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The EPA's Air Quality Index, and Public Transportation Usage in the Chicago Metro Region

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Abstract
This paper assesses whether air quality influences public transportation ridership in the city of Chicago. Urban air pollution is a serious health risk, and a priority of urban municipalities. Public transportation is an attractive option for governments attempting to curb urban air emissions. I use data from the Chicago Transit Authority (CTA) and the EPA's Air Quality Index (AQI) to explore the relationship between a day's air quality and CTA ridership. I employ three different model specifications, rail, bus and total ridership, to test whether high AQI values (poor air quality) result in increased public transportation ridership in the city of Chicago. My results provide several statistically significant estimates, however, the results to not match across my models, suggesting that there are complex underlying differences between rail and bus ridership. My results reveal the value and possibilities of continued research into the differences between rail and bus ridership in Chicago, or public transportation systems in other American cities.

Keywords
air quality, EPA, public transit, public transportation

Cover Page Footnote
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1. Introduction

Transportation is a consistent concern for all cities and municipalities. Each year, staggering amounts of money are spent by governments across the world in the hopes of optimizing how people move around.[1] Public transportation is a public utility that receives tremendous investment in the hopes of reducing the number of cars on the road. For a long time, the primary goal of public transportation initiatives was to reduce congestion and traffic, while providing low cost transportation options for those who might not own a car. Recently, public transportation is increasingly seen as a method of reducing air pollution. Substituting personal car travel with public transit is a simple way for communities to reduce pollution. Government agencies and public transit systems like the U.S. Department of Transportation, and Chicago's Transit Authority are encouraging people to reduce emissions by using public transportation.[2]

Air pollution and emissions are a consistent concern for urban localities. Around the global, governments are attempting to respond to the health issues that coincide with air pollution. These issues are most important in densely populated areas with many people and sources of pollution. International institutions, like the World Health Organization, encourage countries to reduce urban air pollution, and offer guidelines on how to do so.[3] Countless studies have attempted to quantify the health risks associated with urban air pollution.[4] As a result, several countries have adopted policies designed to curtail the emission of air pollutants in an attempt to improve air quality.

Since the passage of the original Clean Air Act (CAA), the United States has implemented policies and regulations through the Environmental Protection Agency (EPA) designed to assuage poor air quality. Over the years since the original CAA, Congress and the EPA have augmented the law and related

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[1] U.S. Department of Transportation, Bureau of Transportation Statistics, *Government Transportation Financial Statistics 2014* available at http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/government_transportation_financial_statistics/2014/index.html as of August 2016.

[2] United States of America, Department of Transportation, U.S. Federal Transit Administration, Public transportation's role in responding to climate change, by Tina Hodges (Washington, D.C.: U.S. Federal Transit Administration, 2010), accessed April, 20, 2017, https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/PublicTransportationsRoleInRespondingToClimateChange2010.pdf.
Chicago Transit Authority, "Going Green," Chicago Transit Authority, accessed April 21, 2017, http://www.transitchicago.com/goinggreen/.

[3] World Health Organization, "Background information on urban outdoor air pollution," WHO, accessed April 21, 2017, http://www.who.int/phe/health_topics/outdoorair/databases/background_information/en/.

[4] Aaron J. Cohen et al., "Urban Air Pollution," in Comparative Quantification of Health Risks: Global and Regional Burden of Disease Attributable to Selected Major Risk Factors, vol. 1 (Geneva: World Health Organization, 2004).

regulations several times. In 1990, the law contained a clause establishing National Ambient Air Quality Standards (NAAQS) for six key criteria pollutants (seven if you count PM10 and PM2.5 as separate pollutants).[5] These NAAQS created incentives for municipalities and local governments to reduce emissions. In 1997, the EPA introduced policy guidance that allowed states to receive credit for including Voluntary Mobile Source Emission Reduction Programs (VMEPs) in their State Implementation Plans (SIPs).[6] Additionally, in 2004, the EPA adopted policy guidance that allowed states to incorporate Transportation Control Measures (TCMs) into SIPs.[7] These regulatory changes further encouraged states to craft plans designed to increase the usage of public transportation to cut pollution and improve air quality.

Government agencies have increasingly focused on providing more information about environmental conditions to citizens. In 1999, the EPA revised the existing Pollutant Standards Index (PSI) to create the modern Air Quality Index.[8] The EPA expanded collection to daily measurements of five key air pollutants, Ozone, PM2.5, PM10, SO_2, and NO_2, across the country.[9] Based on the levels of these five pollutants, the EPA assigns a local “Air Quality Index” score equivalent to the level of the highest measured pollutant. Since the implementation of the AQI, a process for disseminating information regarding the day’s air quality to citizens was also created. Local news media like newspapers, or online weather websites were either required to, or voluntarily included the day’s AQI level.[10]

This paper seeks to explore how air quality, specifically the AQI, affects public transportation usage in Chicago. Because of the increasingly strong

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[5] U.S. Environmental Protection Agency."NAAQS Table," EPA, December 20, 2016, accessed April 20, 2017, https://www.epa.gov/criteria-air-pollutants/naaqs-table.
[6] U.S. Environmental Protection Agency, Office of Air and Radiation, Guidance on Incorporating Voluntary Mobile Source Emission Reduction Programs in State Implementation Plans (SIPs), by Richard D. Wilson, October 24, 1997, accessed April 20, 2017, https://www.epa.gov/sites/production/files/2016-05/documents/vmep-gud.pdf.
[7] U.S. Environmental Protection Agency, Office of Transportation and Air Quality, Policy Guidance on the Adoption and Use of SIP TCM Substitution Mechanisms in State Implementation Plans (SIPs), by Margo Tsirigotis Oge, April 7, 2004, accessed April 20, 2017, https://www3.epa.gov/ttn/naaqs/aqmguide/collection/cp2/20040407_oge_sip_tcm_substitution.pdf
[8] U.S. Environmental Protection Agency, Air Quality Index (AQI) Air Quality Communication Workshop in San Salvador, El Salvador April 16-17, 2012, 2012, accessed April 20, 2017, https://www.epa.gov/sites/production/files/2014-05/documents/zell-aqi.pdf.
[9] *Ibid*.
[10] U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Air Quality Index: A Guide to Air Quality and Your Health (Research Triangle Park, NC: United States Environmental Protection Agency, Office of Air Quality Planning and Standards, Outreach and Information Division, 2014), January 26, 2016, accessed April 20, 2017, https://www.airnow.gov/index.cfm?action=aqi_brochure.index.

connection between public transit and emissions, and increasing access to information about air quality, I hypothesize that poor air quality (represented by a high AQI Value) will encourage potential riders to make environmental conscious transportation decisions by taking public transportation.

Theoretically, there are a few potential forces to consider. The first is of primary interest and motivates my primary hypothesis. I assert that high AQI levels will cause citizens to weight the benefits of environmental conservation more heavily, thus increasing ridership on days with a high AQI. This theoretical relationship leads me to hypothesize a positive relationship between AQI and public transportation ridership. The second theoretical consideration is a potential reduction in ridership caused by a high AQI. This theory is centered around the fact that riding buses or trains requires individuals to wait outside. Because the AQI also contains information on the potential negative health effect of high AQI levels, some people could be discouraged to use public transportation for fear of excessive exposure to poor quality air. If this force were dominant, we would expect a negative relationship between AQI and ridership. Both forces would lead us to expect a non-zero estimate for the effect of AQI on public transportation usage.

2. Literature Review

Economic studies of environmental information-based policy approaches have attempted to identify the relationship between more information about air quality, and public transportation decisions. Cutter and Neidell (2007) use data from the San Francisco Bay area to understand how "Spare the Air" ozone alerts influence transportation. They used data from the BART public transportation system, and traffic cameras to monitor how transportation decisions change on days with or without the ozone alerts.[11] They found evidence that days with ozone alerts experienced slightly reduced road traffic, and increased public transportation usage.[12] The work by Cutter and Neidell (2007) serves as important theoretical motivation for my paper.

In a similar study, Welch, Gu, and Kramer (2005) tried to quantify the effect of ozone alerts in Chicago on CTA ridership. They used an hourly fixed effects model to estimate the effect of alerts throughout the day.[13] The authors found no significant effect of ozone alerts on daily ridership from 2002-2003, but

[11] W. Bowman Cutter and Matthew Neidell, "Voluntary information programs and environmental regulation: Evidence from 'Spare the Air'," Journal of Environmental Economics and Management 58, no. 3 (November 2009): , accessed April 20, 2017, doi:http://doi.org/10.1016/j.jeem.2009.03.003.

[12] *Ibid*.

[13] Eric Welch, Xiaohua Gu, and Lisa Kramer, "The effects of ozone action day public advisories on train ridership in Chicago," Transportation Research Part D: Transport and Environment 10, no. 6 (November 2005): accessed April 20, 2017, doi:http://doi.org/10.1016/j.trd.2005.06.002.

found evidence of hourly effects.[14] Past studies have primarily focused on ozone, and have relied on more limited samples.

This study hopes to build on the work of previous authors by examining the air quality index, which is not limited to ozone alerts, on public transportation usage in Chicago over a long-time frame. The long period of observation will allow me to test robust regressions. Expanding examination from ozone specifically, to the air quality index generally, should offer insights into how the public reacts to the AQI, an important program by the federal government to provide environmental information to local communities and individual citizens.

3. Data

I created a merged dataset complied from three publically available datasets. The first dataset is daily AQI data from the EPA.[15] Their dataset tracks the "Main Pollutant", the day's highest individual pollutant, the "Site Name" where the measurement took place, the relevant "Site ID", and the measured "AQI Value". Data is available from the EPA at the Core-Based Statistical Area level.[16] I merged this data with daily transportation data from the Chicago Transit Authority (CTA).[17] The CTA tracks the type of day (Weekday, Saturday, or Sunday/Holiday), daily total ridership, and daily bus and rail boardings. My final dataset details daily climate conditions from the Midwestern Regional Climate Center (MRCC).[18] The data includes daily precipitation, average temperature, snowfall, and snow depth. For all the datasets, I obtained daily observations for every day from January 1, 2001 to November 30, 2016. This gives me a total of 5,795 daily time series observations for the city of Chicago.[19]

Although I developed a robust dataset, there a few relevant shortcomings. Unfortunately, the regional definitions of the datasets I employ differ slightly. For instance, the EPA reports air quality data by CBSAs, while the MRCC reports data from a specific weather station (Chicago Midway), and the CTA reports data from the whole system. These differences may create a few issues, for instance, if the highest AQI reading comes from outside of service area of the CTA. I'm not too concerned about these discrepancies, because I think that even if my weather data is not necessary perfectly accurate for each person who considers riding

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[14] *Ibid*.

[15] "Air Data: Air Quality Data Collected at Outdoor Monitors Across the US," EPA, March 13, 2017, accessed April 21, 2017, https://www.epa.gov/outdoor-air-quality-data.

[16] I utilize the Chicago-Naperville, IL-IN-WI Combined Statistical Area.

[17] Chicago Transit Authority, "CTA - Ridership - Daily Boarding Totals," City of Chicago Data Portal, February 16, 2017, accessed April 20, 2017, https://data.cityofchicago.org/Transportation/CTA-Ridership-Daily-Boarding-Totals/6iiy-9s97.

[18] "Cli-MATE: MRCC Application Tools Environment," Midwestern Regional Climate Center, accessed April 20, 2017, http://mrcc.isws.illinois.edu/CLIMATE/

[19] I dropped less than 20 observations that were missing some weather variables.

public transportation each day, it will serve as an effective proxy for the general conditions across the city.

A cursory review of the data provides some basic insights into underlying trends. Table 1 reports basic descriptive statistics for the numerical variables used in my analysis. The table is split up into two sections, the first reporting the number of riders by the transportation variables that will be used as dependent variables in the model. The second section includes atmospheric variables like the AQI value, and the relevant daily weather variables: precipitation, snowfall, snow depth, and average temperature.

Table 1: Summary Statistics

Transportation

Variable (Number of riders)	Mean	Median	Std. Dev.	Min	Max
Bus	820,530	913,619	229,738	213,912	1,211,992
Rail	565,715	614,202	176,908	87,992	1,146,516
Total	1,386,245	1,571,539	392,318	301,904	2,049,519

Atmosphere

Variable	Mean	Median	Std. Dev.	Min	Max
AQI Value	74.9	68	27.616	25	223
Precipitation (in.)	0.115	0	0.301	0	4.73
Snow (in.)	0.207	0	3.340	0	9.6
Snow Depth (in.)	2.529	1	3.340	0	17
Average Temperature (℉)	52.3	53.5	19.83	-8	93.5

Per the data, more people use the bus system on an average day than the rail system. Additionally, bus ridership experiences more variation than rail transit. Regarding the atmospheric variables, there are only a few insights to glean. We can see that the AQI Value experiences significant variation between the minimum of 25 and maximum of 223. The difference between the mean and median tell us that the data is slightly right skewed by less frequent large values.

Comparing how the average ridership changes based on categorical variables also gives us additional information about the data and their interrelationship. Table 2 is comprised of two smaller tables which report the number of occurrences of the two main categorical characteristics: the transportation day type, and the air quality pollutant, which represents the day’s leading pollutant.

Table 2: Day Characteristics

Transport Day Type

Types	**Occurrences**
Sunday/Holiday (U)	925
Weekday (W)	4,055
Saturday (A)	824
Total	**5813**

Air Quality Pollutant

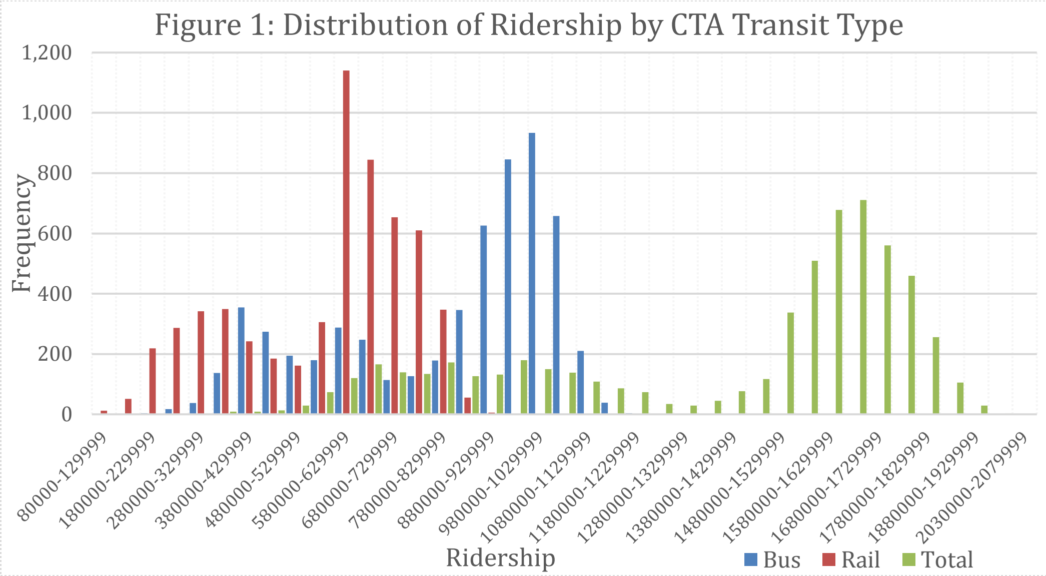
Main Pollutant	**Occurrences**
SO2	929
PM2.5	2,911
Ozone	1,065
PM10	185
NO2	714
Total	**5813**

Obviously, there are significantly more Weekdays than Saturdays or Sundays, but there are still a sufficiently large number of sample sizes. In terms of pollutants, PM2.5 is the most common main pollutant, while PM10 is the least. The relatively low number of observations for PM10 may complicate analysis, especially in the more complex fixed effects model. Tables 3 reports mean ridership by transportation day type. This table does not report statistical significance, simply mean calculations. We can see clear differences in mean ridership by day type. This table reinforces the notion of inherent differences between public transportation usage based on the day of the week. As a result, day type will be an important explanatory variable in my model.

Table 3: Mean Ridership by Transportation Day Type

Day Type (number of riders)	**Bus**	**Rail**	**Total**
Weekday (W)	954,638	665,390	1,620,029
Saturday (A)	609,887	392,785	1,002,672
Sunday/Holiday (U)	419,709	282,430	702,139

To provide additional insights into the variation of ridership across the relevant period, I produced distribution charts displaying the frequency of ridership totals. I developed brackets for each rail, bus and total ridership to group similar frequencies. Figure 1 displays distributions for rail and bus and total ridership.



As we would expect, the distribution of total ridership is concentrated around larger values than either the rail and bus distributions. There are similarities between the bus and rail ridership frequencies, however we can now visualize the increased variation in bus ridership compared to rail ridership. Bus ridership seems to have a cluster of larger ridership totals than the rail ridership, and a larger tail of values below the main concentration of frequencies. The increased variation may suggest that bus ridership is more responsive to variable conditions than rail ridership. Thus, we may expect bus ridership to be more responsive to air quality than rail ridership.

Finally, we can further analyze AQI values by observing temporal changes and distribution variation. Figures 2 and 3 display how AQI Values vary over time, and the distribution of AQI values, respectively.

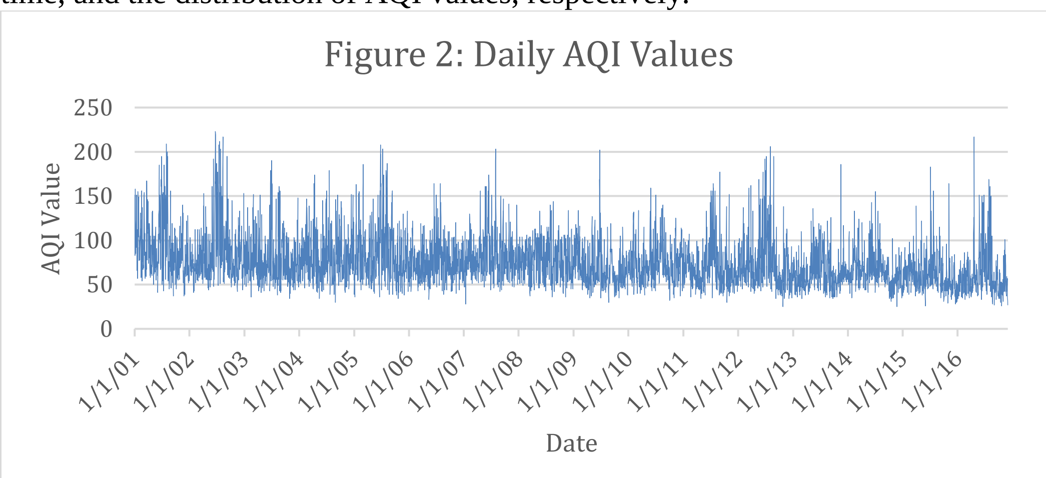


Figure 2 shows that there are some temporal peaks in AQI vales, where Chicago experienced poor air quality for several consecutive days. There is also a general decreasing trend in AQI values across the observed period. These temporal considerations suggest the importance of including a lagged variable to capture any residual effects of the previous day's AQI value.

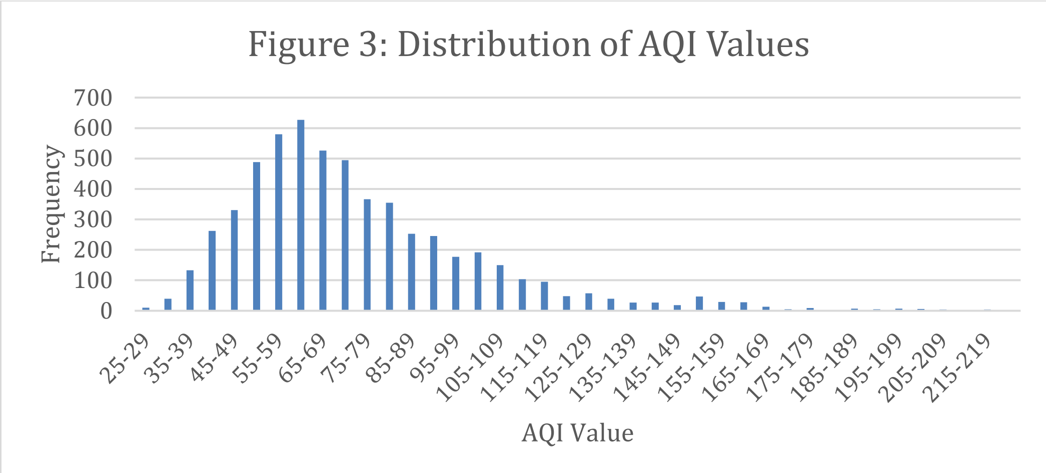


Figure 3 shows a large cluster of AQI values between 50 and 74 and a large right tail. The large tail reveals that there are a few days with AQI values that are much higher than most days.

4. Empirical Method

To test the influence of AQI values on public transportation usage, I have constructed a model to estimate ridership based on air quality, and local weather conditions. The following equation is the most simplified, and generalizable version of my model.

$$(1)\ Ridership_t = \alpha_t + \beta_t(Air\ Quality_t) + \gamma_{jt}W_{jt} + \varepsilon_t$$

$Ridership$ represents daily rail, bus, and total CTA ridership. I will estimate a model for all three dependent variables to observe any variation in patterns by transit type. $Air\ Quality$ is simply the daily AQI value, and W is a vector representing four different weather variables. After reviewing the data and exploring possible limitations of the model, I developed a more nuanced model to capture some of the potentially confounding factors influencing ridership.

$$(2)\ Ridership_t = \alpha_t + \beta_{1t}(Air\ Quality_t) + \beta_{2t}(Air\ Quality_{t-1}) + \delta_t(Ridership_{t-1}) + \gamma_{jt}W_{jt} + \mu_{it}Day\ Type_{it} + \eta_{it}Pollutant_{it} + \varepsilon_t$$

All variables are indexed by t which denotes time, meaning daily observations. I added lagged variables, $t-1$, representing the previous day's air quality and ridership to include any residual effect of poor air quality from the previous day, and any potential serial correlation in ridership. I also include fixed effects of day type and main pollutant, which are indexed by j and i respectively, to see if there are reactions to poor air quality due to differences across these categorical variables. The day type fixed effects will tell us if people in the Chicago area react differently to poor air quality on weekdays, Saturdays, or Sundays/Holidays. The pollutant fixed effects should tell us if people adjust behavior differently according to which of the five monitored pollutants is the day's leading pollutant.

Table 4: Regression Estimates

	Model 1	Model 2	Model 3
	Rail	Bus	Total
Air Quality			
AQI Value	-315.8283***	273.8805***	-92.55308
Lagged AQI Value	-552.6075***	-130.6186***	-704.3285***
Lagged Ridership	0.2672529***	.1819257***	.1670533***
Weather			
Precipitation	-20487.13***	-37864.05***	-58731.15***
Snow	-5326.494***	-9978.047***	-16071.65***
Snow Depth	2362.584***	-3638.818***	107.9022
Average Temperature	1299.294***	713.6504***	2229.176***
Fixed Effects			
Day Type (relative to Saturday)			
Weekday	296122.7***	361275.2***	647611.1***
Sunday/Holiday	-39924.38***	-128012.6***	-200302.1***
Fixed Effects			
Main Pollutant (relative to NO2)			
Ozone	25578.84***	-42767.98***	-15242.79**
PM10	39039.83***	-37896.43***	7996.711
PM2.5	20681.22***	-22730.21***	1616.349
SO2	-4513.892	-11809.24***	-16558.89***
Adj R-Squared	0.875	0.8837	0.9095

Note: ***, ** and * indicate statistical significance at the 99%, 95% and 90% levels, respectively.

The results of my regression estimates are reproduced in Table 4. All models' adjusted R^2 are above .8622, meaning the models explain at least 86.22% of the variation in transportation ridership. Interestingly, my estimates for the primary coefficient of interest, the daily air quality, vary greatly across the three models. The bus model coefficient estimate matches my hypothesis of a positive coefficient, while the rail model produces a negative coefficient. The results are statistically significant at a 1% level of confidence. The total ridership coefficient for air quality was not statistically significant. This is a very surprising result and warrants further research. The results for lagged AQI Value are a little more consistent. The rail and total models both produce statistically significant negative estimates. The estimate for the bus model was not statistically significant. Estimates for the lagged ridership coefficient are consistently positive, showing some evidence ridership is serially correlated.

The local weather variables behave as expected. Estimates for precipitation, snowfall and average temperature all represent the hypothesized sign. One weather variable, snow depth, has differential effects for bus and rail, and an ambiguous effect on total ridership. Weekend fixed effects behave as expected, displaying higher ridership on weekdays than Saturdays, and lower ridership on Sundays or Holidays. These relationships were obvious, and along with the large adjusted R-squared value for all models, prove that the models are capable of predicting ridership if the proper variables are used.

The fixed effects of the main pollutant are difficult to interpret. Relative to NO_2, the bus model predicts a decrease in ridership for all four other main pollutants. These effects hold for Ozone and SO_2 in the total ridership model, but do not hold for PM10 or PM2.5. Meanwhile, the rail ridership model predicts positive coefficients for Ozone, PM10 and PM2.5. The discrepancies between the bus and rail models, and uncertain theoretical mechanisms, make it difficult to make generalizable statements about the effect of each pollutant on transportation decisions.

Following my first round of regression estimates, I was interested in how responses to daily AQI values might vary based on the type of day. Because of the difficulty in interpreting the significance of the main pollutant fixed effects, I decided to drop them from the regressions testing the interaction between AQI value and day type. I also dropped lagged ridership, due to econometric considerations. My refined regression model is reproduced below.

$$(3)\ Ridership_t = \alpha_t + \beta_{1t}(Air\ Quality_t) + \beta_{2t}(Air\ Quality_{t-1}) + \omega_{it}(Air\ Quality_t * Day\ Type_{it}) + \mu_{it} Day\ Type_{it} + \gamma_{jt} W_{jt} + \varepsilon_t$$

The new term $Air\ Quality_t * Day\ Type_{it}$ represents the interaction between daily air quality, and binary variables which represent the type of day, either a weekday, Saturday, or Sunday and Holiday. The day type variables are indexed by i across time, t. The results of the refined interaction regressions for rail, bus and total ridership are presented in Table 5. The effect of AQI on transportation ridership remains inconsistent for rail and bus systems, producing an ambiguous result for total ridership. The estimates for lagged AQI in the rail and total ridership models are negative, while the bus ridership model produces an insignificant result. The results from these regressions match the results from previous regressions. The three new models also all have an adjusted R^2 larger than .81, suggesting the models lose little explanatory power by reducing some of the independent variables. The new interaction estimates produce interesting results. There appears to be a negative relationship between high daily AQI values and ridership on weekdays in the rail and total system models, relative to Saturdays. Per the estimates, there is no significant difference in the effect of the AQI between Saturdays and Sundays.

Table 5: Refined Regression Estimates

	Model 1	Model 2	Model 3
	Rail	Bus	Total
Air Quality			
AQI Value	-264.3859***	293.1684***	28.7825
Lagged AQI Value	-625.5381***	-33.9388	-659.4769***
Interaction Variables (relative to Saturday)			
AQI Value * Weekday	-361.3146***	-95.65881	-456.9734***
AQI Value * Sunday or Holiday	101.3803	-91.46535	9.91496
Fixed Effects			
Day Type (relative to Saturday)			
Weekday	299963.7***	351331.5***	651295.2***
Sunday/Holiday	-118808.9***	-183859.3***	-302668.2***
Weather			
Precipitation	-21274.3***	-36527.06***	-57801.36***
Snow	-5667.198***	-10511.9***	-16179.09***
Snow Depth	3451.336***	-4026.616***	-575.2799
Average Temperature	1853.159***	591.7011***	2444.86***
Adj R-Squared	0.8133	0.8533	0.8872

Note: ***, ** and * indicate statistical significance at the 99%, 95% and 90% levels, respectively.

The variation in the interaction coefficients might allude to the different types of travel that occurs on weekdays and weekends. I expect that weekday ridership consists of more non-discretionary trips related to commuters who use the CTA to get to work. The estimates of the interaction variables show that an increase in daily AQI values on weekdays results in a reduction of riders of the rail system, and the CTA overall. These results are contrary to my original hypothesis, and encourage further exploration.

5. Conclusion

Although my models produce several statistically significant results, the differences across models confound my original hypothesizes. I predicted that an increase in AQI values would result in an increase in ridership of both modes of public transit, and total ridership. My results show a decrease in rail ridership, an increase in bus ridership, and ambiguous results on total ridership following an increase in the day's AQI value. These results are surprising, and suggest that rail and bus riders make their ridership decisions based on different factors. For instance, if the Chicago's bus system carries a larger share of daily non-discretionary travel than the rail system, than the bus system could be resistant to any effects of air quality on ridership.

Another potential explanation is substitution from rail to bus. Maybe people react to poor air quality by substituting rail for bus transit. There is weak theoretically reasoning behind this hypothesis, particularly because we would expect bus trips would take longer, and present more exposure to poor air quality. Additionally, information about the environmental benefits of bus over rail may encourage substitution on poor air quality days. If the CTA used a more environmental friendly energy source for buses than trains, then people may be more likely to ride buses on poor air quality days to maximize the environmental benefit of riding public transit. Further qualitative and quantitative research about the interrelationship between environmental considerations and public transportation policies and usage could illuminate some of these questions.

In an effort to understand whether the timing of the AQI alerts could cause the observed negative relationship between lagged AQI and ridership, I researched details about the AQI system in Chicago. In the Chicago area, the AQI is calculated by a partnership between the U.S EPA and the state-based Illinois EPA.[20] AQI value forecasts are available two days in advance from the Illinois Partners for Clean Energy, a coalition focused on improving air quality.[21] The fact that AQI information is available in advance, means that consumers may plan

[20] Illinois Partners for Clean Air, "Air Quality Index," Illinois Partners for Clean Air, accessed May 08, 2017, http://www.cleantheair.org/air-quality-information/air-quality-index.
[21] Illinois Partners for Clean Air, "Air Quality Forecasts," Illinois Partners for Clean Air, accessed May 08, 2017, http://www.cleantheair.org/air-quality-information/air-quality-forecasts-and-alerts.

transportation decisions to adjust to air quality. It also limits concerns about endogeneity do to pollution caused by high public transportation usage. In Illinois, specifically the Chicago region, there are several ways that citizens can learn about forecasted air quality: The city of Chicago maintains an Air Quality hotline, Illinois Partners for Clean Energy distributes emails, and local media, like the Chicago Tribune or weather stations, report on days with especially poor air quality.[22] The various methods for distribution air quality information make it difficult to use one proxy, like news stories, to capture public awareness of any one day's air quality.

Generally, my results are insufficient to draw significant insights into the role of air quality in influencing public transportation ridership. My results do show that robust econometric models can be developed to predict public transportation ridership. My results provide some initial evidence of differential effects on the Chicago bus and rail systems. Further research could examine the cause of these effects in Chicago, or test for their existence in the public transportation systems of other cities.

[22] Illinois Partners for Clean Air, "Air Quality Index," Illinois Partners for Clean Air, accessed May 08, 2017, http://www.cleantheair.org/air-quality-information/air-quality-index. According the Chicago Tribune database, the term "air quality alert" appeared in the paper 10 times over my period of interest.

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