaginable that bikeshare users would respond to colder temperatures or torrential rain by reducing the number of stops on their trips or ending their trips early.

Lastly, I assume that the effects of weather on rideshare speeds are largely derivative of the effects of weather on overall road speeds. "During inclement weather–particularly snowy and icy conditions–drivers increase headway (or spacing between vehicles), decrease acceleration rates, and reduce speeds" (Goodwin, 2002, Weather Effects section). Furthermore, in a 2013 empirical study of Greater London, Tsapakis et al. find that "heavy rain" and "heavy snow" correspond to respective increases of "4.0-6.0%" and "7.4% to 11.4%" in total travel time.

They find that “light” to “moderate..rain,” as well as “[l]ight snow,” also correspond to “total travel time...increases” (Tsapakis et al., 2013, p.204). Beyond the factors that affect overall traffic speeds, it is possible there are weather impacts more specific to ridehailing that could affect average rideshare speeds. For example, severe weather could make navigation more difficult for rideshare drivers, particularly when operating in less familiar neighborhoods.

4 Empirical Model

I perform three sets of models in this study. The first set of models takes the form:

$$Proportion_t = \alpha + \boldsymbol{\beta} \boldsymbol{w}_t + \gamma t + \boldsymbol{\tau} \boldsymbol{dow_t} + \boldsymbol{\eta} \boldsymbol{month_t} + \epsilon_t$$

where t indexes days. I include vectors ($\boldsymbol{dow_t}$, $\boldsymbol{month_t}$) containing binary variables for days of the week and months of the year in order to account for possible day-of-week or month-of-year differences in the mobility characteristics of interest. In similar fashion to Ngo (2019) and Chan and Wichman (2020), I include weather variables on the right-hand side as discrete bins. The vector $\boldsymbol{w}_t$ contains these binned weather regressors. In order to account for evidence of non-stationarity in some of the variables, I estimate the corresponding equation below:

$$\Delta Proportion_t = \gamma + \boldsymbol{\beta} \Delta \boldsymbol{w}_t + \boldsymbol{\tau} \Delta \boldsymbol{dow_t} + \boldsymbol{\eta} \Delta \boldsymbol{month_t} + \xi_t$$

where $\Delta \boldsymbol{w}_t$ denotes the first-differences of the discrete bins of the weather variables.

In addition, I also study the effects of the weather on average trip durations by considering the following empirical model:

$$Duration_t = \alpha + \boldsymbol{\beta} \boldsymbol{w}_t + \gamma t + \boldsymbol{\tau} \boldsymbol{dow_t} + \boldsymbol{\eta} \boldsymbol{month_t} + \epsilon_t$$

where $Duration_t$ denotes either average bikeshare trip times or average rideshare trip distances. In a manner comparable to the preceding model, I retrieve the coefficient estimates contained in the vector $\boldsymbol{\beta}$ by estimating the corresponding equation:

$$\Delta Duration_t = \gamma + \boldsymbol{\beta}\Delta \boldsymbol{w}_t + \boldsymbol{\tau}\Delta \boldsymbol{dow_t} + \boldsymbol{\eta}\Delta \boldsymbol{month_t} + \xi_t$$

Lastly, I also examine the effect of weather conditions on average rideshare trip speeds as represented in the following empirical model:

$$Avg\ speed_t = \alpha + \boldsymbol{\beta} \boldsymbol{w}_t + \gamma t + \boldsymbol{\tau} \boldsymbol{dow_t} + \boldsymbol{\eta} \boldsymbol{month_t} + \epsilon_t$$

Analogous to the procedure followed in the first two sets of models, I estimate the corresponding equation below in order to obtain the coefficient estimates in the vector $\boldsymbol{\beta}$:

$$\Delta Avg\ speed_t = \gamma + \boldsymbol{\beta}\Delta \boldsymbol{w}_t + \boldsymbol{\tau}\Delta \boldsymbol{dow_t} + \boldsymbol{\eta}\Delta \boldsymbol{month_t} + \xi_t$$

I estimate the preferred specification of this model by first removing trips with missing trip times or missing trip distances from the data.

It is possible that my data on weather and travel activity are serially correlated. For instance, certain weather events (rainfall or heavy snow) could have a tendency of occuring in clusters across multiple days. In order to address this potential serial correlation problem, my regression results include standard errors as given in Newey and West (1987). The lag cutoff for these standard errors is equal to the number of days raised to the 0.25 power. This choice is informed by Greene (2012), which states that "[c]urrent practice specifies" a cutoff that is approximately equal to "$T^{\frac{1}{4}}$", where T in the case of this study can be considered as the number of days in each dataset (p.920).

5 Results

Table 1 gives the results for the models with daily trip proportions as the dependent variable. The columns in Table 1 display the specifications for bikeshare, rail transit, and rideshare, respectively.

For all regression results that follow, 'low precipitation' refers to precipitation levels in the range of (0,0.01] inches, 'medium precipitation' refers to levels in the range of (0.01,0.07] inches, 'high precipitation' refers to levels in the range of (0.07,0.31] inches, and 'very high precipitation' refers to levels greater than 0.31 inches. Additionally, 'medium average wind speeds' refer to speeds in the range of (8,11] mph and 'high average wind speeds' refer to speeds greater than 11 mph. The reference level in the case of precipitation is zero precipitation, and the reference level for average wind speed is 'low average wind speed,' which is defined as speeds less than or equal to 8 mph. The bins for average temperature and average wind speed are based roughly on quantiles. Most of the bins for positive levels of precipitation are also based to some extent on a quantile taken of precipitation amounts greater than zero inches.

There is evidence that the hottest days correspond with lower proportions of rail transit use and higher proportional use of rideshare. Compared to temperatures at the reference level, days with average temperatures greater than 76°F are associated with an approximate 1% decrease and an approximate 1% increase in proportions of trips taken on rail transit and rideshare, respectively. Furthermore, the highest levels of rainfall induce lower proportional use of bikeshare and higher proportions of rideshare use. Relative to days with zero precipitation, days with very high precipitation levels are associated with an approximately 0.5% reduction in bikeshare proportions and a roughly 1% increase in the proportion of trips taken on rideshare.

As expected, bikeshare trip proportions are more sensitive to weather than trip proportions for rail transit or rideshare. Relative to temperatures between 70°F and 76°F, temperatures colder than 70°F are associated with negative and statistically significant reductions in bikeshare proportions. In addition, days with positive levels of precipitation coincide with lower proportional use of bikeshare, as compared to days with zero precipitation. Notably, I do not find evidence that higher average wind speeds or non-zero levels in snowfall have statistically significant effects on bikeshare, rail transit, or rideshare proportions.

Table 1: Trip Proportions models

Variable	Bikeshare	CTA rail	Rideshare
$Avg. Temp. \leq 27$	-0.00992***	-0.01904	0.02896
	[0.00166]	[0.01797]	[0.01813]
$27 < Avg. Temp. \leq 34$	-0.00899***	-0.01542	0.02441
	[0.00163]	[0.0172]	[0.01731]
$34 < Avg. Temp. \leq 41$	-0.00824***	-0.01369	0.02193
	[0.0016]	[0.01508]	[0.01531]
$41 < Avg. Temp. \leq 49$	-0.00592***	0.00417	0.00175
	[0.00155]	[0.01367]	[0.01374]
$49 < Avg. Temp. \leq 62$	-0.00319**	0.01505	-0.01186
	[0.00141]	[0.01258]	[0.01256]
$62 < Avg. Temp. \leq 70$	-0.00128*	0.00569	-0.00441
	[0.00069]	[0.00799]	[0.00789]
$Avg. Temp. > 76$	0.00063	-0.01091**	0.01028**
	[0.00086]	[0.00459]	[0.00461]
$Low\ Precip.$	-0.00142**	-0.00163	0.00304
	[0.00063]	[0.00415]	[0.00429]
$Medium\ Precip.$	-0.00189***	0.00237	-0.00048
	[0.00057]	[0.00449]	[0.00466]
$High\ Precip.$	-0.0031***	0.00382	-0.00072
	[0.00057]	[0.0061]	[0.00597]
$Very\ High\ Precip.$	-0.00496***	-0.00885	0.01381**
	[0.00062]	[0.00686]	[0.00692]
$Medium\ Avg. Wind$	-0.00035	0.00079	-0.00044
	[0.00035]	[0.00557]	[0.00561]
$High\ Avg. Wind$	-0.00068	-0.00049	0.00117
	[0.00043]	[0.00411]	[0.00415]
$Snow > 0$	0.00062	0.00272	-0.00334
	[5e-04]	[0.01084]	[0.01101]
Day of week controls	Yes	Yes	Yes
Month controls	Yes	Yes	Yes
Adjusted R-squared	0.304	0.859	0.856
Number of obs.	425	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

Beyond changes to the composition of travel mode usage, I explore additional dimensions of urban mobility's sensitivity to adverse weather changes. For instance, even in cases when the proportion of trips for a given mode remains unchanged under severe weather, it is possible that travellers respond in other ways, as discussed in the Conceptual Framework section (e.g., not undertaking long distance trips or curtailing trips). This motivates the decision to include regression results for average trip durations, as displayed in Table 2. This table contains two specifications, one for average bikeshare trip times and the other for average rideshare trip distances.

I find that the coldest days are associated with reduced bikeshare trip times. Days with average temperatures less than or equal to 27°F correspond to an approximate 5.7 minute decrease in bikeshare trip times, as compared to days with temperatures between 70°F and 76°F. Moreover, the two highest categories of precipitation levels are associated with reduced bikeshare trip times. Days with high precipitation correspond to roughly a 1.63 minute reduction in bikeshare trip times, relative to days with zero precipitation.

I also find that the hottest daily temperatures and highest levels of rainfall coincide with reduced rideshare trip distances. Likewise, high average wind speeds also induce shorter rideshare trips. Both average temperatures greater than 76°F and high average wind speeds are associated with roughly a 0.07 mile reduction in average rideshare trip distances, as compared to their respective reference levels. I do not find that temperatures less than or equal to 70°F have a statistically significant effect on rideshare trip distances. Additionally, positive snowfall levels do not have a statistically significant effect on bikeshare times or rideshare distances.

Table 2: Average trip duration models

Variable	Bikeshare (min.)	Rideshare (miles)
$Avg.Temp. \leq 27$	-5.7094***	-0.1523
	[0.8102]	[0.1029]
$27 < Avg.Temp. \leq 34$	-5.3817***	-0.0948
	[0.7953]	[0.1027]
$34 < Avg.Temp. \leq 41$	-5.2275***	-0.0481
	[0.7903]	[0.0918]
$41 < Avg.Temp. \leq 49$	-3.6559***	-0.0524
	[0.684]	[0.083]
$49 < Avg.Temp. \leq 62$	-1.9088***	0.0252
	[0.5854]	[0.0751]
$62 < Avg.Temp. \leq 70$	-0.8585***	-0.0545
	[0.2589]	[0.0486]
$Avg.Temp. > 76$	0.2828	-0.0743*
	[0.2823]	[0.039]
$Low\ Precip.$	-0.6813*	-0.0182
	[0.3847]	[0.0311]
$Medium\ Precip.$	-0.8825***	0.0065
	[0.3174]	[0.0324]
$High\ Precip.$	-1.6297***	-0.095***
	[0.2205]	[0.0273]
$Very\ High\ Precip.$	-1.7907***	-0.1763***
	[0.274]	[0.0332]
$Medium\ Avg.Wind$	-0.1893	0.0082
	[0.1817]	[0.0268]
$High\ Avg.Wind$	-0.778***	-0.0673***
	[0.1927]	[0.0249]
$Snow > 0$	0.1837	-0.0386
	[0.2808]	[0.0408]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.557	0.745
Number of obs.	729	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

To complement the previous sets of results, I also consider the linkage between weather conditions and average rideshare speeds. In doing so, I draw attention to some of the potential time costs of adverse weather, specifically in the context of rideshare. Table 3 shows the results for these average rideshare speed models. The "Non-missing only" specification is the preferred model, which is applied to data after first removing trips that have missing trip times or trip distances. I run the "All trips" specification on data that have missing values for trip times or distances set equal to zero.

Table 3: Average speed (mph) models for rideshare

Variable	Non-missing only	All trips
$Avg. Temp. \leq 27$	-0.1918	0.8729
	[0.4177]	[1.0823]
$27 < Avg. Temp. \leq 34$	-0.0398	1.202
	[0.45]	[1.2239]
$34 < Avg. Temp. \leq 41$	-0.0164	1.2775
	[0.3492]	[1.2351]
$41 < Avg. Temp. \leq 49$	-0.1732	1.2336
	[0.3309]	[1.3187]
$49 < Avg. Temp. \leq 62$	-0.1976	1.081
	[0.3096]	[1.2051]
$62 < Avg. Temp. \leq 70$	-0.3689**	0.9182
	[0.1875]	[1.2347]
$Avg. Temp. > 76$	-0.0804	0.184
	[0.1544]	[0.326]
$Low\ Precip.$	0.0635	0.0073
	[0.1402]	[0.1709]
$Medium\ Precip.$	-0.0919	-0.227
	[0.1171]	[0.1819]
$High\ Precip.$	-0.432***	-1.045*
	[0.1505]	[0.5738]
$Very\ High\ Precip.$	-0.6896***	-0.8517***
	[0.1462]	[0.224]
$Medium\ Avg. Wind$	-0.0124	-0.5645
	[0.1178]	[0.5107]
$High\ Avg. Wind$	-0.1988**	-0.4833*
	[0.08]	[0.282]
$Snow > 0$	-0.3517	-0.2028
	[0.2622]	[0.3359]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.632	0.208
Number of obs.	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

Looking to the preferred specification, the results indicate that days with the highest levels of rainfall and average wind speeds coincide with lower rideshare speeds. Days with very high precipitation levels are associated with an approximate 0.69 mph reduction in average rideshare speeds, as compared to days with zero precipitation. Rideshare speeds are, on average, roughly 0.2 mph slower on days with high average wind speeds as compared to low average wind speeds, all else equal. While temperatures between 62°F and 70°F are linked to reduced rideshare speeds, temperatures less than or equal to 62°F are not associated with statistically significant differences in rideshare speeds relative to the reference level for average temperature. Additionally, positive levels of snowfall do not have a statistically significant effect on average rideshare speeds.

6 Robustness Checks

I perform several robustness checks in order to further validate my main findings. I first run placebo checks by comparing my primary regression results with results obtained using weather data from different years. If my results are not spurious, then it would be expected that coefficient estimates obtained using weather data from different years would largely show an absence of an effect in cases where the coefficient estimates obtained using the correct weather data are significantly different from zero. Figures A1-A9 in Appendix A show plots of the subset of coefficient estimates that are statistically significant in the main results section, with 90% confidence bands given by the red dotted lines. The plots show the coefficient estimates computed using weather data from 2006-7, 2008-9, 2010-11, 2012-13, 2014-15, 2016-17, juxtaposed with the results using the correct weather data from 2018-19. In many instances, the estimates obtained from using incorrect weather data either indicate a null effect or a less marked effect in terms of magnitude than the correct estimates. There are cases where a number of the incorrect estimates are significantly different from zero at the 10% level.

In order to determine whether my main results are robust against an alternative functional form for the weather variables of interest, I include specifications of the three previous models with linear and quadratic weather terms in Tables A1-A3. The choice to consider these specifications is influenced by the approach taken by Chan and Wichman (2020) in Tables A.1 and A.2 of their online appendix (A.3-A.4). Some of the broad conclusions that can be gathered from the results in Tables 1-3 also find at least limited support in the results from Tables A1-A3. However, there are also discrepancies between these two sets of results, and I discuss a subset of these discrepancies below.

Looking first to the trip proportions results in Table A1, more precipitation and higher average temperatures are associated with lower and higher proportional bikeshare use, respectively. This is expected from the main results in Table 1. However, the positive estimate on the quadratic term for precipitation in Table A1 suggests that the negative effect of precipitation on bikeshare proportions decreases in magnitude as precipitation increases. This bears some inconsistency with the main results, where the coefficient estimates on the precipitation dummy variables become more negative for higher levels of precipitation.

There is evidence in Table A2 that higher levels of precipitation have an adverse effect on average rideshare trip distances, which is consistent with the main results. I find, however, that snowfall has a statistically significant effect on bikeshare trip times, which is not supported by the results in Table 2. There is also a lack of evidence that average wind speed has an effect on both bikeshare trip times and rideshare trip distances, despite the fact that both measures are sensitive to high wind speeds in the main results. Moreover, increasing average temperature is associated with longer rideshare trips with this alternative functional form specification. This would not be expected from the results in Table 2, which indicate that temperatures greater than 76°F have a negative effect on rideshare trip distances. I find from the results in Table A3 that increasing rainfall is associated with slower rideshare trips, which is consistent with the main findings. However, there is also evidence from these robustness checks results that increasing snowfall has a negative effect on rideshare speeds and that higher average wind speeds do not have a statistically significant effect on rideshare speeds. These two findings do not accord generally with the interpretations of the estimates in the main results section.

I also include results of my three primary models with all bikeshare and rideshare trips included in Tables A4-A6. My rationale for removing certain bikeshare and rideshare trips is explained earlier, but my particular choice of cutoffs (i.e., less than 40 miles for rideshare and 5 minutes to 5 hours for bikeshare) is somewhat arbitrary. Therefore, I include the same specifications as presented in the main results section with all trips included in order to confirm the consistency of my findings across these two sets of models. The primary takeaways that are highlighted earlier in my main results are still generally supported by the coefficient estimates obtained by performing this robustness check. In most cases, the coefficient estimates in Tables A4-A6 match the corresponding estimates in Tables 1-3 both in terms of sign and statistical significance. However, there are a number of discrepancies. For instance, looking at the specifications with average bikeshare trip times as the dependent variable, the coefficient estimates on the variables $27 < Avg.Temp. \leq 34$, $62 < Avg.Temp. \leq 70$, $Medium\,Precip.$, $Very\,High\,Precip.$, and $High\,Avg.Wind$ differ in terms of statistical significance between the robustness checks results and my main findings.

7 Discussion

Taken together, the results of this study provide detailed evidence of how travellers in Chicago respond to adverse weather conditions. With knowledge of these various sensitivities, it might be valuable to have some understanding of how the characteristics of certain weather phenomena in Chicago have changed in the past and how they may be expected to change in the future. A 2013 Chicago Metropolitan Agency for Planning (CMAP) report displays a plot of the annual frequency of "very cold days" (i.e., days when the minimum temperature $\leq 32°$F) from 1959-2011, and it concludes that "there has been a steady decrease" of the frequency of days in this category over time (p.13). The same report also plots "precipitation intensity" (i.e., the "[a]verage accumulation per precipitation event") for the time frame 1959-2011, and concludes "that Chicago has experienced an increase in precipitation intensity over the last few decades" (p.17).

As a complement to these findings, Figure 6 shows plots of the annual frequencies of high and very high precipitation levels for the Chicago O'Hare LCD weather station from 1963 to 2020. Just as the CMAP report includes a "11-year centered mean" in their "very cold days" and "precipitation intensity" plots, Figure 6 includes a 10-year running average overlaid with the annual frequency plots (2013, p.13,17).

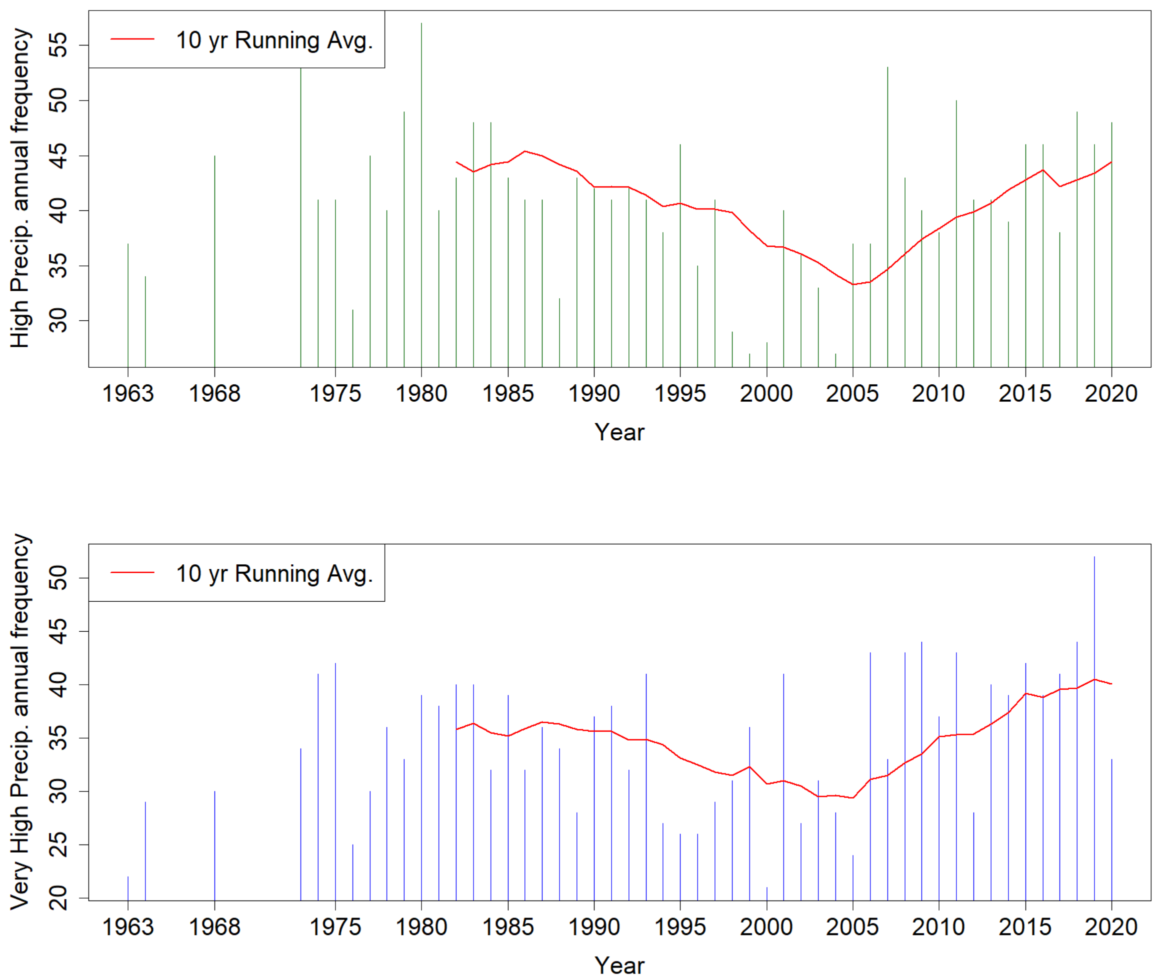

Figure 6: Chicago precipitation annual frequency: 1963-2020

There are mostly increases in the 10-year running average of the annual frequency of high and very high precipitation levels from the mid 2000's to 2020. These trends, however, do not hold in the two decades prior to the mid 2000's. The 10-year running average of annual frequencies increases from 33.3 in 2005 to 44.4 in 2020 for high precipitation events and increases from 29.4 in 2005 to 40.1 in 2020 for very high precipitation events.

In any event, Hayhoe et al. (2010) and Vavrus and Van Dorn (2010), both of which are also cited in the 2013 CMAP report referenced earlier, provide a number of examples of how the incidence of adverse weather in Chicago could undergo future changes. According to Vavrus and Van Dorn (2010), "the number of extremely cold days (the coldest 5% of all days in the present climate) will fall by 40%...to 70%" in Chicago "later this century (p.27). Conversely, "models simulate a 2.4-...to 3.5-...fold increase in very hot days (warmest 5% of all days) by the late 21st century, equivalent to 22 to 58 more days of extreme heat per year" (Vavrus and Van Dorn, 2010, p.29).

Despite evidence that "climate change is expected to bring the Great Lakes region no more than slight increases in annual average precipitation,...[r]elatively large increases in winter and spring precipitation are projected to occur across the region, with larger changes under higher emissions as compared to lower (+30% vs. +20%), and by end-of-century as compared to closer time periods (Hayhoe et al., 2010, p.16). In light of these projections, my findings bring attention to the need for future research that specifically addresses the impacts of climate change on various facets of urban mobility. Although I do not make any claims about how climate change will affect the state of transportation in Chicago, the results of my analysis do indicate potential areas of vulnerability where policies might be able to improve the performance of the city's transportation systems in the present day.

There are at least several limitations regarding the results of this study that are worth noting. Firstly, I do not address the issue raised by Guo et al. (2007) that "[w]eather might have a lagged effect" (p.10). These authors specifically offer the possibility that "a blizzard might affect the travel on the following days even if those days have good weather" (Guo et al., 2007, p.10). This possibly explains why, in most cases, I do not find that positive levels of snowfall have statistically significant effects. It could be that my findings understate the true adverse impacts of snowfall on travel behavior in cities.

Additionally, it is doubtful that my results in this study are readily generalizable to other urban settings. In one analysis, Chan and Wichman (2020) group their “cities into climatic zones” and “plot zone-specific response functions for temperature and precipitation” (p.134). These authors find some evidence of “regional heterogeneity” (Chan and Wichman, 2020, p.135). For instance, they find that “[o]n the warm end of the temperature distribution, the duration of trips is reduced in hotter cities much more than in cooler cities” (Chan and Wichman, 2020, p.135). I echo the sentiments from Guo et al. (2007), which states that “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” (p.10). In any event, the findings from Chan and Wichman (2020) give reason to question the external validity of my results and suggest that the results of my analysis should be conservatively interpreted as relevant for the Chicago area alone.

I should also note that the rideshare dataset contains missing values for some observations. However, for rideshare trips that are less than 40 miles in length, missing values for trip distances never exceed 1% of the number of trips on a given day. Additionally, the Pickup Community Area is missing for a subset of trips in the raw data. It is assumed that in most cases, this field is missing in the raw data because the trip in question originated outside the City of Chicago. However, it is unclear whether it is correct to make this assumption. When asked whether missing data constituted most of the blank values for the Pickup Community Area field, the Chicago Business Affairs and Consumer Protection Public Vehicle Operations Division replied that “[t]he City of Chicago receives required data as reported,” and that “[o]nly trips starting and/or ending in the City of Chicago are required to be reported”. This doesn’t provide an explicit answer to this question, but I should note that the percentage of daily trips that have both Pickup and Dropoff Community Area fields missing does not exceed 0.14% for rideshare trips that are less than 40 miles in length. Having said this, the nature of the missing values in the rideshare data remains uncertain.

8 Conclusion

Given the emergence of new transportation modes such as bikeshare and rideshare in recent years, there is value in understanding how these modes fare in different weather conditions and how the incorporation of these modes affects the overall effect of weather on urban travel patterns. Using Chicago as a case study, I examine how certain weather conditions affect the composition of bikeshare, rail transit, and rideshare use. I also consider the effect of weather on average rideshare trip distances, average rideshare trip speeds, and average bikeshare trip times.

I find that the hottest daily temperatures induce lower proportional use of rail transit and higher proportions of rideshare trips. The highest levels of rainfall are associated with lower proportions of bikeshare trips, higher proportions of rideshare trips, shorter rideshare trips, and lower average rideshare speeds. The coldest days are linked to lower proportional use of bikeshare and shorter bikeshare trips in terms of minutes. The windiest days also correspond to lower average rideshare trip distances and rideshare speeds.

The intent of this study is to raise awareness of the effects of weather on certain aspects of mobility in an evolving transportation landscape. I do not make any projections of how urban travel patterns might be affected in coming decades with the progression of climate change. Future studies in this area of research could focus more specifically on quantifying the potential effects that climate change may have on urban transportation systems.

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ebscohost.com/login.aspx?direct=true&db=edselp&AN=S096585641930919X&site=eds-live&scope=site (2021) (May 1, 2020).

37. Zeileis, A. *sandwich* version 3.0-1. 2021.

A Robustness Checks Figures and Tables

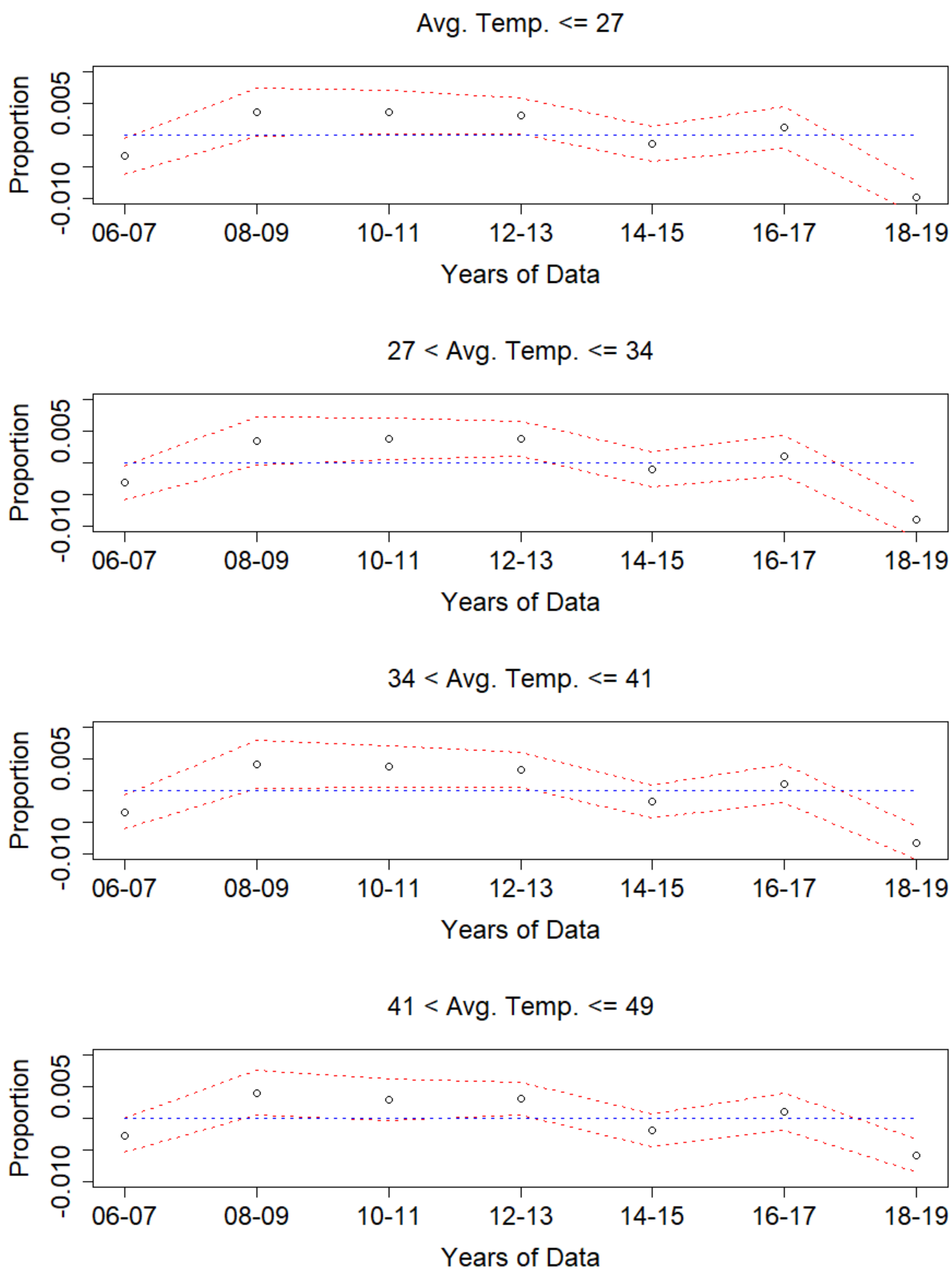

Figure A1: Placebo checks (Bikeshare proportion 1 of 3)

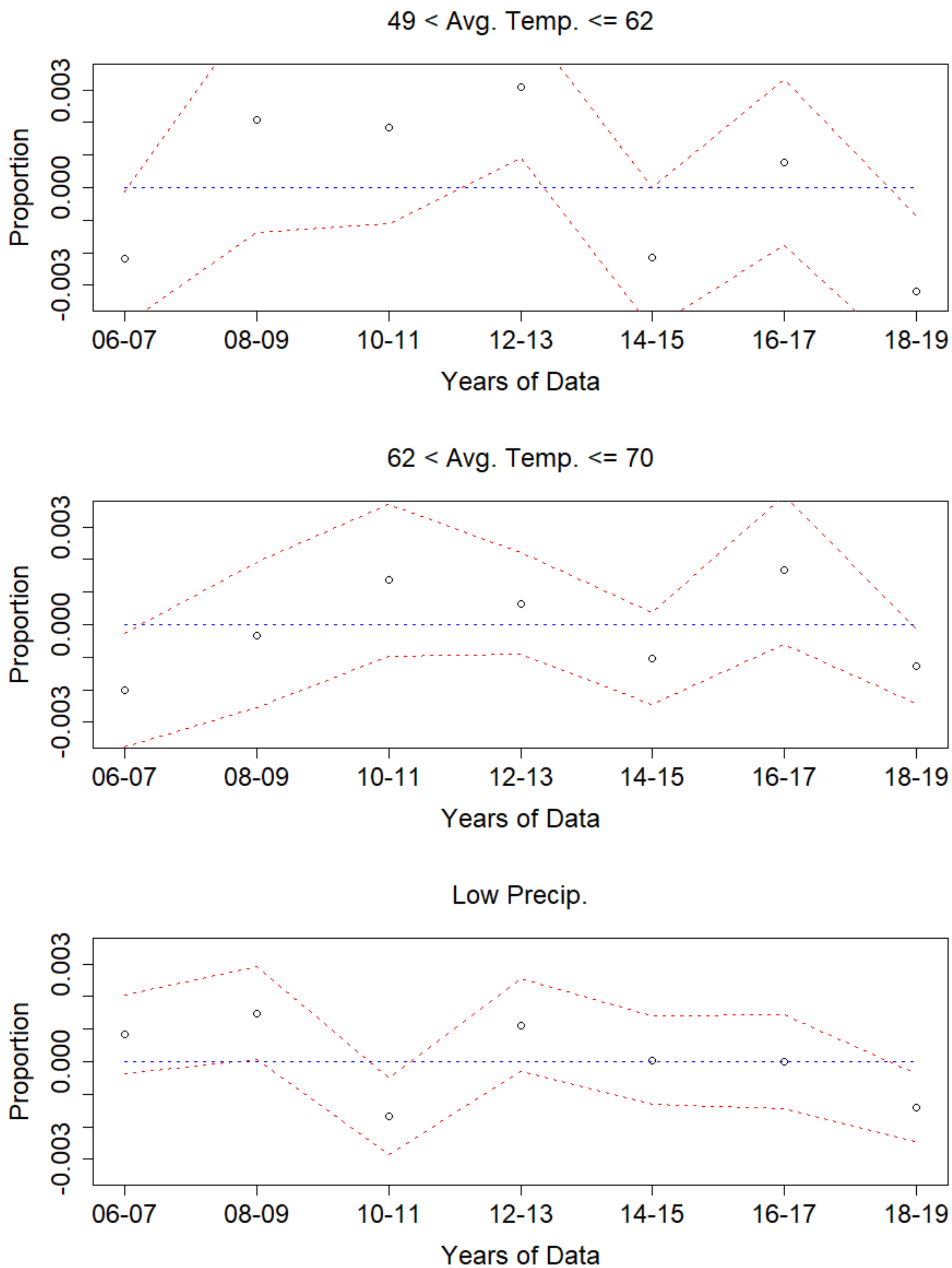

Figure A2: Placebo checks (Bikeshare proportion 2 of 3)

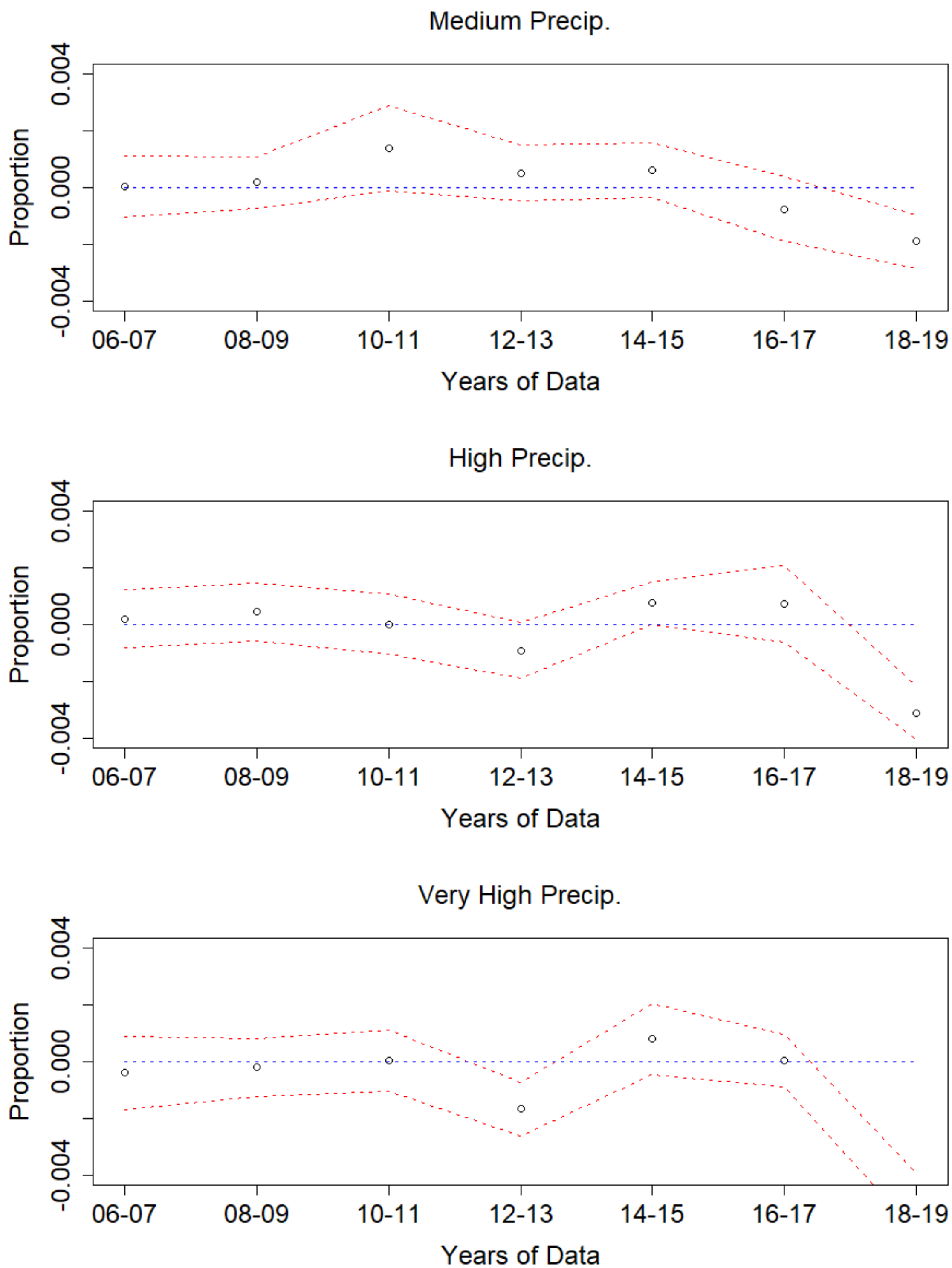

Figure A3: Placebo checks (Bikeshare proportion 3 of 3)

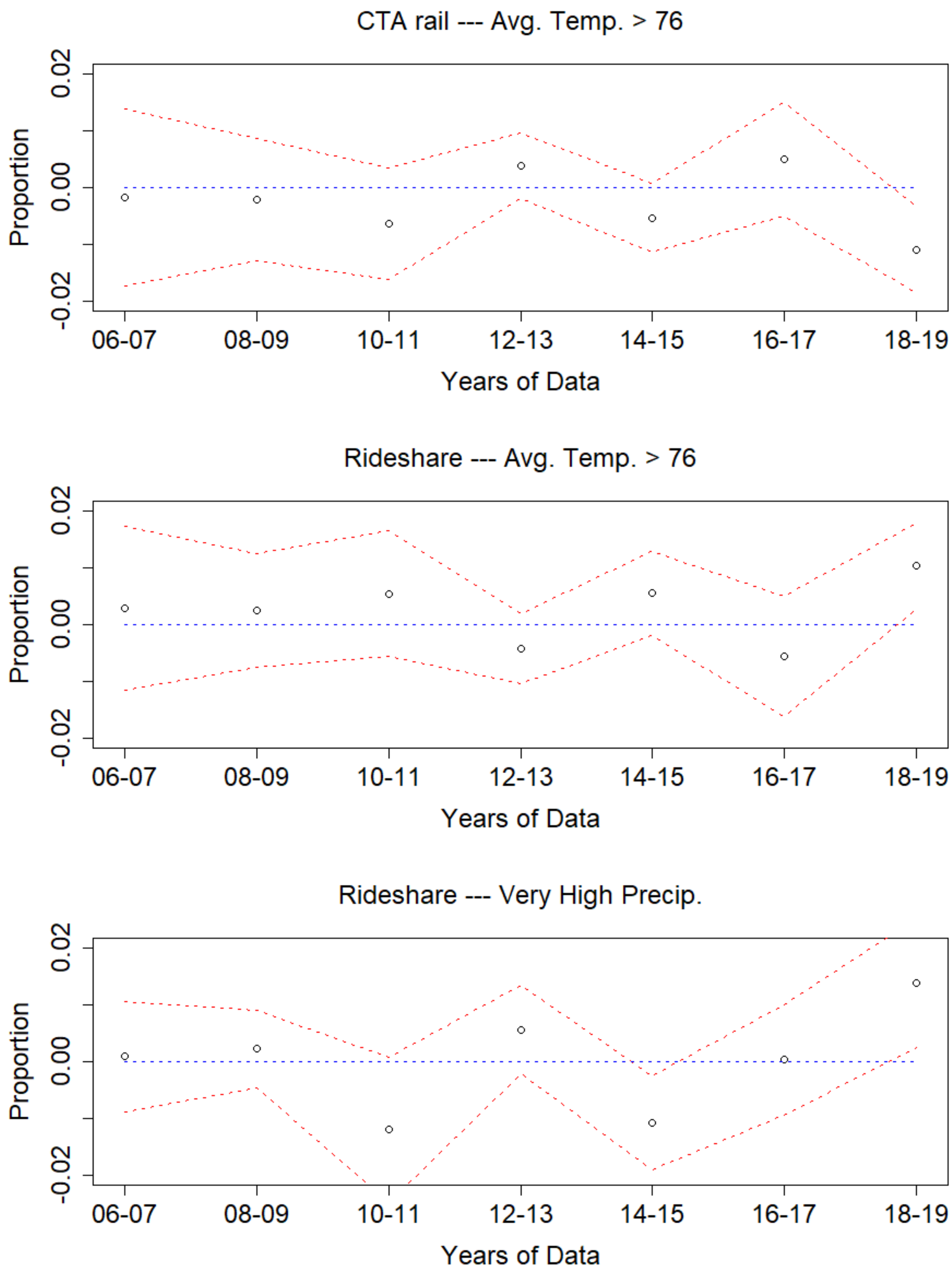

Figure A4: Placebo checks (CTA rail and rideshare proportion)

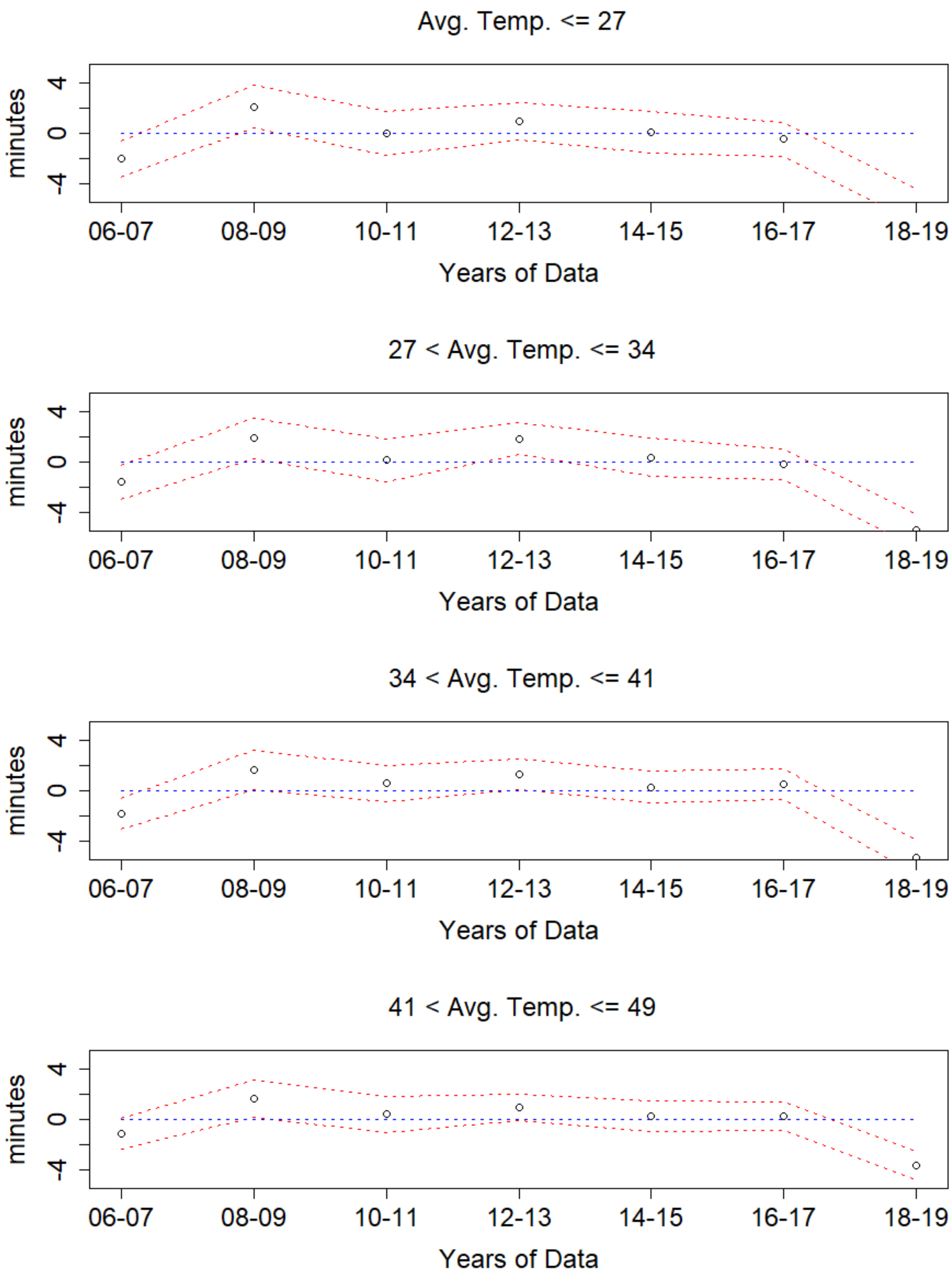

Figure A5: Placebo checks (Bikeshare min. 1 of 3)

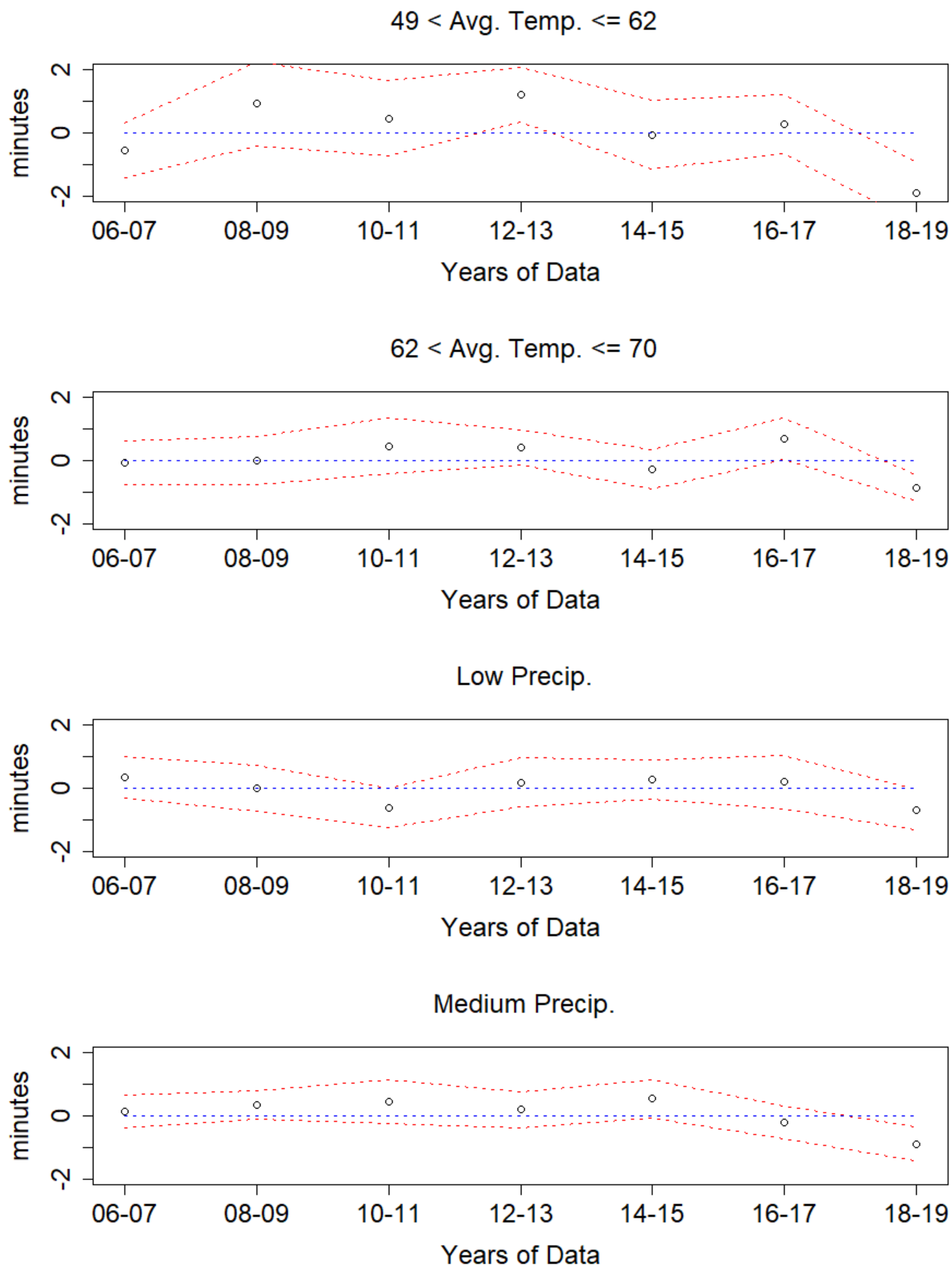

Figure A6: Placebo checks (Bikeshare min. 2 of 3)

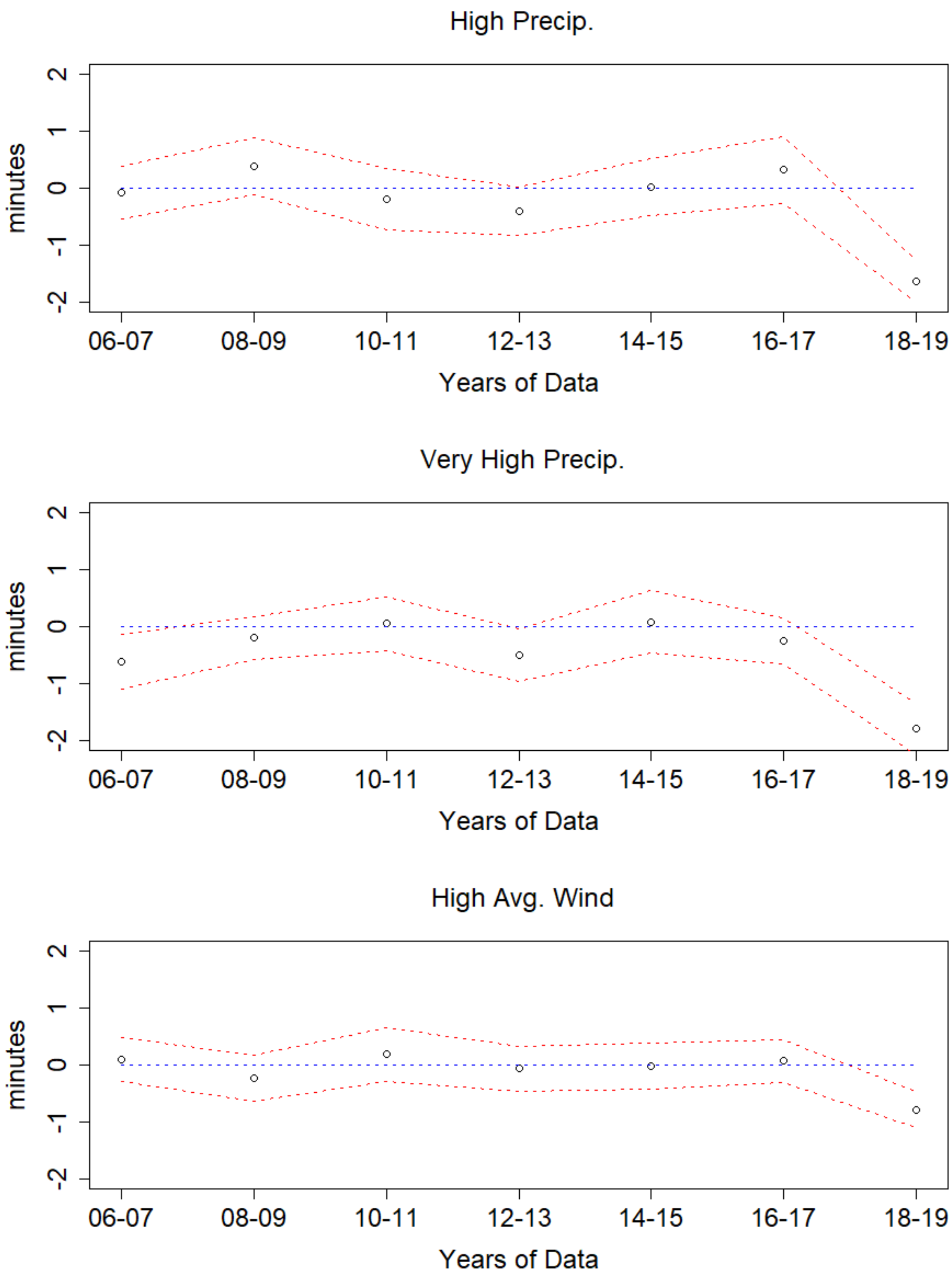

Figure A7: Placebo checks (Bikeshare min. 3 of 3)

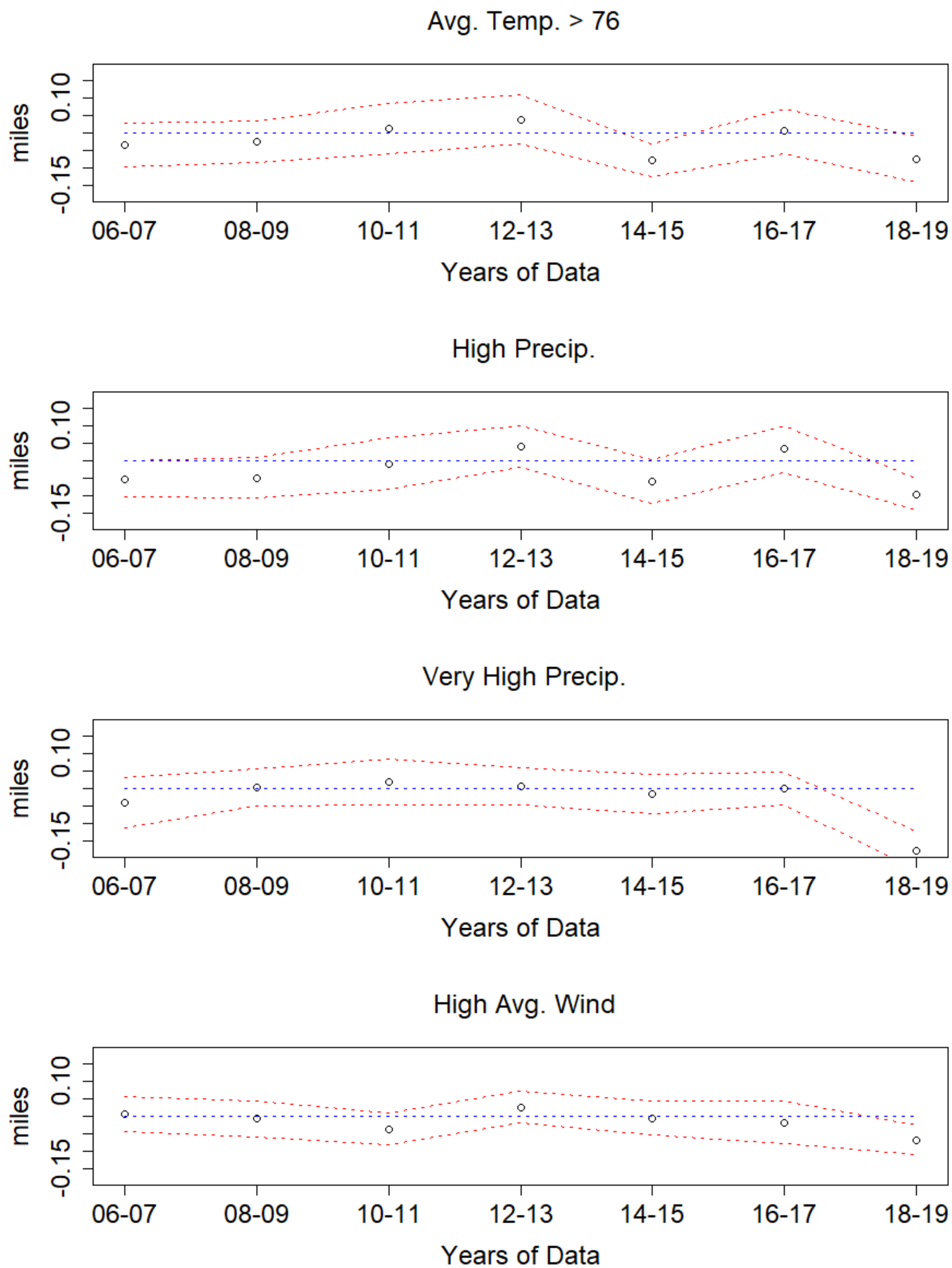

Figure A8: Placebo checks (Rideshare miles)

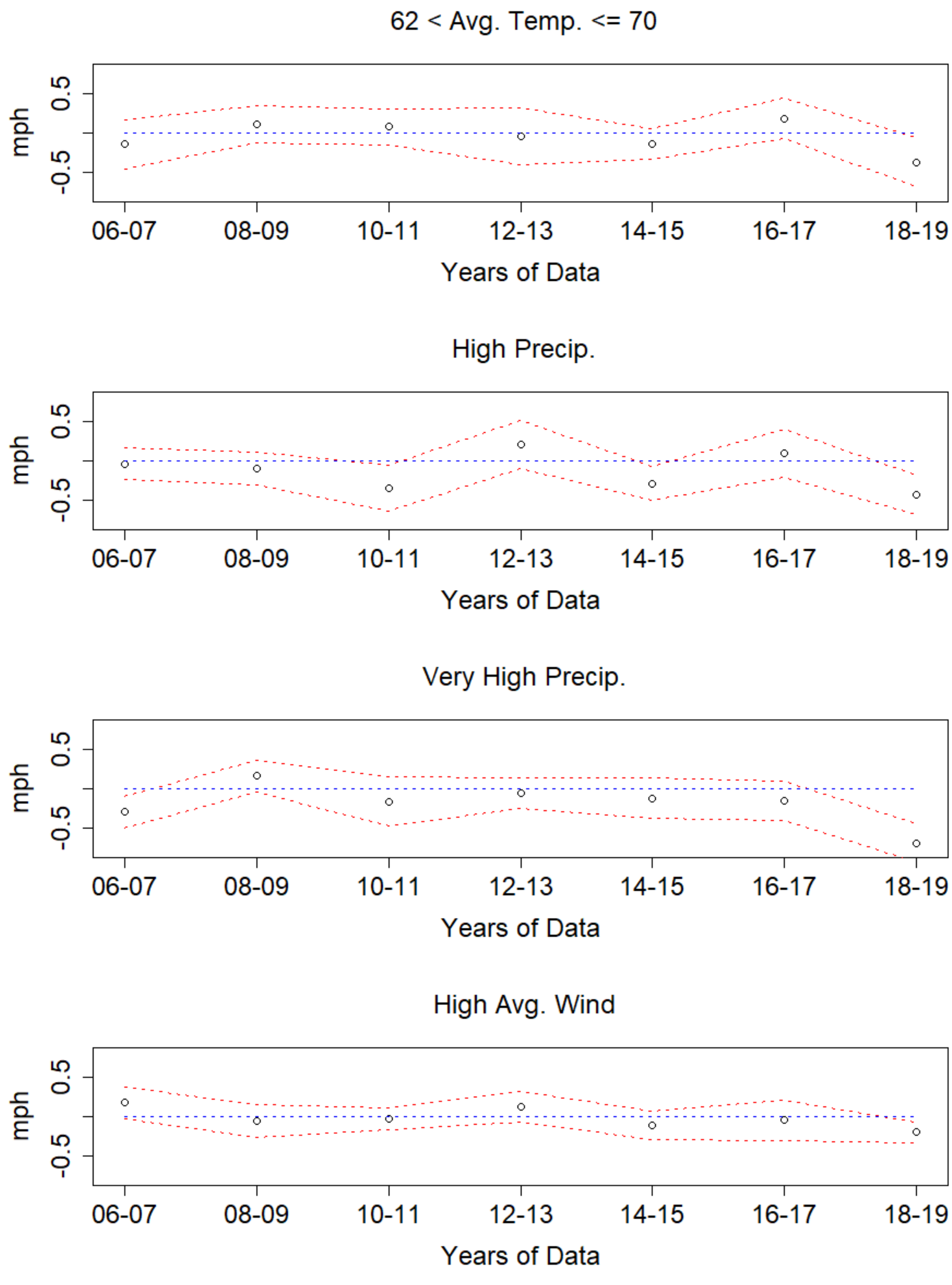

Figure A9: Placebo checks (Rideshare mph)

Table A1: Proportions models – Linear and quadratic weather terms

Variable	Bikeshare	CTA rail	Rideshare
$Avg. Wind\,(mph)$	8.30E-06	0.00103	-0.00104
	[0.0001569]	[0.00153]	[0.00156]
$Avg. Wind^2$	-5.90E-06	-6.00E-05	6.00E-05
	[5.8e-06]	[7e-05]	[7e-05]
$Precip.\,(in.)$	-0.0093884***	0.00894	0.00045
	[0.0016059]	[0.01755]	[0.01723]
$Precip.^2$	0.0029378***	-0.02161	0.01867
	[0.0008584]	[0.0139]	[0.0135]
$Avg. Temp.\,(degF)$	0.0001154**	0.0043***	-0.00442***
	[5.27e-05]	[0.00161]	[0.00162]
$Avg. Temp.^2$	1.10E-06	-4e-05**	4e-05**
	[8e-07]	[2e-05]	[2e-05]
$Snow\,(in.)$	-0.0003627	-0.00503	0.00539
	[0.000557]	[0.00882]	[0.00912]
$Snow^2$	4.63E-05	-0.00015	1.00E-04
	[0.0001226]	[0.00205]	[0.00213]
Day of week controls	Yes	Yes	Yes
Month controls	Yes	Yes	Yes
Adjusted R-squared	0.334	0.876	0.875
Number of obs.	425	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***

Table A2: Average trip duration models – Linear and quadratic weather terms

Variable	Bikeshare (min.)	Rideshare (miles)
$Avg.Wind\ (mph)$	-0.1049	-0.0019
	[0.0873]	[0.0111]
$Avg.Wind^2$	-0.0014	-3.00E-04
	[0.0037]	[4e-04]
$Precip.\ (in.)$	-3.8798***	-0.2065***
	[0.7285]	[0.0776]
$Precip.^2$	1.6632***	0.0089
	[0.4472]	[0.0451]
$Avg.Temp.$	0.0114	0.0101**
	[0.0383]	[0.0045]
$Avg.Temp.^2$	0.0013***	-1.00E-04
	[4e-04]	[1e-04]
$Snow\ (in.)$	-0.7899**	-0.0403
	[0.3692]	[0.0462]
$Snow^2$	0.1859**	-0.0083
	[0.0863]	[0.0088]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.563	0.761
Number of obs.	729	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***

Table A3: Average Rideshare speed models – Linear and quadratic weather terms

Variable	Non-missing only	All trips
$Avg. Wind\,(mph)$	-0.0393	-0.1192
	[0.0513]	[0.0902]
$Avg. Wind^2$	0.001	0.0038
	[0.0024]	[0.0034]
$Precip.\,(in.)$	-1.3889***	-2.4058**
	[0.402]	[1.0431]
$Precip.^2$	0.5609	1.1242*
	[0.3463]	[0.6364]
$Avg. Temp.$	-0.0416	-0.0209
	[0.0421]	[0.0502]
$Avg. Temp.^2$	5.00E-04	1.00E-04
	[4e-04]	[6e-04]
$Snow\,(in.)$	-0.3072*	-0.2166
	[0.1717]	[0.2357]
$Snow^2$	0.0459	0.0367
	[0.0404]	[0.0506]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.629	0.199
Number of obs.	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***

Table A4: Trip proportions models – All trips included

Variable	Bikeshare	CTA rail	Rideshare
$Avg. Temp. \leq 27$	-0.0104229***	-0.01883	0.02926
	[0.0017275]	[0.01793]	[0.01813]
$27 < Avg. Temp. \leq 34$	-0.0093111***	-0.01534	0.02466
	[0.001704]	[0.01717]	[0.01733]
$34 < Avg. Temp. \leq 41$	-0.0084528***	-0.0137	0.02215
	[0.0016724]	[0.01504]	[0.01532]
$41 < Avg. Temp. \leq 49$	-0.0059851***	0.00406	0.00192
	[0.0016233]	[0.01363]	[0.01374]
$49 < Avg. Temp. \leq 62$	-0.003134**	0.01483	-0.0117
	[0.0014701]	[0.01254]	[0.01257]
$62 < Avg. Temp. \leq 70$	-0.0013295*	0.00554	-0.00421
	[0.0007269]	[0.00798]	[0.0079]
$Avg. Temp. > 76$	0.0006229	-0.01089**	0.01027**
	[0.0008707]	[0.00458]	[0.00461]
$Low\ Precip.$	-0.0014254**	-0.00161	0.00304
	[0.0006419]	[0.00414]	[0.00429]
$Medium\ Precip.$	-0.0019818***	0.00245	-0.00047
	[0.0005853]	[0.00448]	[0.00466]
$High\ Precip.$	-0.0033109***	0.00397	-0.00066
	[0.0005971]	[0.00609]	[0.00597]
$Very\ High\ Precip.$	-0.0053603***	-0.00856	0.01392**
	[0.0006454]	[0.00683]	[0.00692]
$Medium\ Avg. Wind$	-0.000413	0.00084	-0.00042
	[0.0003616]	[0.00556]	[0.00561]
$High\ Avg. Wind$	-0.0007932*	-0.00042	0.00121
	[0.000443]	[0.0041]	[0.00415]
$Snow > 0$	0.0004577	0.00283	-0.00328
	[0.0005326]	[0.01083]	[0.01102]
Day of week controls	Yes	Yes	Yes
Month controls	Yes	Yes	Yes
Adjusted R-squared	0.32	0.859	0.856
Number of obs.	425	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

Table A5: Average trip duration models – All trips included

Variable	Bikeshare (min.)	Rideshare (miles)
$Avg. Temp. \leq 27$	-9.6535*	-0.1686
	[5.0045]	[0.1097]
$27 < Avg. Temp. \leq 34$	-2.6576	-0.1097
	[2.519]	[0.11]
$34 < Avg. Temp. \leq 41$	-4.807*	-0.0603
	[2.6408]	[0.0981]
$41 < Avg. Temp. \leq 49$	-3.7886*	-0.0688
	[1.9562]	[0.0892]
$49 < Avg. Temp. \leq 62$	-3.6134**	0.0182
	[1.5819]	[0.0807]
$62 < Avg. Temp. \leq 70$	-0.5331	-0.0635
	[1.1445]	[0.0524]
$Avg. Temp. > 76$	1.1036	-0.079*
	[1.1616]	[0.0415]
$Low\ Precip.$	-5.9082*	-0.0112
	[3.0628]	[0.0325]
$Medium\ Precip.$	-0.3036	0.0108
	[1.9563]	[0.034]
$High\ Precip.$	-4.479***	-0.0945***
	[1.3687]	[0.0287]
$Very\ High\ Precip.$	-1.9101	-0.1774***
	[1.2203]	[0.0346]
$Medium\ Avg. Wind$	-0.5183	0.0085
	[0.8035]	[0.0287]
$High\ Avg. Wind$	-0.6034	-0.0725***
	[0.9035]	[0.0263]
$Snow > 0$	3.8029	-0.0324
	[3.4439]	[0.0426]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.099	0.744
Number of obs.	729	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

Table A6: Average Rideshare speed models – All trips included

Variable	Non-missing only	All trips
$Avg. Temp. \leq 27$	-0.2083	0.8502
	[0.428]	[1.0959]
$27 < Avg. Temp. \leq 34$	-0.0536	1.1837
	[0.4606]	[1.2387]
$34 < Avg. Temp. \leq 41$	-0.029	1.2608
	[0.3592]	[1.2497]
$41 < Avg. Temp. \leq 49$	-0.1936	1.21
	[0.3404]	[1.3342]
$49 < Avg. Temp. \leq 62$	-0.2044	1.0694
	[0.3194]	[1.2196]
$62 < Avg. Temp. \leq 70$	-0.378*	0.9047
	[0.1948]	[1.2486]
$Avg. Temp. > 76$	-0.0865	0.1802
	[0.1591]	[0.3297]
$Low\ Precip.$	0.0806	0.0256
	[0.1432]	[0.1735]
$Medium\ Precip.$	-0.0859	-0.2217
	[0.1198]	[0.1848]
$High\ Precip.$	-0.4324***	-1.0506*
	[0.1527]	[0.5802]
$Very\ High\ Precip.$	-0.6923***	-0.8557***
	[0.1489]	[0.2271]
$Medium\ Avg. Wind$	-0.0151	-0.5718
	[0.1201]	[0.5159]
$High\ Avg. Wind$	-0.208**	-0.4968*
	[0.0817]	[0.285]
$Snow > 0$	-0.3465	-0.1962
	[0.2689]	[0.3427]
Day of week controls	Yes	Yes
Month controls	Yes	Yes
Adjusted R-squared	0.633	0.212
Number of obs.	425	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}

B Trip Counts models

A set of supplementary models that I perform have daily trip counts as the dependent variable. These models have the form:

$$Counts_t = \alpha + \boldsymbol{\beta} \boldsymbol{w}_t + \gamma t + \boldsymbol{\tau} \boldsymbol{dow_t} + \boldsymbol{\eta} \boldsymbol{month_t} + \epsilon_t$$

where $Counts_t$ denotes the daily counts of bikeshare, CTA rail transit, CTA bus transit, or rideshare trips. The corresponding estimation equation for these models is given as:

$$\Delta Counts_t = \gamma + \boldsymbol{\beta} \Delta \boldsymbol{w}_t + \boldsymbol{\tau} \Delta \boldsymbol{dow_t} + \boldsymbol{\eta} \Delta \boldsymbol{month_t} + \xi_t$$

I find that temperatures lower than or equal to 41°F are linked to fewer numbers of bikeshare trips, fewer numbers of bus trips, and greater numbers of rideshare trips. The hottest days coincide with more rideshare trips, but do not correspond with statistically significant differences in the number of bikeshare trips, relative to their respective reference levels. Days with very high precipitation are associated with fewer bikeshare, rail transit, and bus transit trips, as well as a greater number of rideshare trips. The windiest days coincide with fewer numbers of bikeshare trips, but greater numbers of rail transit and rideshare trips. Relative to zero inches of snowfall, the results indicate that positive snowfall levels do not have a statistically significant effect on trip counts for bikeshare, rail transit, bus transit, or rideshare.

Table B1: Trip counts models

Variable	Bikeshare	CTA rail	CTA bus	Rideshare
$Avg. Temp. \leq 27$	-6214.4***	-19629.4	-51924.5**	24164.6***
	[684]	[18036.9]	[22078.6]	[8484.9]
$27 < Avg. Temp. \leq 34$	-5539.4***	-15671.8	-38091.8*	20579.2**
	[675.5]	[17269.6]	[20538.9]	[8399.1]
$34 < Avg. Temp. \leq 41$	-5167.2***	-13103.8	-36127.1**	10573.9*
	[671.4]	[15646.6]	[17987.2]	[6180.5]
$41 < Avg. Temp. \leq 49$	-3918***	-4120.9	-25366.2	9080.3*
	[640.6]	[14807.2]	[16542.5]	[5142.3]
$49 < Avg. Temp. \leq 62$	-2134.3***	11293.4	5750.5	3954.3
	[581.8]	[13700.2]	[14674.1]	[4589.6]
$62 < Avg. Temp. \leq 70$	-610.9	9402	3833.4	6145.5**
	[395.5]	[8878.3]	[10848.8]	[2885.7]
$Avg. Temp. > 76$	101.9	-7759.7	-5049.7	10798.2***
	[251]	[7396.2]	[9450]	[2247.8]
$Low\ Precip.$	-1212.2***	-10785.6	-15042.1	-1046.8
	[282]	[8812]	[12306.6]	[2051.4]
$Medium\ Precip.$	-1051.3***	144	-2300.8	-446.1
	[246.7]	[4807.7]	[6591.3]	[2814.3]
$High\ Precip.$	-2011.9***	-4024.4	-11958.2	4138
	[214.9]	[6508.5]	[8045.9]	[2905.2]
$Very\ High\ Precip.$	-3184.5***	-19660.1**	-36548.9***	7716.3***
	[300.4]	[8637.3]	[11158.7]	[2935.1]
$Medium\ Avg. Wind$	-156.2	3457.1	-3144.1	2378.6
	[162.1]	[5090.7]	[6476.4]	[2114.3]
$High\ Avg. Wind$	-410.6**	7649.6*	6653.2	4173.6*
	[183.2]	[4320.8]	[5544.2]	[2292]
$Snow > 0$	324.6	-0.2	-8776	1195.5
	[210.3]	[10610.7]	[13274.6]	[5795.4]
Day of week controls	Yes	Yes	Yes	Yes
Month controls	Yes	Yes	Yes	Yes
Adjusted R-squared	0.447	0.837	0.835	0.793
Number of obs.	729	729	729	425

Note: Newey-West std. errors given in brackets; significance levels: 0.1=*, 0.05=**, 0.01=***; variable definitions: low prcp=(0,0.01] in., medium prcp=(0.01,0.07] in., high prcp=(0.07,0.31] in., very high prcp={>0.31 in.}, medium avg wind=(8,11] mph, high avg. wind={>11 mph}