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Quantifying Impacts of the COVID-19 Pandemic on Ridership of CTA Rail and Bus Systems in Chicago

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16. Abstract

This study's research team conducted a comprehensive statistical analysis to help transit agencies better understand factors that may have contributed to transit ridership loss and the extent of its impacts. Building off ICT-IDOT project R27-SP45, they developed a series of statistical models for the Chicago Transit Authority's rail and bus systems. Data-driven analysis of the COVID-19 pandemic's impacts on CTA bus and rail ridership can help the Illinois Department of Transportation and Regional Transportation Authority, as well as other transit agencies, make policy decisions on planning resources and services during and after the pandemic. This study's research team observed that most of the identified pandemic and socioeconomic factors, especially work occupancy rates, vaccination rates, discount programs, and crime rates, have affected over 80 to 90 percent of all CTA rail stations and bus lines. It is also observed that different population groups may react differently to policy decisions. The fare discount program, for example, may be most successful in attracting transit trips from the employed population in the health and retail industries. In particular, the temporal and spatial analyses show that work occupancy rates are crucial to answering most of the ridership loss at all of CTA's bus lines and rail stations because workplace commute trips have driven a large proportion of CTA ridership. Therefore, transit ridership recovery may depend on individual industries' remote work policies rather than city-wide quarantine executive orders. This could further suggest that transit agencies may need to collaborate closely with specific industry sectors to expedite the recovery of public transit ridership.

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EXECUTIVE SUMMARY

Overview

This study's research team statistically analyzed the latest ridership fluctuations on the Chicago Transit Authority's (CTA's) rail and bus systems (up to May 31, 2022) to gather insights into how the COVID-19 pandemic continues to affect transit ridership's trends. The Chicago Transit Authority, Regional Transportation Authority (its parent organization), and other agencies can use this information to help with their strategic decision-making about what transit services they may provide in the future.

The research team first reviewed qualitative and quantitative research findings on travel demand and behavioral changes during the COVID-19 pandemic between mid-2021 and late 2022. Their previous Illinois Department of Transportation and Illinois Center for Transportation study on how this pandemic affected transit ridership with particular emphasis on CTA's rail system (R27-SP45) was published in August 2021. This study picks up on the literature review where the previous one left off. The research team determined that crime rates, discount ride programs, gas prices, unemployment rates, vaccination rates, and workplace occupancy rates have affected transit ridership.

Next, they collected data for each of these factors, entered it into their information database, developed new statistical models that accounted for each of these factors, and ran the models to generate data on the effects each of these factors had on CTA's bus and rail ridership. The revised statistical model, based on the statistical analysis framework from project R27-SP45, integrated a Bayesian structural time-series model, a regression model for temporal ridership variations, and an ordinary least square regression module to explain spatial disparities of transit losses.

Literature Review

The literature review revealed that executive orders and work-from-home policies were the most significant factors behind ridership loss in the pandemic's first year. Evidence from major U.S. cities implied that the magnitude and speed of ridership loss and ridership recovery were spatially heterogeneous. This finding was closely related to the population's sociodemographic features, such as age, employment status, race, sex, and vehicle ownership. The literature also frequently mentioned risk perception to the COVID-19 virus and crime as impediments for people using transit.

Studies looking into ridership on ridesharing and bikesharing during this pandemic documented how these modes also plummeted at the beginning of this pandemic. The two modes had observed spatial disparities in ridership reduction and recovery trends, which suggests that service providers should consider spatial heterogeneity when adjusting their services to facilitate the recovery process.

Several studies after 2021 noted new factors that may have affected transit ridership's recovery, including COVID-19 variant outbreaks, vaccination adoption, and the trend of work-from-home adoptions.

Statistical Models

Building upon the findings from the literature review, the research team expanded and extended the modeling efforts of project R27-SP45 by (i) collecting more comprehensive data to explore the potential factors behind ridership variations and (ii) updating statistical analysis to quantify the latest ridership trends of CTA bus and rail systems. The research team collected and processed a series of explanatory variables, including crime rates, CTA fare promotion programs, cumulative counts of fully vaccinated individuals per day, daily COVID-19 cases, daily workplace occupancy data, monthly unemployment rates, stay-at-home orders, and weekly gas prices in the CTA service area. A preliminary analysis showed that the temporal ridership trend is closely correlated with the temporal trend of these factors.

To develop the Bayesian structural time-series model, the research team examined historical ridership data on the CTA rail system and bus network between January 1, 2001, and March 1, 2020, to estimate long-term ridership trends, monthly and weekly seasonal effects on ridership, holiday effects on ridership, and other explicit factors. Using this data, they predicted counterfactual ridership for each CTA rail station and bus route between March 1, 2020, and May 31, 2022. This forecast showed what ridership would have been if the COVID-19 pandemic never broke out. It provided a basis for comparison with actual CTA rail and bus ridership data; the difference between the two forecasts was the effect of the COVID-19 pandemic on CTA rail and bus ridership during this time.

The research team then turned their attention to how the aforementioned factors caused temporary changes to CTA's rail and bus ridership (temporal effects). This would allow them to determine the duration and impact of each of these effects. The research team tested different statistical models and chose a linear regression model because of its accuracy, simplicity, and interpretability.

Finally, the research team input each of the key factors from the temporal regression analysis into a spatial ordinary least square regression model to analyze the correlation between the impacts of temporal factors on ridership and the sociodemographic and land-use characteristics for each neighborhood in CTA's service area. The output from this model showed who was taking (or not taking) CTA's rail or bus service and in which neighborhoods they were living.

Conclusions

This temporal analysis showed that pandemic-related factors and socioeconomic characteristics explained why most of the observed ridership decreased at 80% to 90% of CTA rail stations and bus lines. The most influential factor in explaining ridership loss was workplace occupancy, which was statistically significant at all CTA rail stations and bus lines. The spatial analysis showed that this part of ridership loss was particularly correlated with people younger than 40 years old and the proportion of the black population within a neighborhood.

Vaccines and fare discount programs have effectively helped CTA recover some of their rail and bus ridership. By May 2022, vaccinations seemed to have helped CTA recover approximately 8% of their transit ridership, on average, likely by building an increased sense of safety. The discount program was found to be effective in recovering approximately 5% to 7% of CTA's ridership, on average. Essential workers from the health and retail industries were positively correlated with ridership recovery from discount programs. In contrast, crime rates were significantly correlated to ridership loss, especially for those older than 24 years.

On the policy implications, the very strong influence of workplace occupancy on ridership may indicate that decreased commuting trips have primarily driven CTA ridership loss. Further ridership recovery will likely depend on industries' remote-work policies. This implication is also evidenced by the current observation that, even though COVID-19 restrictions have been lifted and approximately 70% of the population has been vaccinated, transit ridership is still about half of the pre-pandemic level. The strong influence of workplace occupancy on ridership may further motivate transit agencies to collaborate with the private sector on developing adequate policy strategies; this was also suggested based on previous findings from R27-SP45 (Liu et al., 2021, Osorio et al., 2022).

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CHAPTER 1: INTRODUCTION

As the COVID-19 pandemic continues to evolve after three major outbreaks in the U.S., many questions remain about its long-term consequences on travel demand. Various regulatory strategies (e.g., mask mandates for indoor activities, remote study/work, sanitation protocols for public services, social distancing, and stay-at-home executive orders) and perceived risk of infection from shared vehicles have altered people's travel needs and mode choice behaviors after the first major outbreak in March 2020. This has led to significant and prevailing public transit ridership reductions (Hu & Chen, 2020; Liu et al., 2021). Transit agencies, as well as other policymakers, therefore need to better understand the factors that have contributed to transit ridership loss and the extent of their impacts. Transit agencies and other policymakers can then anticipate demand and plan services long-term.

Major U.S. cities likely suffered the sharpest decreases in transit ridership worldwide, ranging from 65% to 90% reductions within the pandemic's first few months (Hu & Chen, 2020; Gao et al., 2020; Wilbur et al., 2020). Significant ridership losses have prevailed even after one year of the pandemic in major U.S. cities such as New York City, San Francisco, and Chicago (Penney, 2021; City of San Francisco, 2022; RTAMS, 2022). Approximately 45% of full-time employees in the U.S. worked from home by September 2021, and 91% of these workers responded in a survey that they hope their ability to work at home will remain after the pandemic (Saad & Wigert, 2022).

These ridership losses vary spatially among different neighborhoods as well as sociodemographically. Studies typically show that lower-income people, less-educated people, and minority groups experienced the least changes in their travel behaviors in the U.S. (Bliss et al., 2020; Brough et al., 2020; Garza et al., 2020; Sy et al., 2020; Transit 2020; Wilbur et al., 2020; Hu et al., 2021; Tirachini et al., 2020; Liu et al., 2020; Mclaren, 2020; Fissinger, 2020; Hu & Chen, 2021; Liu et al., 2021). Their jobs were more likely to be "in-person" as parts of society's "essential" functions, and, thus, these population groups had less options for flexible work and mode choices (Kantamneni, 2020).

In November 2020, the Illinois Department of Transportation (IDOT) and the Regional Transportation Authority (RTA) funded a six-month project, R27-SP45, through the Illinois Center for Transportation. The research team examined (i) previous disruptive events such as epidemics, pandemics, and terrorist attacks to draw insights into the current COVID-19 pandemic and (ii) the impacts of the COVID-19 pandemic on Chicago Transit Authority (CTA) rail ridership by developing a statistical model based on findings from previous events (Liu et al., 2021). The research team found that all epidemics in recent decades led to drastic ridership reductions on public transit during the outbreak, possibly due to fear-induced travel avoidance behaviors, reduced commercial activities, executive orders, and diminished commuting needs. These effects were mostly short-term (i.e., lasting less than six months).

The research team used available data on CTA's rail ridership up to March 2021 to develop a statistical model to determine how the COVID-19 pandemic impacted the CTA rail system. Their analysis showed that people's fear of COVID-19; federal, state, and local policies; and stay-at-home executive orders were the primary drivers of the CTA rail system's ridership losses (and possibly recovery) (Liu et al., 2021). RTA has used this study's results to inform strategic planning for their three service operators (i.e., CTA, Metra, and Pace) since August 2021 (Macomber, 2022).

Since that study's completion, new transit data became available that reflected the many events and developments regarding COVID-19. IDOT, RTA, their service operators, and the research team, therefore, requested a follow-up study from the Illinois Center for Transportation. The research team updated the research from the previous study, examined the impacts of other COVID-19-related events that occurred after the previous study, focused on COVID-19's impacts on CTA bus and rail ridership, and began finding ridership data for Metra and Pace that they could use to develop statistical models looking at COVID-19's impacts in depth on Metra and Pace's transit systems. They will build these statistical models for Metra and Pace in a subsequent study that IDOT's Office of Intermodal Project Implementation is funding.

Figure 1 shows the daily percentage systemwide ridership change on CTA buses, CTA rail, Metra, and Pace from March 2020 to February 2022 along with the daily reported COVID-19 cases in northeastern Illinois. It shows pandemic events continuing to affect these transit systems. Figure 1 also shows a consistent recovery period for all modes from around April 2021 to October 2021, probably since vaccine distribution and use made people feel more comfortable traveling. In January 2022, people significantly changed their travel behavior again after the Omicron variant caused very high surges in new COVID-19 cases. Liu et al. (2021) showed that people's fear of getting a COVID-19 infection affected people's travel choices. This may explain why peaks in the number of COVID-19 cases have agreed with times of lower ridership numbers.

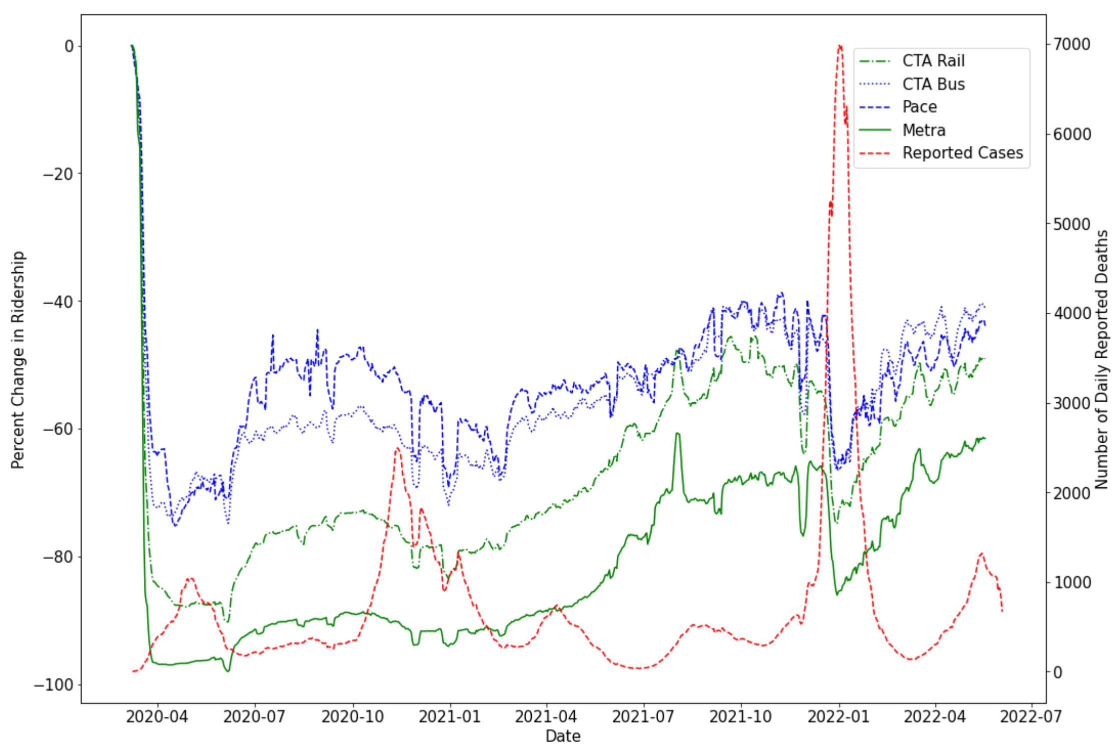

Figure 1. Graph. Daily reported COVID-19 cases and the percentage change in systemwide ridership by mode from March 2020 to July 2022 (as compared to pre-pandemic ridership levels on March 1, 2020).

A survey in the Chicago metropolitan area also showed that over 93% of Chicago travelers considered transit to be a medium- to extremely high-risk activity (Shamshiripour et al., 2020). In June 2022, CTA introduced discount fares to try to persuade people to overcome this fear and return to CTA's rail and bus systems (CTA, 2022). In the next section, the research team explore the impacts of a series of factors, including COVID-19 cases, cumulative vaccinated individuals, stay-at-home orders, crime counts, gas prices, workplace occupancy, unemployment rate, and fare discount, on CTA's bus and rail ridership.

With the updated CTA bus and rail ridership data, the research team developed a series of state-of-the-art Bayesian structural time series (BSTS) models to generate counterfactual ridership and regression models to quantify ridership temporal variations, given more recent factors such as CTA discount programs, new Centers for Disease Control and Prevention (CDC) recommendations, the Omicron variant's breakout period, and vaccine distribution and use. They also developed spatial regression models to quantify the relationship between ridership loss and the region's sociodemographic characteristics.

This report is organized as follows. Chapter 2 focuses on the most recent literature review of relevant studies on public transportation ridership and COVID-19 in the Chicago Metropolitan Area. Chapter 3 describes the data collection, data process, and preliminary data analysis. Chapter 4 presents the statistical modeling framework that the research team developed for this study. Then, Chapter 5 presents the results for the CTA rail and bus networks. Chapter 6 provides concluding remarks.

CHAPTER 2: LITERATURE REVIEW

In their previous study, project R27-SP45, the research team extensively reviewed literature on the impacts of terrorism, epidemics, and pandemics on transit ridership up to early 2020. They continue this literature review focusing on COVID-19's impacts on transit ridership and the implications for Chicago since that time.

Hu and Chen (2021) studied ridership decline on CTA's rail system in Chicago for the pandemic's first 1.5 months (up to April 30, 2020). They used a Bayesian structural time-series (BSTS) model to produce counterfactual ridership numbers and a partial least squares (PLS) regression model to evaluate sociodemographic factors and land-use characteristics that may have explained this decline. Hu and Chen (2021) found that sociodemographic characteristics, level of education, and household income were significantly correlated with transit ridership during the study period. Their findings agree with several studies conducted for other cities in the U.S. (Brough, 2020; Sy, 2020; Wilbur, 2020; Liu, 2020).

Fissinger (2020) studied travel behavior among Chicago travelers before and during the current pandemic. This study used daily account-based data from Ventra's fare payment system to study each individual rider's trips (as opposed to aggregated numbers of riders). It found that ridership changes were highly heterogeneous among two identified groups of riders: (i) "high range frequent peak rail riders," primarily higher-income, and mostly Caucasian, individuals from Chicago's north side and (ii) "high range frequent off-peak bus riders," mostly from Chicago's south side. The trip number declined 80% for the former group during the pandemic's first few months, but only 33% for the latter group. Spatial regression analysis also showed that transit pass holders had contributed relatively higher ridership during the pandemic, most likely due to their dependence on transit services. This study also found a significant racial disparity, showing that black and Spanish-speaking residents were more likely to remain transit riders.

Osorio et al. (2022) used data from both CTA bus and rail systems to determine whether public fear or policy decisions (such as stay-at-home and remote-work orders) primarily drove ridership losses during the pandemic's first year. They implemented a Bayesian structural time-series (BSTS) model to forecast counterfactual ridership and then applied a dynamics model and ordinary least squares (OLS) regression to explain temporal and spatial variations of ridership losses. They found that 50% to 60% of ridership losses in the first year can be attributed to executive orders. Pandemic-related fear accounted for 18% to 21% of ridership losses in the pandemic's beginning, but its effects had diminished over time likely due to caution fatigue. By the end of the pandemic's first year, fear-based ridership loss decreased 1% to 3%. This finding shows the significance of travel loss due to policy factors and a need for proactive campaigns from service providers to boost ridership recovery.

Meredith-Karam et al. (2021) explored the relationship between ride-hailing trips and public transit trips in Chicago. They categorized transportation network company (TNC) trips into substitutive, complementary, or independent trips with respect to public transit. Substitutive ride-hailing trips replaced public transit trips when public transit would have provided comparable travel times. Complementary ride-hailing trips provided first-/last-mile connections to transit. Independent ride-hailing trips did not have comparable public transit trips to the rider's origins or destinations, or both. Meredith-Karam et al. (2021) evaluated the correlations between sociodemographic/network characteristics and changes in the proportion of trip types before (from January 28, 2020) and during the pandemic up to June 2, 2020. They used an ordinary least squares (OLS) regression model, a fractional regression model, a spatial lag model, and a spatial error model. They found that approximately 5% or less of TNC trips complemented public transit trips, approximately 45% to 50% of these trips potentially substituted for public transit trips, and 48% to 53% of these trips were independent of public transit. After the COVID-19 pandemic occurred, the volume of TNC trips went down approximately 92% in March 2020. The TNC trips increased gradually to approximately a quarter of the pre-pandemic volume by June 2020. Meredith-Karam et al. (2021) also found that the number of substitutive trips proportionally decreased to that of transit-independent trips, likely given less work-based trips during rush hours.

Yang et al. (2022) explored the change in Divvy ridership given the current pandemic up to April 15, 2020. Divvy is the bike-sharing system in Chicago. Yang et al. (2022) implemented a geographically weighted regression to evaluate the relationship between "5D" built environment variables (i.e., density, design, diversity, distance, and destination accessibility) and bike-sharing ridership. They found that total bike-sharing ridership declined by approximately half during the pandemic. Built environment variables significantly affected pandemic spatial demand patterns. Some other "5D" variables, such as education level, entertainment availability, office employment densities, distance to subway, and accessibility of working-age population, were negatively correlated with Divvy ridership during the pandemic. Household density, COVID-19 cases, and percentage of households with no vehicles, however, were positively correlated.

Yang et al. (2022) suggested that bike-sharing services should consider new emerging post-pandemic spatial patterns to adjust capacity, station location, and rebalancing strategies to potentially improve bike-sharing services. However, researchers from other studies have shown that bike-sharing overall is a very resilient transportation mode compared to other modes. Its ridership showed the highest recovery rate after its initial decline when compared to transit, walking, and driving a private vehicle (Padmanabhan et al., 2021; Hu et al., 2021).

More recently, Lei and Ukkusuri (2022) studied the correlation between COVID-19-related factors such as government policies, number of cases, and vaccination rates and ridership of on-demand mobility services (i.e., ride-hailing, bike-sharing, and taxi services) in New York and Chicago. Lei and Ukkusuri (2022) used a Bayesian structured time-sequence model to estimate regression coefficients and inclusion probabilities for all time-varying factors. They found that the state of emergency declaration and stay-at-home policies in 2020 were the most impactful factors related to ridership of on-demand services. This result conforms with those found for CTA rail and bus modes (Liu et al., 2021; Osorio et al., 2022). They also concluded that on-demand ridership generally does not bounce back quickly. Instead, ridership recovery speed is highly heterogeneous across cities. Lei and Ukkusuri (2022) noted that this study also highlighted the need for on-demand service providers to consider evolving demand patterns during the pandemic recovery to avoid unsatisfactory service performance.

Researchers also observed reductions in the supply of transportation services (e.g., due to staff shortages in transit agencies) during the COVID-19 pandemic, which had reduced transportation accessibility and ridership. Hegde et al. (2022) studied the attrition of ride-hailing drivers during the pandemic. By analyzing the number of drivers who were willing to accept rides during 2020, they found a sharp 71.6% decrease in the number of drivers in April 2020 as compared to March 2020. The lower driver supply also closely mirrored the number of COVID-19 cases in the City of Chicago. Hegde et al. (2022) used survival analysis to measure a driver's dropout rate for those newly joining ride-hailing services during the pandemic. Only 20% of these newly joined drivers stayed with their ride-hailing service after six months and only 4% after 11 months. These numbers showed significant decreases compared to driver retention rates of 30% and 16%, respectively, before the pandemic.

Kar et al. (2022) investigated decreased accessibility to essential services given transit service cuts during the COVID-19 pandemic in 22 U.S. cities (including Chicago) using publicly available General Transit Feed Specification data. They found that census tract block groups with socioeconomic disadvantages were significantly more likely to lose accessibility to essential services. These census tract block groups typically had high poverty rates, large minority populations, or low vehicle ownership. Block groups with two or more of these characteristics had even higher probabilities of losing accessibility. Fortunately, thanks to the continued service of Chicago's public transportation systems, Kar et al. (2022) found that approximately two block groups lost accessibility during the pandemic's lockdown phases.

Other studies have conducted surveys to understand how the population's risk perception and individuals' socioeconomic factors contributed to ridership loss in Chicago. Shamshiripour et al. (2020) conducted a survey from April to August 2020 with questions on perceived risk levels on various transportation modes. They showed that people perceived personal vehicles and private bicycles as lowest-risk modes, while 93% perceived transit, taxi, and ride-hailing as medium- to extremely high-risk modes during the COVID-19 pandemic.

Soria et al. (2022) surveyed transit riders from November to December 2020 and again from January to February 2021. They sought to examine how factors including sociodemographic, employment, transportation-related, and investment allocation variables affected transit riders in Chicago. Soria et al. (2022) found that the following factors most influenced lapsed riders: the ability to telework during the majority of the week, being unemployed, and owning private cars in the household. Lapsed riders were those people who used transit more than once a week before the pandemic but less than one day a week during the pandemic. They also showed that minority riders were less likely to reduce their transit trips but were also less likely to return to transit once they shifted to other modes. The pandemic's disproportional impact on Chicago's minority communities could have caused this reluctance. Sanitation, safety, social distancing, and ventilation were among the top concerns among minority riders. This is similar to nationwide survey results, which showed that Hispanic or Latinx, females, and nonbinary genderqueer riders were more likely to cite harassment concerns as the reason for reducing their transit use (He et al., 2022).

Cities across the U.S. and around the world have struggled to recover from abrupt changes in daily activities that the pandemic has caused. Calderón Peralvo et al. (2022) reviewed 130 articles related to COVID-19 transport policies and mitigation strategies worldwide. Numerous social factors and policy regulations continue to emerge and require further study; examples include new transit service cuts (Kar et al., 2022), vaccination adoption rates (Mashrur et al., 2022), new COVID-19 variant rates (Liu et al., 2022), fare discount programs, and long-term remote work policies (Saad & Wigert, 2021). Trends from past decades show that recent gas price increases will likely cause ridership fluctuations (Erhartd et al., 2022).

Researchers have also cast insights on the recovery process once the pandemic ends. Hsieh and Hsia (2022) studied how early post-pandemic policy decisions could affect ridership and found that promotion programs may not need to focus on loyal transit users. They also suggested that recent on-going mask mandates in Taiwan have helped boost ridership, even when COVID-19 transmission rates were relatively low. This suggests that people's fear may still prevail when the pandemic slows down and may explain why the third wave of the Omicron variant caused significant ridership losses in early 2022 (e.g., see Figure 1) despite caution fatigue, lack of travel restrictions, presence of discount programs, and vaccine rollouts. Kiriazes and Edison (2022) found a similar result. They performed a survey in Atlanta from October to November 2020, which showed that approximately 40% of respondents did not feel comfortable using transit even if vaccines were available to the public. This closely agrees with the ridership numbers observed in Chicago since 2021—as of September 2022, ridership across all public transportation modes remain close to about 60% of pre-pandemic levels. However, people's risk perception may have also been influenced by the magnitude of the third wave of the COVID-19 outbreak in January 2022, because the pandemic reached an all-time high of over 12,000 cases per day in Chicago (more than double the second wave in November 2020) (New York Times, 2022).

Although the pandemic's evolution has been slowing down after January 2022, there are still many open questions about the effects of emerging behavior trends, the efficacy of new regulatory policies, and transit users' perceived risk of infection. This study's research team, therefore, considered fear levels about taking CTA trains and buses throughout the pandemic and the effects of new factors such as crime rates, gas prices, vaccine distributions, and workplace occupancy rates to better inform decision makers and to expand the knowledge of the COVID-19 pandemic's long-term effects on transit ridership in a broader context.

CHAPTER 3: DATA COLLECTION AND PROCESSING

This project focuses on transit ridership patterns over time and space in the Chicago Transit Authority's bus and rail systems. CTA has intentionally kept its service frequency and coverage unchanged during the pandemic (DeWeese et al., 2020). Any transit service adjustments thus were too minor to have caused more than negligible ridership losses.

Pandemic-related factors (e.g., COVID-19 rates, stay-at-home orders, and vaccine use rates), and socioeconomic changes during the pandemic (e.g., crime rates, fluctuating unemployment rates, spiking gas prices, and work-from-home trends) could be the major reasons behind ridership losses on CTA's rail system and bus network. Below is a list of collected pandemic- and ridership-related data types and sources.

- The research team extracted ridership data for CTA's rail and bus systems from the Chicago Data Portal (CTA, 2022) for a 21.5-year period from January 1, 2000, to May 31, 2022. They also collected city-level ridership data for CTA rail and bus systems from March 1, 2020, to September 17, 2022, from the Regional Transportation Authority Mapping Statistics database (RTAMS, 2022). CTA collected their rail ridership data at the station entrances, while they collected their bus ridership data as daily boardings per bus line.

- The research team obtained COVID-19 related data, including daily cases and cumulative number of completed vaccine series, from the Chicago Data Portal (City of Chicago, 2022a). They obtained detailed information about stay-at-home orders from the City of Chicago's website (2022b). According to this website, two stay-at-home orders officially took place, one from March 26, 2020, to October 31, 2020, and the other from November 16, 2020, to October 31, 2021.

- Socioeconomic changes since the COVID-19 outbreak, including crime, CTA discount promotion programs, gas prices, and the labor market may directly impact transit ridership. Many businesses were suspended or closed under executive orders (e.g., stay-at-home orders in Chicago) in 2020, resulting in sharp job losses.

- The research team retrieved monthly unemployment rates in Chicago between January 2001 and September 2022 from the U.S. Bureau of Labor Statistics to represent changes in the labor market and further approximated the daily employment rate based on monthly average values.

- Moreover, the widely adopted work-from-home policy significantly reduced commuting needs for people who were working during the pandemic. This policy led to a substantial decline in transit ridership. The research team collected daily workplace occupancy data from Kastle (2022) to capture these effects. Kastle is a consulting company that provides services to improve business offices and enterprises. It estimated the benchmark of normal workplace occupancy based on the average activity level of its clients between February 3, 2020, and February 13, 2020, and then quantified daily weekday workplace occupancy in Chicago as a percentage relative to the benchmark. The research team obtained workplace occupancy data from March 1, 2020, to October 31, 2022, for this analysis.

The workplace occupancy data in major U.S. cities are plotted in Figure 2. Note that the reduction in workplace activities in Houston, Dallas, and Austin displayed different trends as compared to other cities, e.g., with much smaller magnitudes and different peak times. Among the rest of metropolitan areas, Chicago observed a very significant drop in workplace occupancy during the first year (i.e., ranked the third lowest among all considered metropolitan areas). After January 2021, it observed a steady recovery of workplace activities, toward a 19.6% increase by December 2021. This was the sixth highest recovery rate among all 10 cities, following Austin, Houston, New York, Dallas, and Washington, DC. As the Omicron variant hit from December 2021 to January 2022, workplace occupancy plummeted in all major cities in a three-month period. By the end of October 2022, Chicago recovered 25.9% of workplace activities, which was the fourth highest rate following only New York, Washington, DC, and Austin. The current (October 2022) workplace occupancy in Chicago is about 45.4% of the pre-pandemic level, which is the fifth highest level among the major U.S. cities presented in Figure 2.

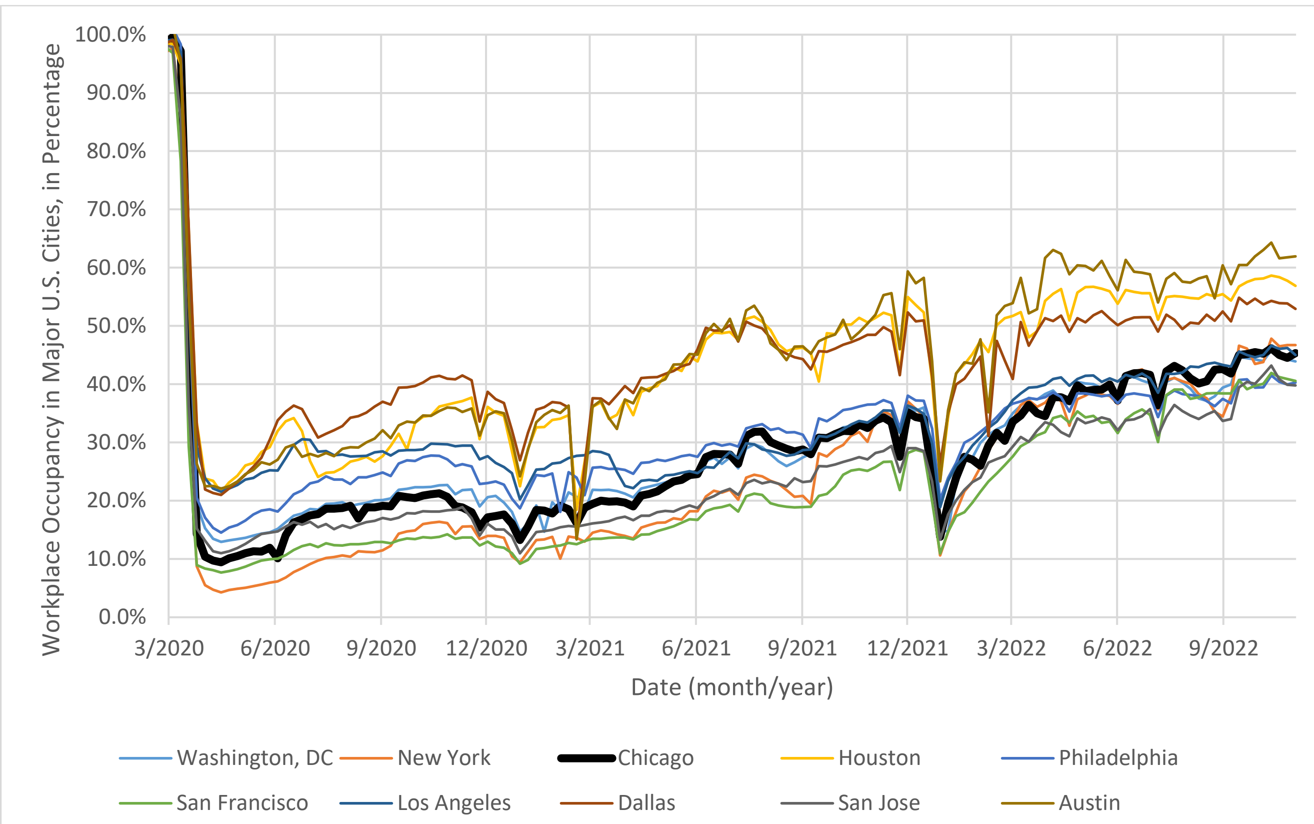

Figure 2. Graph. Percentages of workplace occupancy in major U.S. cities from March 2020 to October 2022 compared to the pre-pandemic level.

While nonwork trips (e.g., recreational and leisure trips) were also impacted during the pandemic given a variety of factors, such as the closure of parks and small businesses, there is a lack of data on the variation of nonwork activities. In this study, the research team considered workplace occupancy data as a proxy of the level of overall activities in Chicago and used linear interpolation to estimate activity levels during weekends and holidays.

- Crime rates spiked during the pandemic and hate crimes were reported on transit systems in many major U.S. cities (Mekouar, 2022; WTTW; 2021; Meyer et al., 2022). These factors may have further discouraged transit use. Hence, the research team retrieved crime incident reports from the Chicago Data Portal (City of Chicago, 2022c). They focused on the daily counts of crimes that might have deterred transit use, such as arson, assault, battery, criminal sexual assault, homicide, intimidation, stalking, and theft. They collected this data for a period between January 1, 2001, to October 31, 2022.

- To counteract transit ridership losses on their rail and bus systems during the pandemic, CTA offered discounts on three types of unlimited-ride programs: reducing the one-day pass price from $10 to $5, the three-day pass from $20 to $15, and the seven-day pass from $28 to $20. These discounts have been effective since May 28, 2021.

- Finally, gas prices surged in 2022, which may have discouraged driving and helped transit systems restore some of their ridership. The research team obtained weekly average prices of regular reformulated retail gasoline from the U.S. Energy Information Administration (EIA, 2022) between June 5, 2001, and October 31, 2022. They used this data as a proxy for daily gas prices in Chicago.

The research team plotted CTA rail and bus ridership from March 1, 2020, to May 31, 2022, in Figures 4 and 5, respectively. They also plotted the temporal trends of pandemic-related factors (e.g., COVID-19 cases and fully vaccinated population) and socioeconomic factors (e.g., workplace occupancy, crimes, gas prices, and unemployment rates) in each of these graphs. The horizontal axis indicates the number of days since March 1, 2020. The research team normalized all of these factors to a relative value between 0 and 1 on the vertical axis for visualization purposes. Let x represent a time-series value in a dataset and $x_{\min}$ and $x_{\max}$ represent this dataset's minimum and maximum values, respectively. The research team plotted this dataset with the following value:

$$x_{\text{plotted}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \qquad (1)$$

Figure 3. Equation. Linear normalization of data for visualization.

CTA rail and bus ridership fell to approximately 20% to 25% of pre-COVID-19 ridership levels on March 16, 2020, when the first stay-at-home order began. Meanwhile, unemployment rates exploded, and crime rates, gas prices, and workplace occupancy rates dropped sharply. CTA rail and bus ridership seemed to slowly bounce back from that time until July 2020. The unemployment rates gradually declined, and crime rates, gas prices, and workplace occupancy rates started to increase, indicating the recovery of people's activities. CTA rail and bus ridership stabilized at approximately 30% of pre-COVID-19 ridership levels between July 2020 to the end of October 2020. It started to decline again from November 2020 to January 2021, when reported COVID-19 cases spiked again. It gradually increased for a few months until the Omicron variant became widespread, and cases spiked in December 2021. CTA bus and rail ridership plummeted at this time, and crime rates, gas prices, and workplace occupancy rates mildly dropped. After December 2021, CTA rail and bus ridership has steadily but gradually recovered. Chicago ride-sharing services, Metra, and Pace also have had similar ridership trends (Fissinger, 2020; Tyler, 2021; Regional Transportation Authority Mapping and Statistics, 2021).

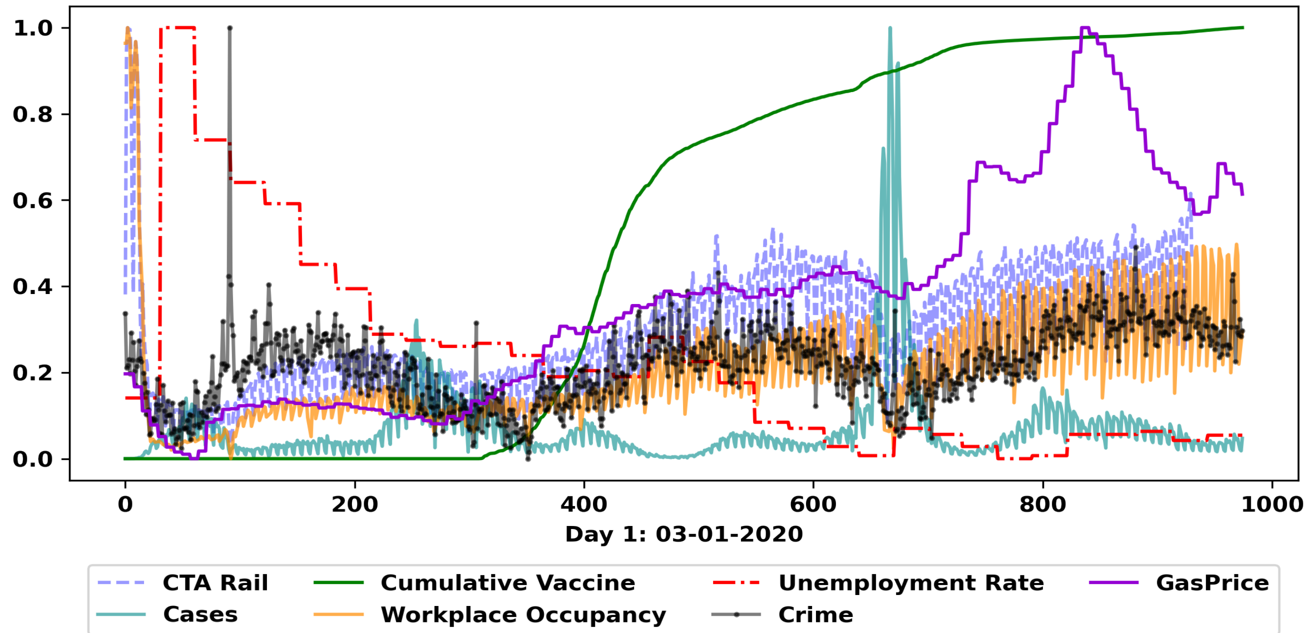

Figure 4. Graph. Normalized time-series plot of CTA rail ridership, pandemic-related factors, and socioeconomic factors.

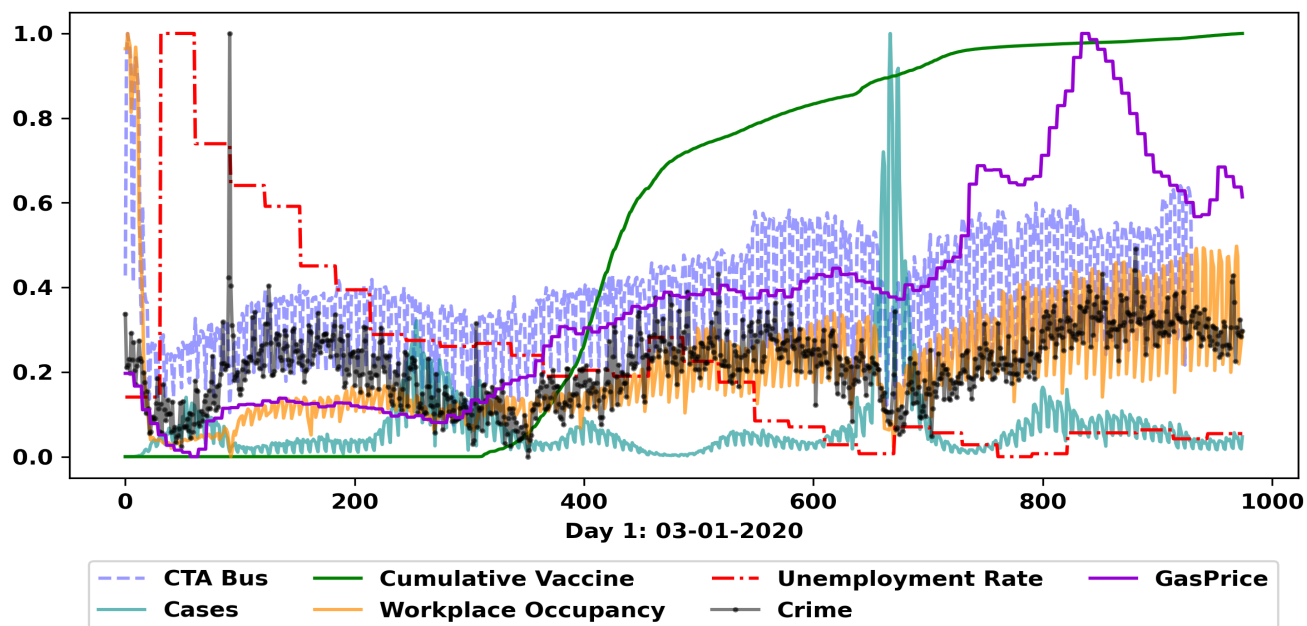

Figure 5. Graph. Normalized time-series plot of CTA bus ridership, pandemic-related factors, and socioeconomic factors.

Building upon project R27-SP45, the research team collected sociodemographic data from the U.S. Census Bureau (2019) and the Chicago Metropolitan Agency for Planning (CMAP, 2015) to address spatial disparity in ridership losses. This information is listed in Table 1. They also calculated the entropy-based land-use mix index (LUM) using raw land-use data to evaluate the degree of mixed land uses in each land parcel. LUM equal to 0 represents a completely homogeneous land-use mixture and LUM equal to 1 represents the maximum land-use mixture (i.e., a parcel that has an equal split for all land-use types) (Cervero & Kockelman, 1997). The equation is as follows:

$$LUM = \begin{cases} -\frac{1}{\log N}\sum_{i=1}^{N} p_i \log p_i \,, & N > 1 \\ 0, & N = 1, \end{cases} \qquad (2)$$

Figure 6. Equation. Linear normalization of data for visualization.

where N is the number of land-use types in a parcel, and p_i is the ratio of land-use type i in this parcel.

In addition, park-to-ride service is available at some CTA rail stations, which could impact transit ridership trends after the outbreak of pandemic. Therefore, the research team collected information on the park-to-ride availability at CTA rail stations from Chicago Transit Authority (CTA, 2022b) and included it into the spatial regression analysis.

Table 1. Socioeconomic and Land-Use Variable Descriptions

Variable	Description	Spatial Unit	Source
prop_male	% of male population	Census Tracts*	US Census Bureau 5-year ACS
prop_age_0_24	% of population between 0 and 24 years old		
prop_age_25_39	% of population between 25 and 39 years old		
prop_age_40_64	% of population between 40 and 64 years old		
prop_white	% of white population		
prop_black	% of black population		
prop_asian	% of Asian population		
prop_edu	% of population with at least a high school degree		
prop_employ	% of population employed		
prop_poverty	% of population under the poverty line		
prop_W_manuf	% of workers with jobs in the manufacturing industry		
prop_W_trade	% of workers with jobs in the wholesale or retail trade industry		
prop_W_edu	% of workers with jobs in the educational service industry		
prop_W_health	% of workers with jobs in the health industry		
prop_LU_residential	% of residential land	Parcel	CMAP
prop_LU_commercial	% of commercial land		
prop_LU_industrial	% of industrial land		
prop_LU_education	% of educational institutional land		
prop_LU_medical	% of medical institutional land		
prop_LU_openspace	% of open space land		

* Proportion of workers counted at workplace locations.

To simultaneously consider ridership temporal variations and spatial trends, the research team assumed that riders always access the closest rail station or bus stop from their origins. Since CTA collected rail ridership data at the station level and bus ridership data at the route level, the research team matched the sociodemographic characteristics of each neighborhood in the CTA service area to each rail station or bus route through the following procedure.

For CTA rail stations, the research team first determined their catchment areas via a Voronoi tessellation (Du et al., 1999). For the outer-most stations, they set a maximum range of five miles to avoid unrealistic catchment area sizes and to account for larger catchment areas that may result from CTA's park-and-ride facilities at peripheral stations. Figure 7 shows the resultant station catchment areas. The research team then spatially joined catchment areas with socioeconomic and land-use data and prorated those layers with population and parcel area, respectively.

For CTA buses, the research team only had route-level bus ridership data. They assumed for simplicity that every bus stop equally contributes to a bus route's ridership and that sociodemographic data from the census tract containing the bus stop represents the sociodemographic characteristics near the bus stop. The research team, therefore, identified each bus route's stops and matched them with its census tracts and corresponding sociodemographic data. They aggregated each bus stop's sociodemographic data at the census tract level for each bus route and used the number of bus stops within each census tract as the weight to obtaining the average sociodemographic characteristics along the bus route.

During this process, the research team excluded all rail stations and bus routes that had missing sociodemographic data, experienced significant service disruptions due to cancellations or reconstruction, or operated less than every weekday. These removals enabled the research team to directly compare the pandemic's impacts on the remaining CTA rail stations and bus routes. Despite these removals, the remaining 139 "L" stations and 62 bus routes still span the entirety of CTA's service area, as shown in Figure 7, ensuring that the analysis covers every neighborhood in the City of Chicago and nearby communities. The summary statistics of sociodemographic data at the rail station level and bus route level are summarized in Table 4 in Appendix A.

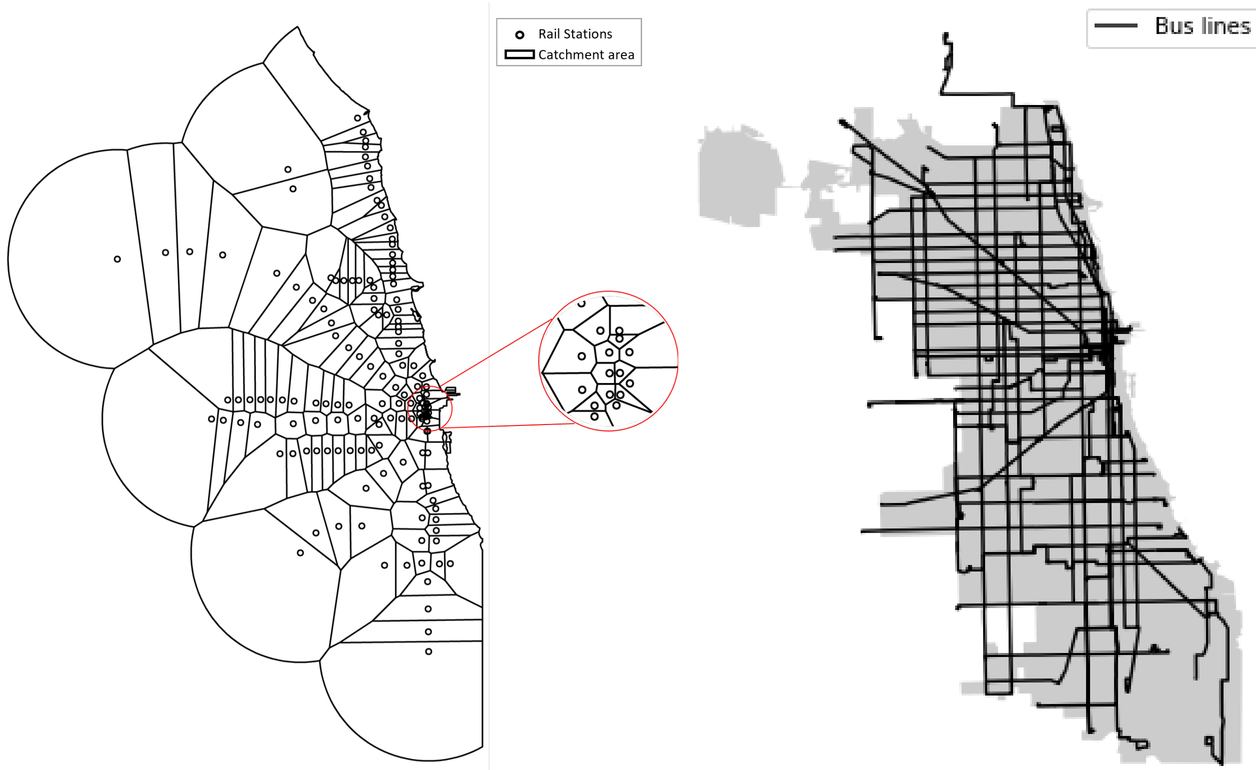

Figure 7. Map. This study's CTA rail station catchment areas and bus routes.

CHAPTER 4: MODELING

To further understand the latest observed temporal variations of transit ridership and to provide insights into the underlying reasons for spatial heterogeneity in ridership losses, the research team extended and modified their analysis from R27-SP45. Their statistical modeling efforts included a sequential statistical modeling framework that integrated the following main components:

i. A Bayesian structural time-series (BSTS) model, which considered the historical trend of transit ridership, seasonality, and holidays to predict counterfactual transit ridership after March 1, 2020.

ii. A linear regression model for temporal analysis, which quantified the temporal variations of each station or bus route's ridership loss with pandemic-related factors (e.g., COVID-19 cases, cumulative counts of fully vaccinated individuals, and stay-at-home executive orders) and socioeconomic changes (e.g., workplace occupancy, unemployment rate, gas price, crime records, and discounts for CTA unlimited passes). The research team predicted explanatory variables and used this model to forecast and observe ridership trends from June 2022 to December 2022.

iii. A linear regression model for spatial analysis, which analyzed the connections between socioeconomic characteristics of census tracts within the CTA service area and the impacts of pandemic-related factors and socioeconomic changes.

Furthermore, these three components in the modeling framework are highly flexible as the prediction and regression models can be adapted to address various data and forecasting needs. Therefore, the models are applicable to other disruptive events in the future that may cause prolonged changes in transit ridership (e.g., pandemics, energy crisis, economic crisis, terrorist attacks) and even other application contexts. For example, the research team can use the approach to analyze the impacts of less disruptive events such as policy changes (e.g., temporary discounts, increased security at stations) or the effects of marketing campaigns to improve transit ridership.

COUNTERFACTUAL RIDERSHIP

The BSTS is an analysis technique that combines feature selection (i.e., the process of selecting relevant input variables) and time-series forecasting (Scott & Varian, 2014). A structural time-series model typically contains three components: a Kalman filtering for long-term trends and seasonal components, a spike-and-slab regression for contemporaneous covariates, and a Bayesian model averaging for the final model selection (Scott & Varian, 2015). Bayesian model averaging is a statistical method that combines multiple models based on their posterior probabilities, allowing for the incorporation of uncertainty and the selection of the most plausible model.

An observation equation that relates the observed time-series variables to a set of latent state variables and a set of state equations that dictate how these latent state variables evolve over time under uncertainties generally define BSTS models. In this study, the research team set up the observation equation of the BSTS model to connect daily ridership, r_t, with a vector of latent variables. These variables included (i) a semi-local linear trend, which is related to the value of trend at time t (denoted as μ_t), the slope of μ_t from time t to $t+1$ (denoted as δ_t), long-term slope of μ_t (denoted as D), and the learning rate of local trend (denoted as ρ, where ρ < 1); (ii) a day-of-week seasonality component, with the s-th element at time t being denoted by $\gamma_{t,s}^{w}$; (iii) a monthly annual seasonality component, with the s-th element at time t being denoted as $\gamma_{t,s}^{m}$; (iv) and contemporaneous x_t with static coefficients β_t, which captures effects of special days such as holidays.

The research team attempted to incorporate external variables into the time-series model, such as crime rates, gas prices, transit fares, and unemployment rates, to capture their impacts when predicting counterfactual ridership. However, the results indicated that the inclusion probabilities of these external variables were very low (even zero) for most rail stations and bus routes. Therefore, the research team did not include these factors in the BSTS model but formulated them into the temporal regression model instead. This model will be introduced in the next section.

The research team also defined a series of error terms to capture the uncertainties, i.e., ϵ_t, $\eta_{\mu,t}$, $\eta_{\delta,t}$, $\eta_{d,t}$ and $\eta_{m,t}$, and they are each assumed to follow a zero-mean Gaussian distribution, but with variances σ_{ϵ}^2, ${\sigma^2}_{\mu,t}$, ${\sigma^2}_{\delta,t}$, ${\sigma^2}_{d,t}$, and ${\sigma^2}_{m,t}$, respectively. The BSTS models for counterfactual ridership prediction are written as follows:

$$r_t = \mu_t + \gamma_t^w + \gamma_t^m + \beta_t^T x_t + \epsilon_t \tag{3}$$

Figure 8. Equation. Bayesian structural time-series observation equation.

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t} \tag{4}$$

Figure 9. Equation. BSTS semi-local linear trend equation.

$$\delta_{t+1} = D + \rho(\delta_t - D) + \eta_{\delta,t} \tag{5}$$

Figure 10. Equation. BSTS semi-local linear trend transition equation.

$$\gamma_{t+1,1}^{w} = -\sum_{s=2}^{7} \gamma_{t,s}^{w} + \eta_{d,t} \tag{6}$$

Figure 11. Equation. BSTS day-of-week seasonality equation.

$$\gamma_{t+1,1}^{m} = -\sum_{s=2}^{12} \gamma_{t,s}^{m} + \eta_{m,t} \tag{7}$$

Figure 12. Equation. BSTS monthly annual seasonality equation.

Where Equation (3) defined the observation equation, Equations (4) and (5) defined the semi-local linear trend, and Equations (6) and (7) defined the weekly and monthly seasonality components, respectively.

To evaluate the BSTS models' performance, the research team first used ridership data from a training set (e.g., those from 2001 to 2018) to train the BSTS models and then predict the ridership data in a test set (e.g., those in 2019) with the trained models. The research team measured the forecasting errors with the weighted mean absolute percentage error (WMAPE) between the actual observation r_t and the predicted counterfactual ridership $\overline{r_t}$, defined as follows:

$$WMAPE = \frac{\sum_{t=1}^{T}|r_t - \overline{r_t}|}{\sum_{t=1}^{T}|r_t|} \tag{8}$$

Figure 13. Equation. Weighted mean absolute error.

The research team focused on station-level ridership at Chicago “L” stations and historical data obtained through the Chicago Open Data Portal (CTA, 2021). Therefore, this study does not include data pertaining to Metra commuter trains or Pace suburban buses. To perform the final model fitting for each “L” station and to obtain counterfactual ridership $\overline{r_t}$ during the pandemic, the research team used the “bsts” (Bayesian structural time series) package in R statistical software (Scott, 2020). In this context, variable r_t denotes observed ridership at time t.

TEMPORAL ANALYSIS

The research team obtained many new types of data on pandemic-related factors that might explain the temporal evolution of transit ridership during the pandemic. The research team categorized data into two groups: (i) pandemic related data, including a cumulative count of fully vaccinated individuals, daily COVID-19 cases, and stay-at-home orders; and (ii) socioeconomic related data, including crime rates, CTA promotional discounts, gas prices, reduction of workplace occupancy rates, and unemployment rates.

In this module, the research team sought to develop statistical models that quantify the temporal variations of transit ridership loss during the pandemic with the aforementioned data. The research team thus implemented and tested a variety of models, including a linear regression model, a logistics regression model, and an expanded dynamics model from R27-SP45 (with newly collected data). They found that the linear regression model delivered the best performance, yielding a good balance among simplicity, interpretability, and accuracy and therefore used it to conduct this temporal analysis to explain ridership fluctuations.

The research team defined $\mathcal{R}$ to denote the set of rail stations and $\mathcal{B}$ to denote the set of bus routes. They used i to index each rail station or bus route and assumed that the study period started on day 0 and ended on day T, i.e., $t \in \{0, 1, \dots, T\}$. The observed and predicted counterfactual ridership of a rail station or bus route i were denoted by r_{it} and $\bar{r}_{it}$, respectively. Let integer variables c_t and v_t denote the number of reported cases on day t and the number of cumulative fully vaccinated people by day t, respectively. Binary variable s_t is equal to 1 if the stay-at-home order is effective on day t. Positive variables u_t, o_t, g_t, and e_t denote the unemployment rate, workplace occupancy reduction, gas price, and crime counts on day t, respectively. Binary variable d_t is equal to 1 if CTA’s discounts on unlimited passes are effective on day t.

The research team hypothesized that on each day t, the observed ridership reduction on each rail station $i \in \mathcal{R}$ or each bus route $i \in \mathcal{B}$, $\overline{r_{it}} - r_{it}$ is produced from the estimated counterfactual ridership (from BSTS). As such, the research team assumed the following form,

$$\overline{r_{it}} - r_{it} = \overline{r_{it}} \cdot f_i(c_t, v_t, s_t, u_t, o_t, g_t, e_t, d_t)\ , \quad \forall t, i \tag{9}$$

Figure 14. Equation. Regression model for temporal analysis.

For simplicity, the research team assumed that the *f*(.) function above takes the following linear specification,

$$\begin{aligned} &f_i(c_t, v_t, s_t, u_t, o_t, g_t, e_t, d_t) \\ &\quad = \alpha_{ic} \cdot c_t + \alpha_{iv} \cdot v_t + \alpha_{is} \cdot s_t + \alpha_{iu} \cdot u_t + \alpha_{io} \cdot o_t + \alpha_{ig} \cdot g_t + \alpha_{ie} \cdot e_t + \alpha_i, \quad \forall t, i \end{aligned} \tag{10}$$

Figure 15. Equation. Formula for linear regression model for temporal analysis.

where α_i is a constant for the station/route i, and α_{ic}, α_{iv}, α_{is}, α_{iu}, α_{io}, α_{ig}, α_{ie}, and α_{id} are the percentage ridership losses of the station/route i associated with each COVID-19 case, each fully vaccinated individual, the stay-at-home order, each unit of unemployment rate, each percentage reduction of workplace occupancy, each unit of gas price, each unit of crime rate, and the presence of a CTA promotional discount. This regression model can be estimated via ordinary least squares (OLS), using the “lm” function in R Studio.

Please note that other popular options for the *f*(.) function include the well-known Cobb-Douglas production form (1928), which contains exponentials or polynomials of the independent variables. Such a model can also be transformed into a linear regression model. Per the preliminary test, the results were very similar, so the research team chose this simpler linear regression form shown above.

The temporal analysis model seeks to not only explain ridership loss on the CTA rail/bus systems, but also forecast ridership evolution in the near future. As explained above, daily ridership loss is estimated as a function of the pandemic- and socioeconomic-related factors as well as the estimated counterfactual ridership. Hence, to predict future ridership on the Chicago Transit Authority’s rail/bus systems, all these independent variables (i.e., inputs to our model) need to be forecasted as well.

In this project, the research team collected available ridership data up to May 2022 (the latest data), and other input factor data up to a different time of 2022. For example, unemployment data was only available up to September 2022, while vaccination data and many other data were available up to the writing of this report in early November 2022. The research team used the latest available data on all input factors, and if recorded data ended earlier than October 31, 2022, then the research team used linear projections into the future based on the trend observed in the last three months of recorded data.

SPATIAL ANALYSIS

The final phase of the models investigates whether each of the modeled temporal effects due to pandemic-related and socioeconomic factors on transit ridership loss vary across geography and sociodemographic groups. The research team set up a series of linear regression models to reveal the relationships between coefficients from the temporal regression model components (i.e., α_{ic}, α_{iv}, α_{is}, α_{iu}, α_{io}, α_{ig}, α_{ie}, and α_{id}), and sociodemographic and land-use characteristics. Let K denote the set of sociodemographic and land-use characteristics as summarized in Table 4 and let k index each characteristic. Let x_{ik} denote the value of characteristic k of a rail station $i \in \mathcal{R}$ or a bus route $i \in \mathcal{B}$. Moreover, they included the squares of sociodemographic and land-use variables in the model to capture potential nonlinear relationships. Therefore, the regression models for spatial analysis are as follows,

$$\alpha_{ij} = \sum_k \left(\theta_{jk}^R \cdot x_{ik} + \theta'^R_{jk} \cdot x_{ik}^2\right), \quad \forall i \in \mathcal{R}, j \in \{c, v, s, u, o, g, e, d\}, k \in K$$
$$\alpha_{ij} = \sum_k \left(\theta_{jk}^B \cdot x_{ik} + \theta'^B_{jk} \cdot x_{ik}^2\right), \quad \forall i \in \mathcal{B}, j \in \{c, v, s, u, o, g, e, d\}, k \in K$$

(11)

Figure 16. Equation. Regression model for spatial analysis.

where α_{ij} is the regression coefficient obtained from the temporal analysis of the station/route i with respect to factor j, and θ_{jk}^R and θ_{jk}^B are the regression coefficients for spatial analysis of rail and bus systems, respectively, between sociodemographic and land-use characteristic k and the percentage ridership loss associated with a type-*j* factor.

Because the spatial analysis involves various observation units (e.g., catchment areas), the research team conducted the Breusch-Pagan test to check for heteroskedasticity for each model, using the R package's "lmtest" function (Zeileis & Hothorn, 2002). Despite that the observation units are spatially heterogeneous in size, the research team observed no strong evidence of heteroskedasticity, probably because the dependent variables in these regression analyses, i.e., $\{\alpha_{ij}\}$, were used in the temporal analysis to estimate percentage ridership losses (which were bounded in value). Hence, the above linear regression model could be directly used for OLS analysis.

Because some of the explanatory variables might not be significant, the analysis required a proper method for model variable selection. For each regression model, the research team started the model with all possible explanatory variables and then considered how deleting a variable affected the Akaike information criterion (AIC) or the Bayesian information criterion (BIC). They conducted a backward search on the explanatory variables under both criteria and selected the model with the smallest leave-one-out cross-validation (LOOCV) root mean square error.

CHAPTER 5: NUMERICAL RESULTS

COUNTERFACTUAL DATA AND TEMPORAL ANALYSIS

The research team developed two sets of BSTS models: one for each CTA rail station and one for each CTA bus route. They fitted these models to 130 valid rail stations and 62 valid bus routes.

Counterfactual Data

The research team evaluated the error of BSTS predictions, by first training BSTS models with CTA rail and bus ridership for the years 2001–2018, using BSTS models to predict 2019 CTA ridership, and then calculating WMAPE. The resulting WMAPE values across all valid CTA rail stations and bus lines were 0.115 and 0.0978, respectively. The vast majority of WMAPE values, as shown in Figure 17, are substantially smaller than 1, indicating very good fits of the BSTS models. The research team also inspected the residuals' Q–Q plots for all CTA rail stations and bus lines. These Q-Q plots generally followed a normal distribution.

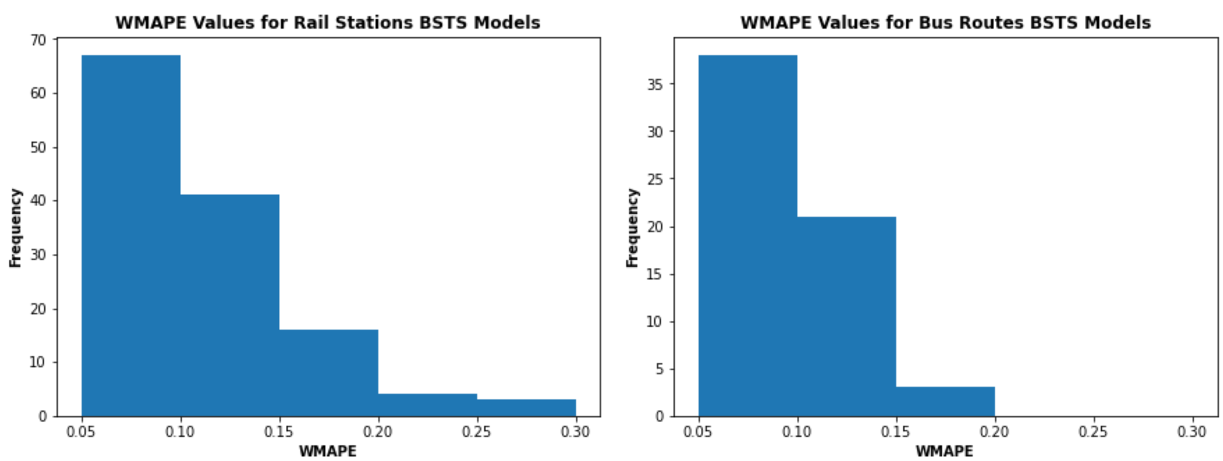

Figure 17. Graph. WMAPE of the BSTS models for all rail stations (left) and bus lines (right).

Temporal Models

Once the research team had developed the BSTS model, they fitted the linear regression models for temporal analysis as respectively shown in equations (9) and (10) for each valid CTA station and bus route. The R^2 values for the linear model fit are shown in Figure 18 and the statistics of the linear model parameters over all valid CTA rail stations and bus routes are shown in Table 2. The histograms in Figure 18 show a very good fit because most of the values are above 0.8 and only seven total models combined fell below 0.7, indicating the models' good explanatory power. The summary statistics in Table 2 help provide a sense of the overall correlations and magnitudes of each parameter's effect on ridership loss across the CTA service area. The table presents the min, max, and mean, as well as the percentage of valid CTA stations or routes for which a parameter was statistically significant with 95% confidence intervals. Additional sample curve fittings from the dynamic model are shown in Figures 19 and 20 for illustrative purposes. Detailed results for each station and route are included in Appendix E.

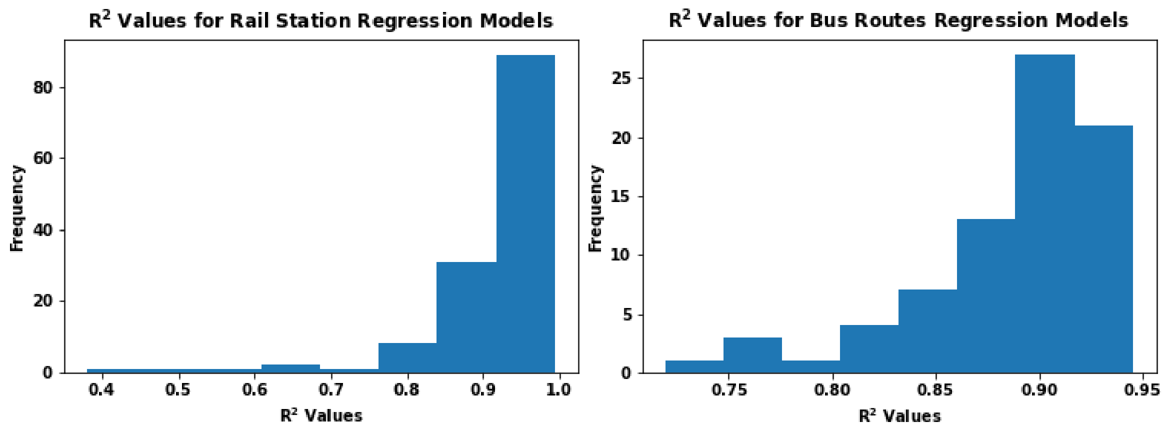

Figure 18. Graphs. R-squared values of linear regression analysis for rail station-level (left) and bus route-level (right) ridership temporal variations.

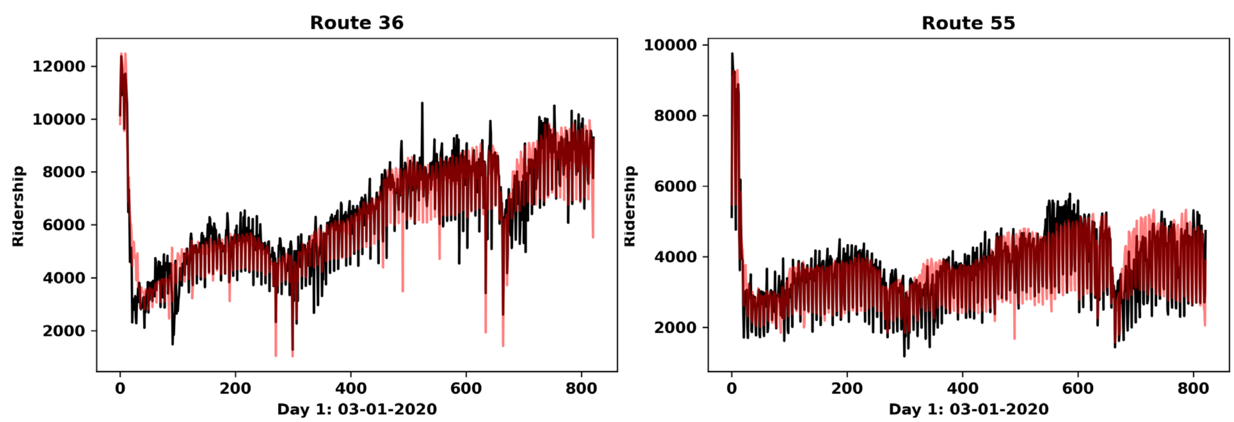

Figure 19. Graphs. 1Examples of temporal regression model fits for CTA bus routes: Routes 36 (Broadway) and 55 (Garfield).

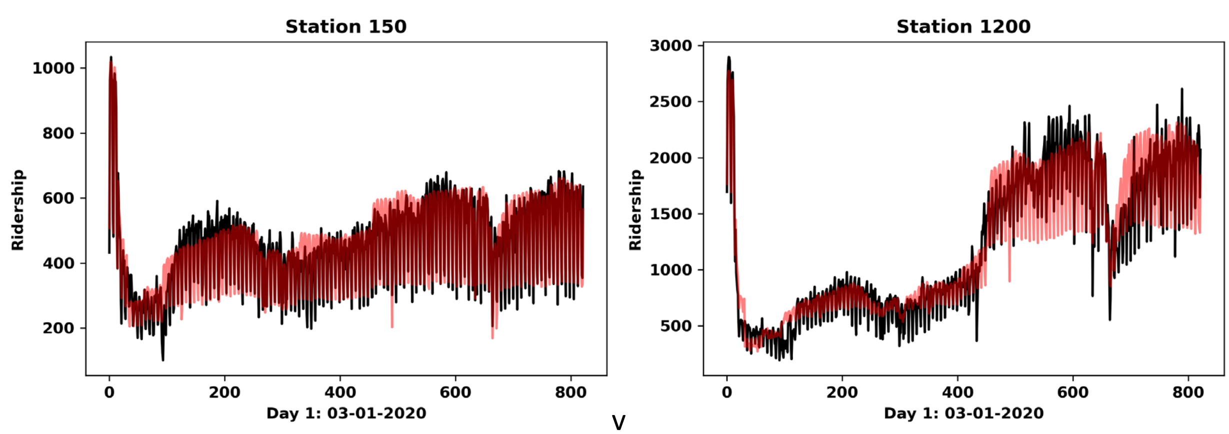

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Figure 20. Graphs. Examples of temporal regression model fits for CTA rail stations: Stations 150 (Pulaski-Cermak) and 1200 (Argyle).

For the CTA rail system, the parameters that were statistically significant for over 85% of all valid stations included workplace occupancy reductions, number of daily COVID cases, gas prices, unemployment rates, and the presence of CTA fare discount programs. The total number of vaccinations, stay-at home executive orders, and crime rates were also significant for 76.9%, 63.1%, and 53.8% of all valid CTA stations, respectively. Workplace occupancy reductions are positively correlated with rail ridership losses and significant for 100% of the valid stations. The parameter value indicates that CTA ridership is expected to go up by approximately 0.53%–1.17% (relative to the counterfactual ridership) for every 1% of the workforce that is back into their offices. This makes sense because the ability for people to work remotely directly influences people's travel needs. This means that commuting work trips have significantly driven ridership on CTA trains and buses, so this potentially indicates that agencies may struggle to bring ridership fully back to pre-pandemic levels if public agencies and private companies continue to have long-term remote work allowances. Similarly, the unemployment rate was also positively correlated with ridership loss, as expected.

The number of COVID-19 cases is usually positively correlated with CTA ridership loss, reducing 0.37%–4.15% of ridership for every 1,000 new COVID-19 cases. In contrast, cumulative vaccinations are negatively correlated with CTA ridership loss. For every 1,000 newly vaccinated persons, ridership loss is expected to decrease by about 0.00476%, on average. By May 2022, total ridership recovery associated with cumulative vaccinations is approximately 8%. The difference in magnitude between the per-case and per-vaccination impact is not surprising because cumulative vaccinations may indicate a sustained recovery (i.e., the number of vaccinated individuals does not decrease), while the number of daily cases may affect ridership only for a short time. In addition, the results indicate that the CTA discount programs effectively boosted CTA rail ridership up to 25.4% at some valid stations and approximately 7.43% on average at all valid stations.

The analysis also showed two seemingly counterintuitive results. Crime rates are negatively correlated and gas prices are positively correlated with ridership loss at valid CTA rail stations. These results may be from collinearity among independent variables, but they may also provide some insights. The positive correlation between crime rates and CTA rail ridership loss might simply indicate that more people are exposed to crime risks as more people ride transit and as more socioeconomic activities resume. The positive correlation between gas prices and ridership loss might indicate that transit riders are deterred from traveling instead of driving when gas prices are high because higher gas prices might indicate higher inflation rates (Koeze, 2022). Although gas price effects might be short-term, mode choices might be longer-term so that the immediate impact might be minimal after considering all other pandemic-related variables. This explanation is plausible because workplace occupancy reduction factors primarily capture "necessary" work-related trips while other variables (including gas prices) likely to capture "non-work" trips.

Table 2. Summary Statistics of All Temporal Model Estimates

Parameters	CTA Rail				CTA Bus			
	Max	**Min**	**Mean**	**%Significant**	**Max**	**Min**	**Mean**	**%Significant**
Constant	4.89E+02	-3.13E+03	-4.89E+02	99.2	-9.11E+01	-2.65E+03	-8.56E+02	98.4
Cases	4.15E-05	3.68E-06	1.19E-05	89.2	1.66E-05	4.36E-06	1.04E-05	93.5
Cumu. Vaccine	8.41E-08	-1.56E-07	-4.76E-08	76.9	4.66E-08	-1.15E-07	-4.31E-08	71.0
Workplace Occup. Reduct.	1.17E+00	5.34E-01	8.11E-01	100	9.14E-01	5.46E-01	7.28E-01	100
Stay-at-home	8.86E-02	-1.49E-02	3.72E-02	63.1	9.78E-02	1.51E-02	4.02E-02	88.7
Crime	3.70E-11	-1.60E-01	-2.73E-02	53.8	-1.05E-02	-1.41E-01	-5.15E-02	83.9
Gas Price	1.22E-01	1.55E-02	5.43E-02	98.5	7.21E-02	-1.81E-02	3.14E-02	87.1
Unemployment	1.96E-02	1.95E-03	7.81E-03	9.69E-01	1.64E-02	-7.85E-03	5.96E-03	7.42E-01
Discount	-2.08E-02	-2.49E-01	-7.46E-02	8.69E-01	4.37E-02	-1.07E-01	-5.24E-02	5.32E-01

Most valid CTA bus routes observe similar trends to CTA rail stations, including the correlation and approximate magnitude of model parameters. However, some differences are worth noting. First, the CTA discount program seems to be significantly more effective in encouraging ridership for the rail system than for the bus system. The discount program's effect on CTA bus ridership was only statistically significant for approximately half of the valid bus routes and only had an average effect of recovering 5.24% of its ridership (ranging from 4.37% to 10.7%). Secondly, the crime rate's effect on CTA bus ridership is significant and has larger magnitudes for a larger proportion of valid bus routes than valid rail stations. The larger magnitudes on valid bus routes are reasonable, because the total number of bus stops significantly exceeds the total number of rail stations. In addition, bus riders might be more vulnerable to criminal activities because rail stations may provide a relatively higher sense of security due to limited access points to stations and presence of station personnel. Finally, stay-at-home orders significantly affect 88.7% of valid CTA bus lines, which is approximately 25% higher than the proportion of valid rail stations. These larger magnitudes might indicate that valid CTA bus routes serve a higher share of workers who need to be present at the workplace but could not travel due to stay-home orders, which may make this rider group more susceptible to face economic hardship due to executive orders.

The research team used the estimated models and parameters for forecasting purposes after all the curves were fitted. They carried the forecast out up to October 31, 2022, given the limited availability of input factor data. The data of all independent variables in the temporal regression model were available up to October 31, 2022, except for the unemployment rate. Unemployment data was only until September 2022. For simplicity, the research team estimated the unemployment rate on October 2022 based on the average unemployment rate from June 2022 to September 2022. For illustrative purposes, Figures 21 and 22 present forecasted ridership for CTA rail stations 1200 and 150 and CTA bus routes 36 and 55, respectively. Appendices B and C show all the fitted curves and forecasting for valid CTA rail stations and bus routes, respectively.

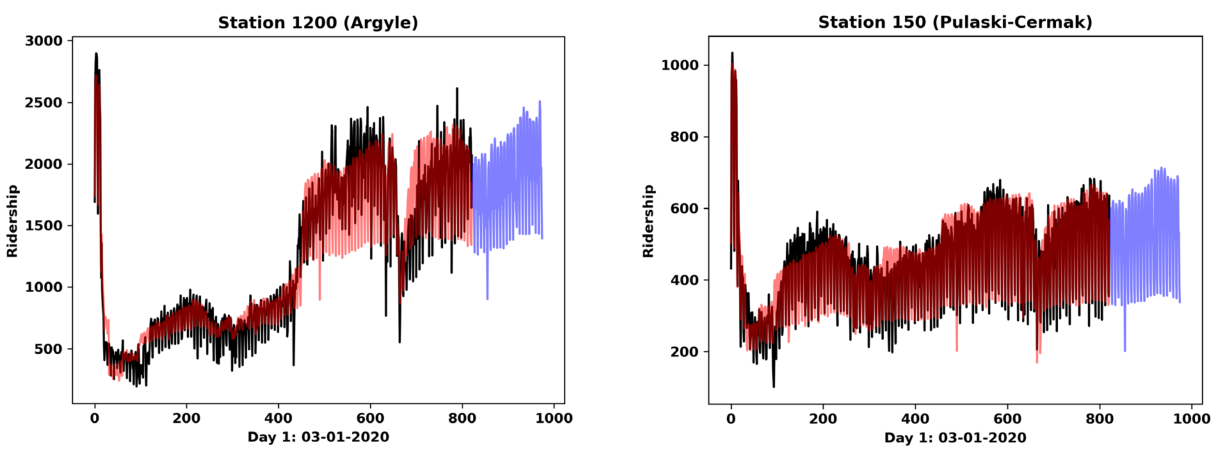

Figure 21. Graphs. Examples of hypothetical forecast for CTA rail station up to October 31, 2022: Stations 150 (Pulaski-Cermak) and 1200 (Argyle).

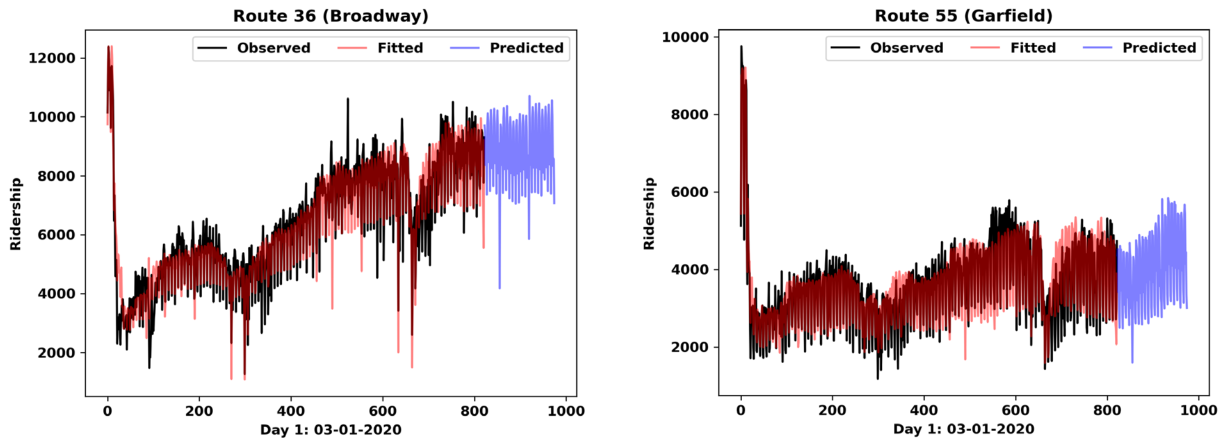

Figure 22. Graphs. Examples of hypothetical forecast for CTA bus route up to October 31, 2022: Routes 36 (Broadway) and 55 (Garfield).

The predictions, based on data analysis before May 2022, indicated a mild drop of CTA station-level and route-level transit ridership in June 2022. This prediction agrees very well with the actual observation of city-level ridership data in Figures 3 and 4.

SPATIAL ANALYSIS

This section describes the spatial dimension of this analysis and the relationships between the socioeconomic variables and their dynamics model regression estimates. Because larger magnitudes of positive (negative) dependent variables imply higher (lower) percentages of ridership loss, an independent variable's positive (negative) coefficient in the spatial analysis regression models indicates that an increase (decrease) in this variable will lead to more (less) ridership loss. When an independent variable and its squared term appear in a regression analysis and have coefficients with different signs (as is the case for many variables in the CTA's bus and rail modes), this independent variable has a diminishing marginal influence.

In this study, the research team's correlation analysis focused on cases when the independent variables were statistically significant in the model at a 95% confidence interval (with the p-value < 0.05). It also focused on independent variables that only had a linear term, only a quadratic term, or both linear and quadratic terms when their coefficients had the same sign in the regression model. In this latter case, the correlation between the independent variable and the dependent variable was monotonic. Table 3 presents the summary of the statistically significant variables resulting from the spatial analysis models.

The research team divided the regression parameters into "pandemic" parameters (which included ridership losses associated with COVID-19 cases and cumulative vaccinations), and "socioeconomic" parameters (which included ridership losses associated with unemployment rates, workplace occupancy reductions, gas prices, crime rates, and promotional discounts). The detailed regression results for all model parameters along with their statistical significance are shown in Tables 9 and 10 of Appendix D and Tables 11 through 14 of Appendix E.

Table 3. Summary of Correlations for Spatial Analysis of CTA Rail and CTA Bus Systems

Variables	COVID Cases, α_c		Vaccine, α_v		Workplace Occup. Reduction, α_o		Unemployment Rate, α_u		Gas Price, α_g		Crime, α_e		Discount, α_d	
	Bus	Rail	Bus	Rail	Bus	Rail	Bus	Rail	Bus	Rail	Bus	Rail	Bus	Rail
prop_male								+						
prop_age_0_24							+							
prop_age_25_39						+		−					+	+
prop_age_40_64					+	−		−	−				+	
prop_white			−		+							−		
prop_black	+	−		+	+	+		−	+					+
prop_asian						+		−						−
prop_poverty		+		−		−		+		+				−
prop_employ					−		+			+			−	
prop_W_Manuf	−							−					−	
prop_W_Trade	−										−		−	
prop_W_Health			+		−								−	
prop_LU_residential		+		−						+			+	
prop_LU_commercial													+	
prop_LU_industrial	+				−									
prop_LU_education		+	−		+					+	+		+	
prop_LU_medical		−		+										
prop_LU_openspace	+			−		+	+					−	+	
LUM					−									

In general, the model results for the bus system identified relatively stronger relationships between temporal model effects and socioeconomic and land-use characteristics compared to rail system models. For rail station models, only the cumulative vaccination model had an R^2 above 0.7, while four of the seven regression models from the bus system had R^2 values above 0.7. In Table 3, the proportion of the black population was negatively correlated with CTA ridership losses associated with daily COVID-19 cases. This agreed with previous findings (Liu et al., 2021). The proportions of the population under the poverty line were positively correlated with CTA ridership losses. This also agreed with previous findings, which showed that the pandemic disproportionally affected disadvantaged populations (Kashem, 2021).

In relation to land-use characteristics, the proportion of land use for medical institutional land was negatively correlated with ridership loss. This is intuitive because medical institutions are considered essential facilities and the number of COVID-19 cases might have generated more travel trips from/to clinics during the study period due to essential workers working in multiple shifts employed in healthcare. Both the proportion of residential and educational land were positively correlated with α_c, which may be intuitively related to both school closures reducing the number of daily trips and quarantine requirements after infection.

Ridership losses associated with cumulative number of vaccinations, α_v, is negative for all CTA rail stations, affirming the link between vaccinations and ridership recovery. Although the research team associated it with “ridership loss” for consistency, the use of vaccinations is clearly associated with ridership recovery, i.e., “negative ridership loss,” as shown in Table 2. The parameter α_v is positively correlated with the proportion of the black population, indicating that vaccines may not have as strong an influence on their decision to return to transit. On the contrary, α_v is negatively correlated with the proportion of the population under the poverty line, indicating that the vaccine supported this group’s return to transit.

The proportion of medical institutional land use was positively correlated with ridership losses, given vaccinations. This was likely because vaccinations reduced symptom severity and might have reduced trips to/from medical institutions as well as alleviated the need for essential workers to take on a high number of shifts. On the other hand, the proportion of land use for residential areas and open space were negatively correlated with the observed ridership loss, which makes sense given that vaccinations increased people’s comfort traveling, so they may have started to return to daily out-of-home activities.

The ridership losses associated with reductions in workplace occupancy, α_o, were positively correlated with proportion of the population aged 25–39 but negatively correlated with ages 40–64. This may be due to most of the working population being composed of the former group (Statistical Atlas, 2018), while this may also indicate that, proportionally, younger workers were more likely to work remotely during the pandemic.

The rail ridership losses due to work occupancy reduction were positively correlated with the proportions of the Asian and black populations, but negatively correlated with the proportion of the population living under the poverty line. This tells us that proportions of the Asian and black populations were more likely to have been laid off or lost their job because of the pandemic during the study period. On the other hand, the negative correlation may reflect the fact that essential workers comprise about half of all workers in low-paid occupations (Kinder & Stateler, 2021), and therefore are less likely to get fired during the pandemic.

Unemployment rates are shown to be a significant factor for nearly all rail stations, possibly given its prominent peak value during the initial phase of the pandemic (many service jobs were lost or suspended). The ridership loss associated with unemployment, α_u, varies significantly across sociodemographic groups. The proportion of the population that was 25–64 years old was negatively correlated with ridership loss due to unemployment. This was probably because most of the labor force in more permanent jobs were likely within this age range and their trip reduction has been captured by the "work-from-home" factor or other influential factors.

The proportions of the Asian and black population were negatively correlated with CTA rail ridership loss associated with the unemployment rate, which may indicate that these sectors of the population were more likely to continue traveling to work during the lockdowns.

Gender also played a significant role, as the proportion of men was positively correlated with ridership loss associated with unemployment rates.

The proportion of the population under the poverty line was positively correlated with ridership loss given unemployment, which may support findings from other studies stating that the pandemic disproportionately affected the population's more economically vulnerable sectors (Kasheem, 2022).

Ridership loss associated with gas prices, α_g, was positively correlated with the proportion of employed people, people living in poverty, and residential and educational institutional land uses. This result was somewhat counterintuitive because higher gas prices made driving more expensive and was expected to increase transit usage (Erhardt et al., 2022). However, as mentioned in the previous section, this might suggest that people chose not to travel at all or that short-term gas price fluctuations minimally affected their long-term mode choice decisions during the pandemic.

Ridership losses associated with crime rates, α_e, were negatively correlated with the proportion of white people and the proportion of open-space land use. These correlations might indicate that crime least affected transit riders from this sector of the population and from this land-use type. This finding may have two explanations. First, minority groups could be more likely to witness or become a victim of criminal activity, i.e., during the pandemic and the associated surges of hate crimes, they reported crime as one of the major reasons for transit avoidance (He et al., 2022; Meyer, 2022). Second, crimes are less likely to occur in open spaces (Branas et al., 2011), and riders can feel safer in open-space (low-density) neighborhoods.

In the case of discount programs, both the proportion of Asian people and the proportion of people living in poverty were significantly and negatively correlated with α_d. Similar to vaccinations, the discount program is associated with ridership recovery. On the other hand, the proportion of people younger than 40 years old and the proportion of black population were both positively correlated to discount programs for the CTA system. This meant that the discount programs did not sufficiently incentivize these sectors of the population to return to riding on the CTA system.

Table 3 also shows that the spatial models for the bus system yield vastly different correlation patterns. This is partly due to differences in measurement of socioeconomic characteristics associated with rail stations and bus routes (catchment areas for rail stations with more distinct patterns while more blended demographic characteristics of a bus line due to aggregation of many census tracts along its alignment).

Ridership losses on the CTA bus system due to COVID-19 cases, α_c, was negatively correlated with the proportion of workers with jobs in the manufacturing, wholesale, and trade industries. This was expected because these jobs were among the first to be labeled as essential. These sectors of the population continued commute trips despite the surge of daily infection cases. The proportion of the black population riding the CTA bus system is positively correlated with ridership loss due to fear, in contrast to their ridership on the CTA rail system. It is possible that this sector of the population may have switched modes (or given up traveling) due to fear, because people may feel safer traveling via rail than bus. The effect of fear is also positively correlated with the land uses for industrial land use and open space.

Regarding the effect of vaccinations, α_v, ridership loss due to cumulative vaccination counts is negatively correlated with the proportion of white people and the proportion of educational institutional land use. The wide adoption of vaccines in Illinois allowed schools to speed up their reopening processes. This also indicated that the proportion of the white population was more encouraged to return to transit after vaccination. On average, the white population were able to work remotely at a higher rate and had a chance to defer commuting until vaccines became available. On the other hand, the proportion of workers in the health industry was positively correlated with ridership loss due to vaccinations. This is likely because, after vaccinations, trip rates to health-related workplaces may have gone down since these workers worked overtime or these workers shifted to another mode to travel non-typical hours.

Ridership loss due to work occupancy reductions, α_o, is positively correlated with the proportions of both black and white people. This makes sense because it indicates that people who either stayed at home due to pandemic-related fear, or whose jobs were lost due to pandemic-related closures, were predominately black or white. The proportion of the population aged 40–64 is positively correlated with ridership loss, contrary to the correlation found with the bus system. This could indicate that that people aged 40–64 who are reducing their work trips are predominately traveling via bus instead of rail.

The proportions of workers with jobs in the health industry and the proportion of employed population are negatively correlated with ridership loss given work occupancy; heath-related jobs occupancies remained high throughout the pandemic because they performed essential functions in society. It is also expected that regions with higher employed population produced a higher number of transit trips despite work occupancy decreasing.

In terms of land-use characteristics, the proportion of industrial land uses was negatively correlated, while the proportion of educational institutional land use was positively correlated, with CTA's ridership loss. On one hand, this was expected because educational institutions went remote for a significant portion of the pandemic's first two years. On the other hand, the negative correlation with the proportion of industrial land use was also expected because the number of offices likely increased with industrial land use. Therefore, the possibility of people traveling from these areas was higher than others, even at low office occupancy periods. With the same logic, it was reasonable that the LUM index was negatively correlated with ridership loss given workplace occupancy reductions.

The ridership loss associated with unemployment rates, α_u, was positively correlated with the population younger than 24 years old and the proportion of employed population. This agrees with labor statistics reports, which found that employment of men and women ages 16 to 24 declined by about one-fourth in 2020. This was more than double the share of employment men and women in other age groups lost (US Bureau of Labor Statistics, 2022). Nonetheless, the data also shows that after the initial wave of unemployment in 2020, youth labor recovered substantially.

The gas price effect, α_g, shows that the proportion of people who are 40–64 years old was negatively correlated with CTA's ridership loss due to gas price increases, suggesting that gas price fluctuations least affected older transit riders. The opposite can be said about the positive correlation between α_g with the proportion of the black population.

The only strong positive correlation regarding CTA bus ridership loss due to crime, α_e, was the proportion of land use for educational institutional land. This might be related to increasing crime trends in general that the city has experienced despite school closures (Redden, 2021; Vera, 2021). The only strong negative correlation is with the proportion of workers in the retail or trade industry, which may be a consequence of essential workers having to continue traveling and exposing themselves at emptier bus stops at unusual hours.

The effect of ridership loss associated with discount programs, α_d, was negatively correlated with the proportion of employed people, the proportion of workers with jobs in the wholesale or retail trade industry, the proportion of workers with jobs in the health industry, and the proportion of workers in the manufacturing industry. These correlations did not appear in the CTA rail system model; this might indicate that CTA's bus and rail systems fundamentally served different sectors of the population in CTA's service area. Workers in the health, manufacturing, and retail industries had probably already contributed many travelers during the pandemic given their essential functions in society. Hence, these correlations might indicate that the discount programs benefited these sectors due to their consistent travel activity during the pandemic.

Overall, the availability of the park-n-ride facility at CTA rail stations is found to be insignificant for all factors related to the reduction of CTA rail ridership.

As a final remark, the temporal and spatial models highlighted the substantial impacts that many emerging factors/events have had on the ongoing evolution of public transportation use. The temporal analysis showed that most of the identified pandemic and socioeconomic factors affected over 80% to 90% of all CTA rail stations and bus routes. Particularly, the cumulative vaccination counts were shown to have a strong positive impact on recovering ridership for both modes. While vaccines were associated with approximately 8% to 9% of the recovery, the discount program was also effective in recovering 5% to 7% of CTA's transit ridership, on average. The spatial analysis model also showed that the discount program successfully attracted transit trips from the employed population in the health and retail industries, in other words, essential workers. The results also confirmed that crime rates influenced people's travel behavior and transit usage on CTA's rail and bus modes, especially for areas with educational land.

The results for the temporal and spatial models showed how significant work occupancy rates were in explaining CTA's rail and bus ridership reductions. Workplace occupancy was significant for 100% of CTA's bus lines and rail stations. It primarily affected ridership of people younger than 40 on CTA's rail system as well as the proportion of black riders on CTA's rail and bus modes. This is relevant and insightful because it indicates that workplace commute trips drove a large proportion of CTA ridership, and, therefore, transit ridership recovery might depend on the individual industries' remote work policies rather than city-wide quarantine executive orders. This could further serve as a piece of strong evidence that transit agencies may need to partner up with industry sectors to further push the recovery of public transit ridership, as suggested in previous findings from R27-SP45 (Liu et al., 2021; Osorio et al., 2022).

CHAPTER 6: CONCLUSIONS

This study built upon the exploratory modeling efforts of Illinois Department of Transportation and Illinois Center for Transportation project R27-SP45. The research team developed a series of statistical models to further understand ridership fluctuations and disparities on the CTA rail system and bus network. They carried out a comprehensive data collection effort to enhance the models' explanatory power and to provide more insights. The modeling framework integrated Bayesian structural time-series (BSTS) models to generate counterfactual ridership during the pandemic, temporal analysis models to quantify the ridership loss due to time-varying pandemic and socioeconomic factors, and spatial regression models to quantify the relationship between ridership loss and sociodemographic characteristics of neighborhoods in the CTA service area. The newly considered pandemic and socioeconomic factors included the number of daily COVID-19 cases, the cumulative number of vaccinated individuals, workplace occupancy reductions, unemployment rates, gas prices, crime rates, and CTA promotional discounts. The research team collected ridership data up to May 2022 and consequently developed the models for each CTA rail station and bus line to generate a ridership forecast for the following five months up to October 31, 2022. The results showed a gradual and slow recovery of CTA bus and rail ridership in these months, and the predictions matched very well with the actual observations.

The results from the temporal analysis showed that pandemic and socioeconomic factors could explain most of the reductions in ridership at CTA rail stations and on CTA bus routes. In both cases, the models had great explanatory power with most of the R^2 values being greater than 0.75. The most influential factor in explaining ridership loss was work occupancy reductions, which were statistically significant for all rail stations and bus lines. The spatial regression showed that ridership losses associated with workplace occupancy reductions were positively correlated with the population under 40 years old and the proportion of the black population. Furthermore, CTA promotional discounts and the total number of vaccinated individuals were shown to be correlated with average ridership recoveries of approximately 8% to 9% and 5% to 7%, respectively. Essential worker's presence was correlated with a decrease in ridership loss related to discount programs. Unemployment was also found to be positively correlated with ridership loss for CTA rail and bus, especially for men, those living in poverty, and those with at least a high school degree. The number of crimes near or in the catchment areas were found to be significantly correlated with ridership loss, especially for those older than 24 years old. This supports recent findings in the literature claiming transit users have cited crime concerns as one of their main reasons for decreased transit use.

The statistical findings cast strong insights on policy strategies. Workplace occupancy had the biggest effect on ridership fluctuations, which suggested that the loss of commuting trips primarily drove CTA ridership losses on its trains and buses. Therefore, industry policies on workers' flexibility to work remotely will be a key factor in determining ridership recovery. Now that COVID-19 restrictions have been lifted and approximately 70% of the population have been vaccinated, executive orders will likely have relatively small effects in ridership recovery in the future. This result supports the findings from R27-SP45 (Liu et al., 2021; Osorio et al., 2022), which recommended that CTA and other transit agencies collaborate with the public and private sectors to develop policy instruments for ridership recovery.

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APPENDIX A: SOCIOECONOMIC & LAND-USE CHARACTERISTICS

Table 4. Socioeconomics and Land-Use Characteristics Summary

Characteristics	Bus			Rail		
	MEAN	MIN	MAX	MEAN	MIN	MAX
prop_male	4.75E-01	4.08E-01	5.19E-01	4.90E-01	4.23E-01	5.98E-01
prop_poverty	1.82E-01	7.04E-02	3.33E-01	3.04E-01	1.12E-01	6.22E-01
prop_age_0_24	3.04E-01	1.74E-01	3.99E-01	3.06E-01	1.13E-01	5.97E-01
prop_age_25_39	2.52E-01	1.64E-01	3.72E-01	2.78E-01	1.52E-01	3.67E-01
prop_age_40_64	2.96E-01	2.32E-01	3.53E-01	5.38E-01	1.28E-02	8.93E-01
prop_edu	2.67E-02	1.21E-02	5.27E-02	2.43E-01	1.47E-02	9.64E-01
prop_employ	7.98E-01	6.16E-01	8.76E-01	9.87E-02	5.33E-05	6.52E-01
prop_white	4.60E-01	1.79E-02	8.75E-01	3.64E-02	9.66E-03	1.90E-01
prop_black	3.33E-01	1.00E-02	9.60E-01	8.37E-01	7.00E-01	9.84E-01
prop_asian	6.12E-02	1.63E-03	2.33E-01	1.67E-01	4.05E-02	4.79E-01
prop_R_Manuf	6.63E-02	3.12E-02	1.24E-01	5.88E-02	2.15E-02	1.47E-01
prop_R_Trade	1.29E-01	8.65E-02	1.85E-01	1.18E-01	5.89E-02	1.78E-01
prop_R_Edu	8.77E-02	6.25E-02	1.48E-01	9.06E-02	5.03E-02	3.11E-01
prop_R_Health	1.41E-01	9.78E-02	2.03E-01	1.33E-01	5.14E-02	2.30E-01
prop_W_Manuf	5.33E-02	6.08E-03	2.08E-01	4.86E-02	0.00E+00	3.90E-01
prop_W_Trade	1.66E-01	6.39E-02	4.47E-01	1.29E-01	5.81E-03	4.17E-01
prop_W_Edu	6.71E-02	2.09E-02	2.02E-01	6.65E-02	0.00E+00	7.77E-01
prop_W_Health	2.07E-01	8.21E-02	4.11E-01	2.06E-01	0.00E+00	8.78E-01
prop_LU_residential	3.49E-01	1.61E-01	5.12E-01	2.94E-01	2.39E-04	5.34E-01
prop_LU_commerical	7.50E-02	3.14E-02	1.40E-01	1.07E-01	1.49E-02	5.52E-01
prop_LU_medical	5.14E-03	0.00E+00	3.26E-02	5.30E-02	0.00E+00	3.45E-01
prop_LU_education	3.62E-02	1.25E-02	1.16E-01	6.83E-03	0.00E+00	1.60E-01
prop_LU_industrial	4.94E-02	1.51E-03	1.67E-01	3.73E-02	0.00E+00	3.87E-01
prop_LU_transportation	6.90E-02	8.37E-03	2.45E-01	7.34E-02	0.00E+00	2.90E-01
prop_LU_openspace	6.11E-02	1.12E-02	3.70E-01	6.59E-02	0.00E+00	7.29E-01
LUM	5.83E-01	4.66E-01	7.34E-01	6.67E-01	2.01E-01	9.27E-01

APPENDIX B: TIME-SERIES PLOTS FOR CTA RAIL STATIONS

For reference, the ID and names of valid CTA rail stations and bus routes are listed in Tables 5 and 6, respectively. Then, the figures present the time-series fit and the forecasted ridership up to December 2022.

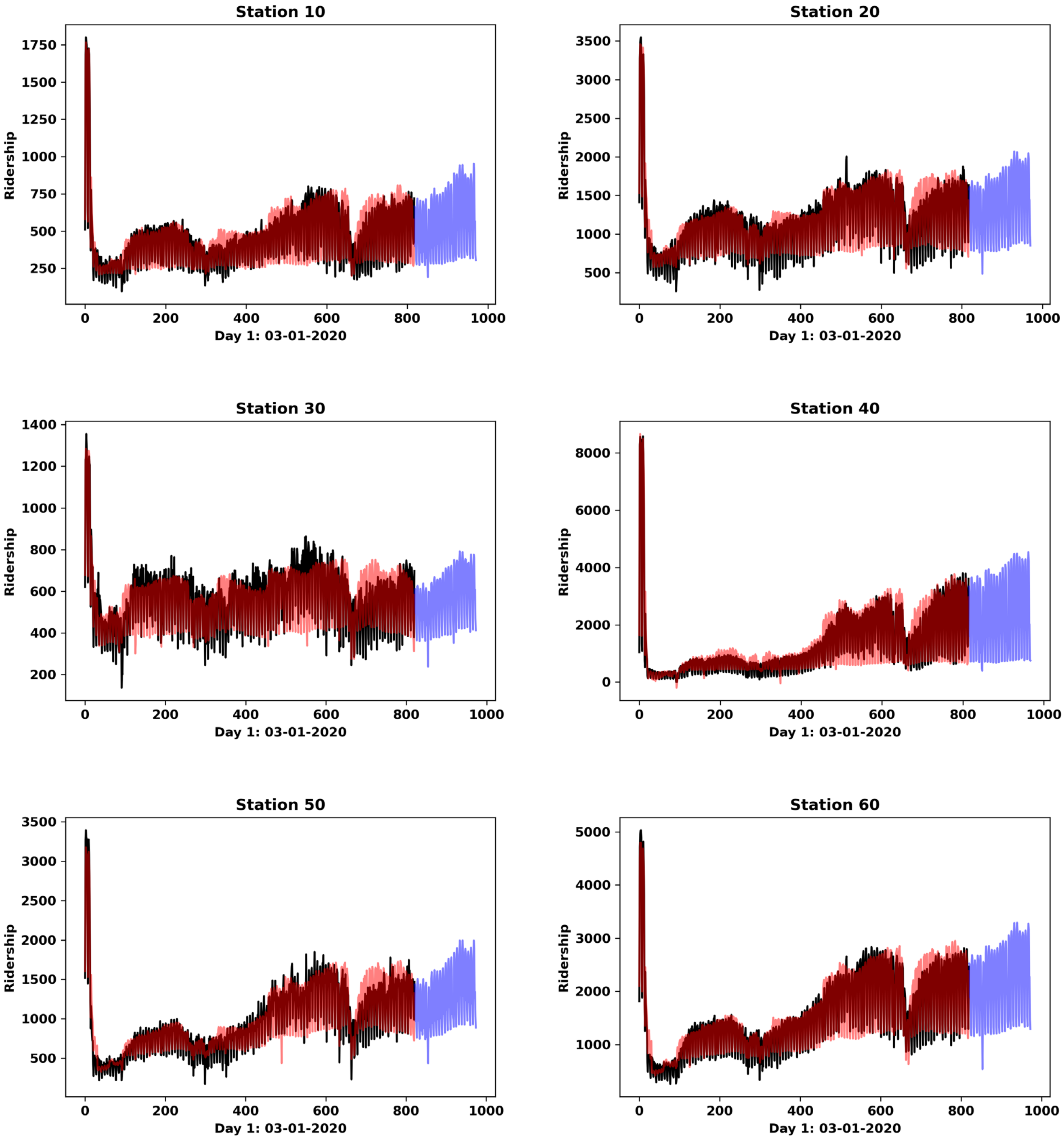
Table 5. ID and Names of Valid CTA Rail Stations

ID	Station Name	ID	Station Name	ID	Station Name
10	Austin-Forest Park	550	Irving Park-O'Hare	1060	Ashland-Orange
20	Harlem-Lake	560	Jackson/State	1070	Kedzie-Lake
30	Pulaski-Lake	570	California/Milwaukee	1080	47th-South Elevated
40	Quincy/Wells	580	54th/Cermak	1090	Monroe/State
50	Davis	590	Damen/Milwaukee	1120	35-Bronzeville-IIT
60	Belmont-O'Hare	600	Kostner	1130	Halsted-Orange
70	Jackson/Dearborn	610	Ridgeland	1140	King Drive
80	Sheridan	630	Clark/Division	1150	Kedzie-Midway
90	Damen-Brown	650	North/Clybourn	1160	Clinton-Lake
100	Morse	660	Armitage	1170	Garfield-Dan Ryan
120	35th/Archer	670	Western/Milwaukee	1180	Kedzie-Brown
130	51st	680	Adams/Wabash	1190	Jarvis
140	Dempster-Skokie	690	Dempster	1200	Argyle
150	Pulaski-Cermak	700	Laramie	1210	Wellington
160	LaSalle/Van Buren	710	Chicago/Franklin	1220	Fullerton
170	Ashland-Lake	720	East 63rd-Cottage Grove	1230	47th-Dan Ryan
180	Oak Park-Forest Park	740	Western-Cermak	1240	Addison-O'Hare
190	Sox-35th-Dan Ryan	750	Harlem-O'Hare	1260	Austin-Lake
240	79th	760	Granville	1270	43rd
250	Kedzie-Homan-Forest Park	780	Central Park	1280	Jefferson Park
260	State/Lake	800	Sedgwick	1290	Kimball
270	Main	810	Medical Center	1300	Loyola
280	Central-Lake	820	Rosemont	1310	Paulina
290	Ashland/63rd	830	18th	1320	Belmont-North Main
300	Indiana	840	South Boulevard	1330	Montrose-O'Hare
320	Division/Milwaukee	850	Library	1340	LaSalle
330	Grand/State	870	Francisco	1350	Oak Park-Lake
350	UIC-Halsted	880	Thorndale	1360	California-Lake
360	Southport	890	O'Hare Airport	1380	Bryn Mawr
370	Washington/Dearborn	900	Howard	1400	Roosevelt
380	Clark/Lake	910	63rd-Dan Ryan	1410	Chicago/Milwaukee
390	Forest Park	920	Pulaski-Forest Park	1430	87th
400	Noyes	930	Midway Airport	1440	Addison-Brown
420	Cicero-Cermak	940	Halsted/63rd	1450	Chicago/State

ID	Station Name	ID	Station Name	ID	Station Name
430	Clinton-Forest Park	960	Pulaski-Orange	1460	Irving Park-Brown
440	California-Cermak	970	Cicero-Forest Park	1480	Western-Brown
450	95th/Dan Ryan	980	Harlem-Forest Park	1490	Harrison
460	Merchandise Mart	990	69th	1500	Montrose-Brown
470	Racine	1000	Cermak-Chinatown	1510	Morgan-Lake
480	Cicero-Lake	1010	Rockwell	1660	Lake/State
490	Grand/Milwaukee	1020	Logan Square	1670	Conservatory
520	Foster	1030	Polk	1680	Oakton-Skokie
530	Diversey	1040	Kedzie-Cermak	1690	Cermak-McCormick Place
540	Wilson				

Table 6. ID and Names of Valid CTA Bus Routes

ID	Route Name	ID	Route Name	ID	Route Name
103	West 103rd	44	Wallace-Racine	71	71st/South Shore
106	East 103rd	47	47th	72	North
112	Vincennes/111th	49B	North Western	73	Armitage
119	Michigan/119th	4	Cottage Grove	74	Fullerton
126	Jackson	50	Damen	75	74th-75th
12	Roosevelt	52A	South Kedzie	76	Diversey
146	Inner Drive/Michigan Express	52	Kedzie/California	77	Belmont
151	Sheridan	53A	South Pulaski	78	Montrose
152	Addison	53	Pulaski	81	Lawrence
155	Devon	54B	South Cicero	82	Kimball-Homan
18	16th/18th	55	Garfield	84	Peterson
20	Madison	56	Milwaukee	85	Central
21	Cermak	60	Blue Island/26th	87	87th
22	Clark	62	Archer	88	Higgins
29	State	63W	West 63rd	8A	South Halsted
30	South Chicago	63	63rd	90	Harlem
34	South Michigan	65	Grand	91	Austin
35	35th	66	Chicago	92	Foster
36	Broadway	67	67th-69th-71st	94	South California
3	King Drive	68	Northwest Highway	97	Skokie
43	43rd	70	Division		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Station 30
Station 40
Station 50
Station 60
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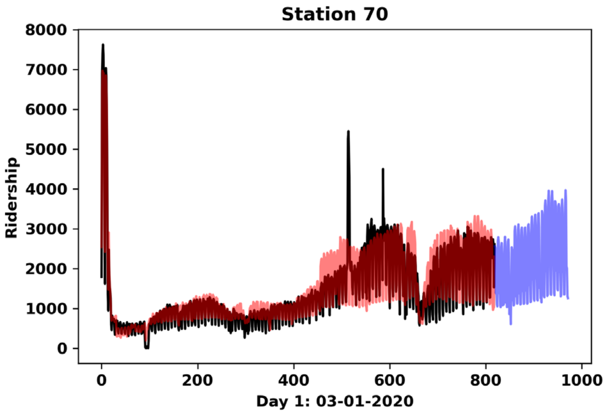
Day 1: 03-01-2020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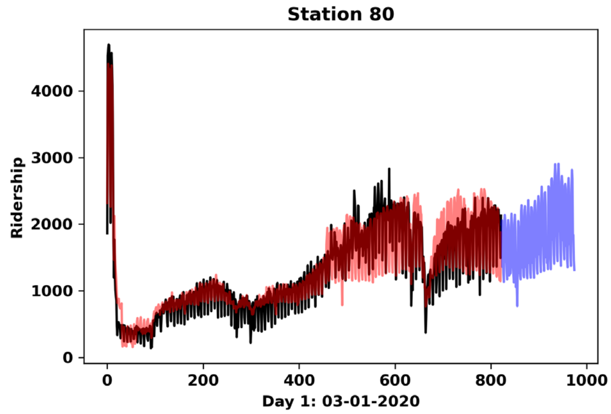
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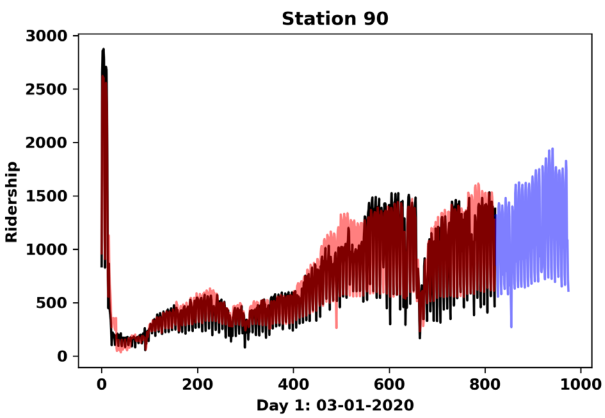
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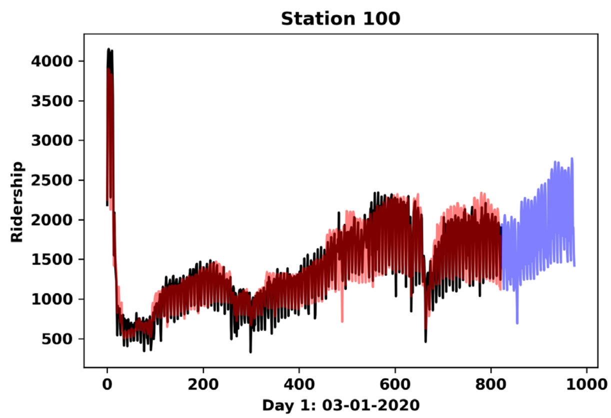
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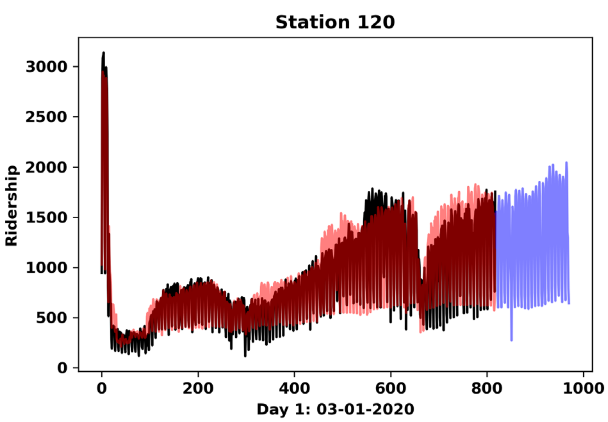
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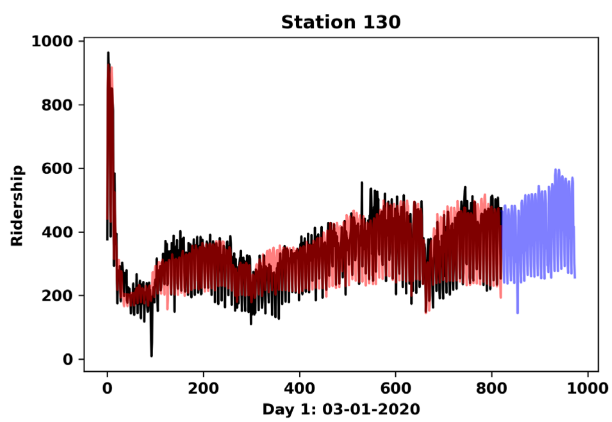
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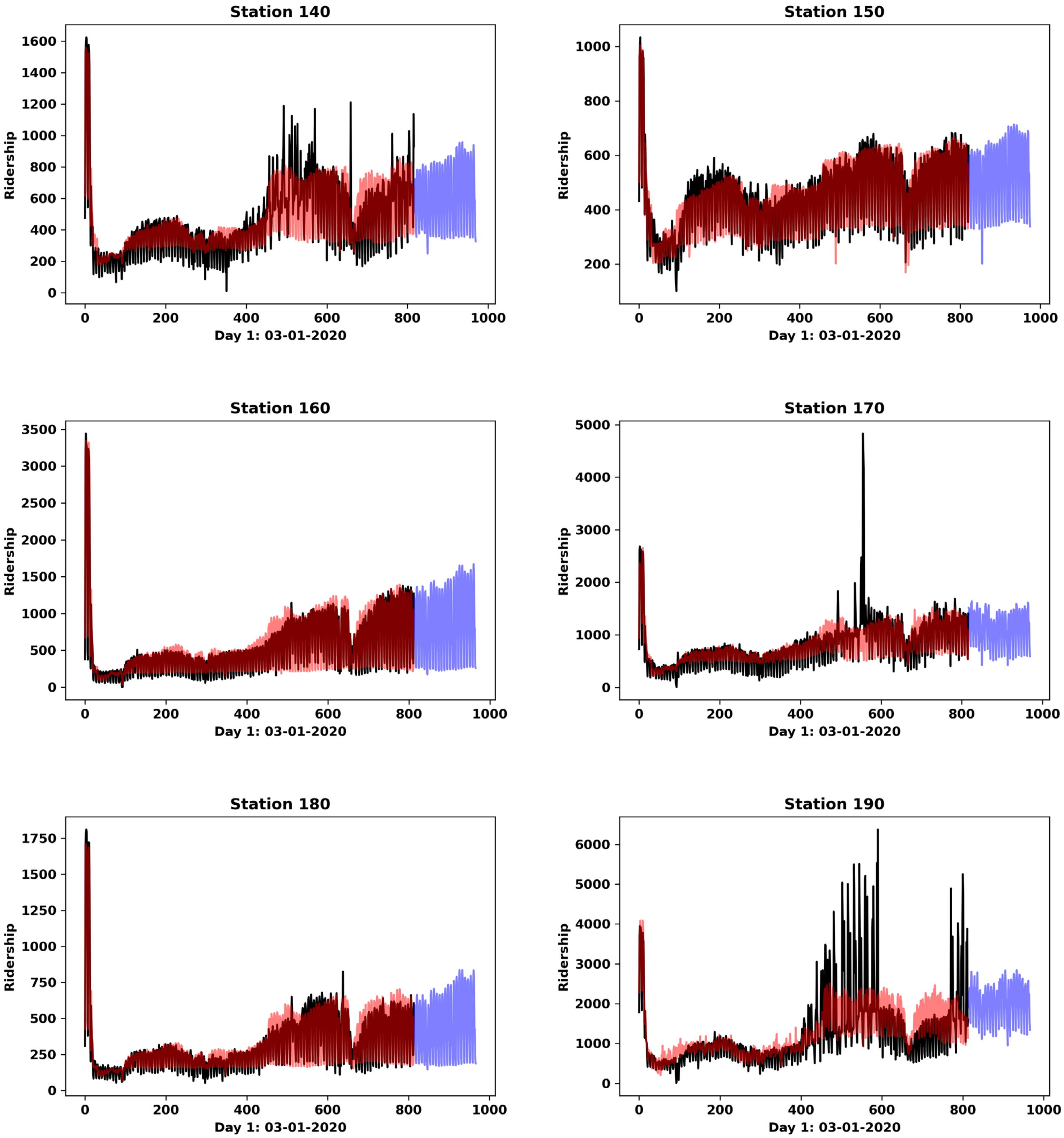
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1200
1400
1600
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400
600
800
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Station 150
Ridership
200
400
600
800
1000
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 160
Ridership
0
500
1000
1500
2000
2500
3000
3500
0
200
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Day 1: 03-01-2020
Station 170
Ridership
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400
600
800
1000
Day 1: 03-01-2020
Station 180
Ridership
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500
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1250
1500
1750
0
200
400
600
800
1000
Day 1: 03-01-2020
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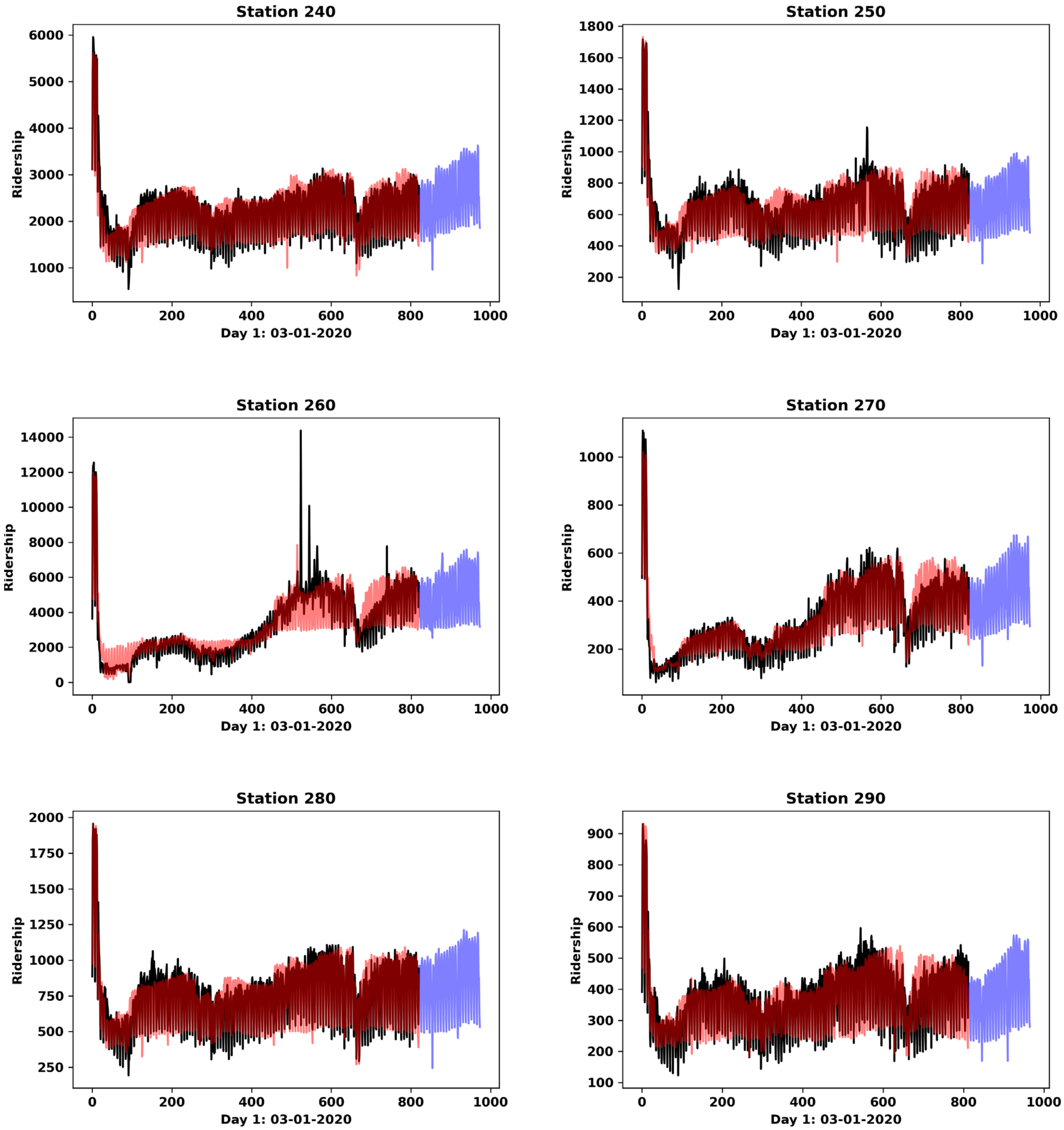
800
1000
Day 1: 03-01-2020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600
800
1000
Day 1: 03-01-2020
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Ridership
1800
1600
1400
1200
1000
800
600
400
200
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 260
Ridership
14000
12000
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 270
Ridership
1000
800
600
400
200
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 280
Ridership
2000
1750
1500
1250
1000
750
500
250
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 290
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700
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400
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200
100
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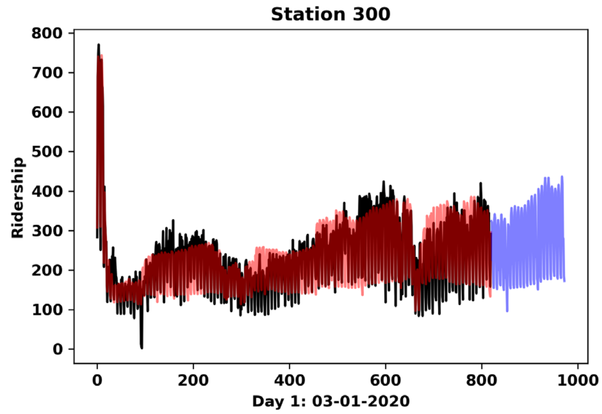
800
1000
Day 1: 03-01-2020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100
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200
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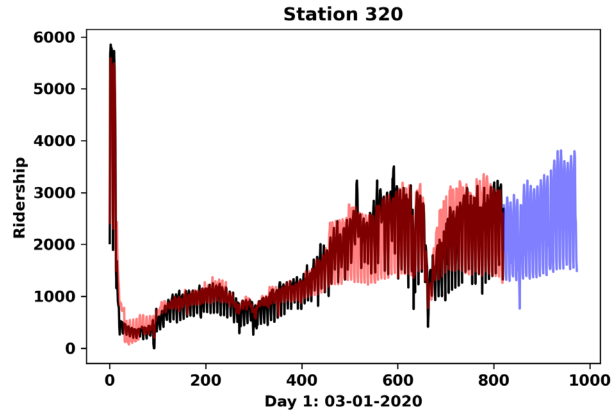
800
1000
Day 1: 03-01-2020


Station 320
Ridership
6000
5000
4000
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200
400
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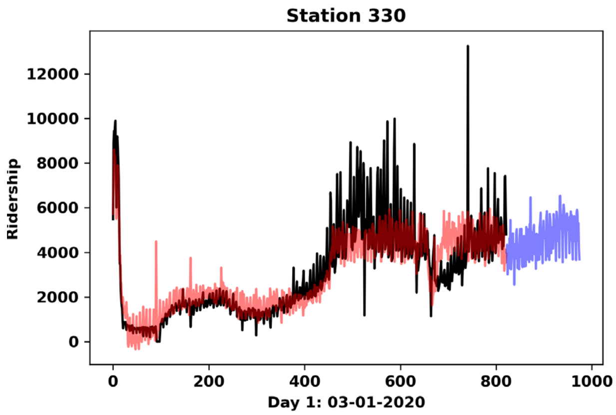
Day 1: 03-01-2020


Station 330
Ridership
12000
10000
8000
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2000
0
0
200
400
600
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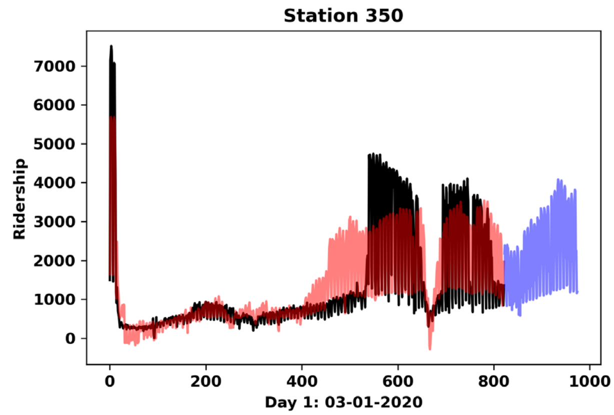
Day 1: 03-01-2020


Station 350
Ridership
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6000
5000
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200
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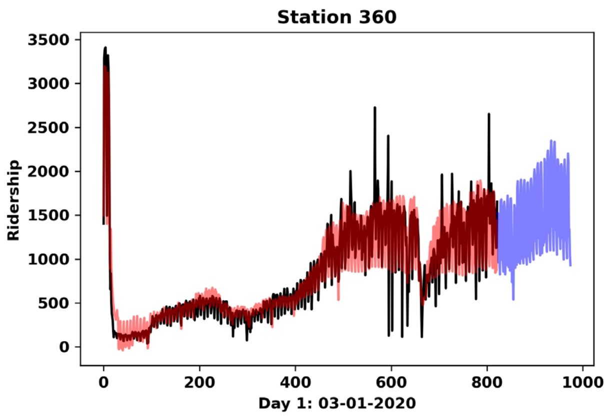
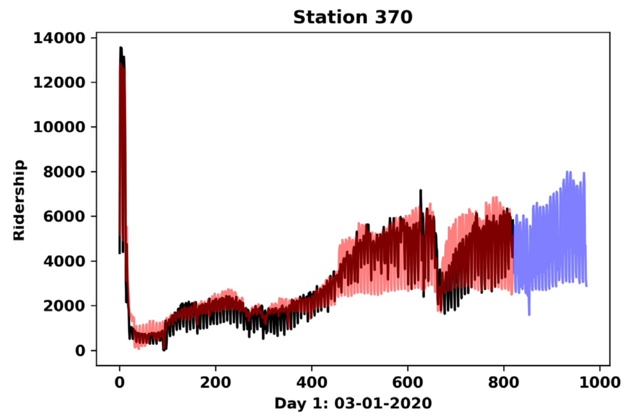
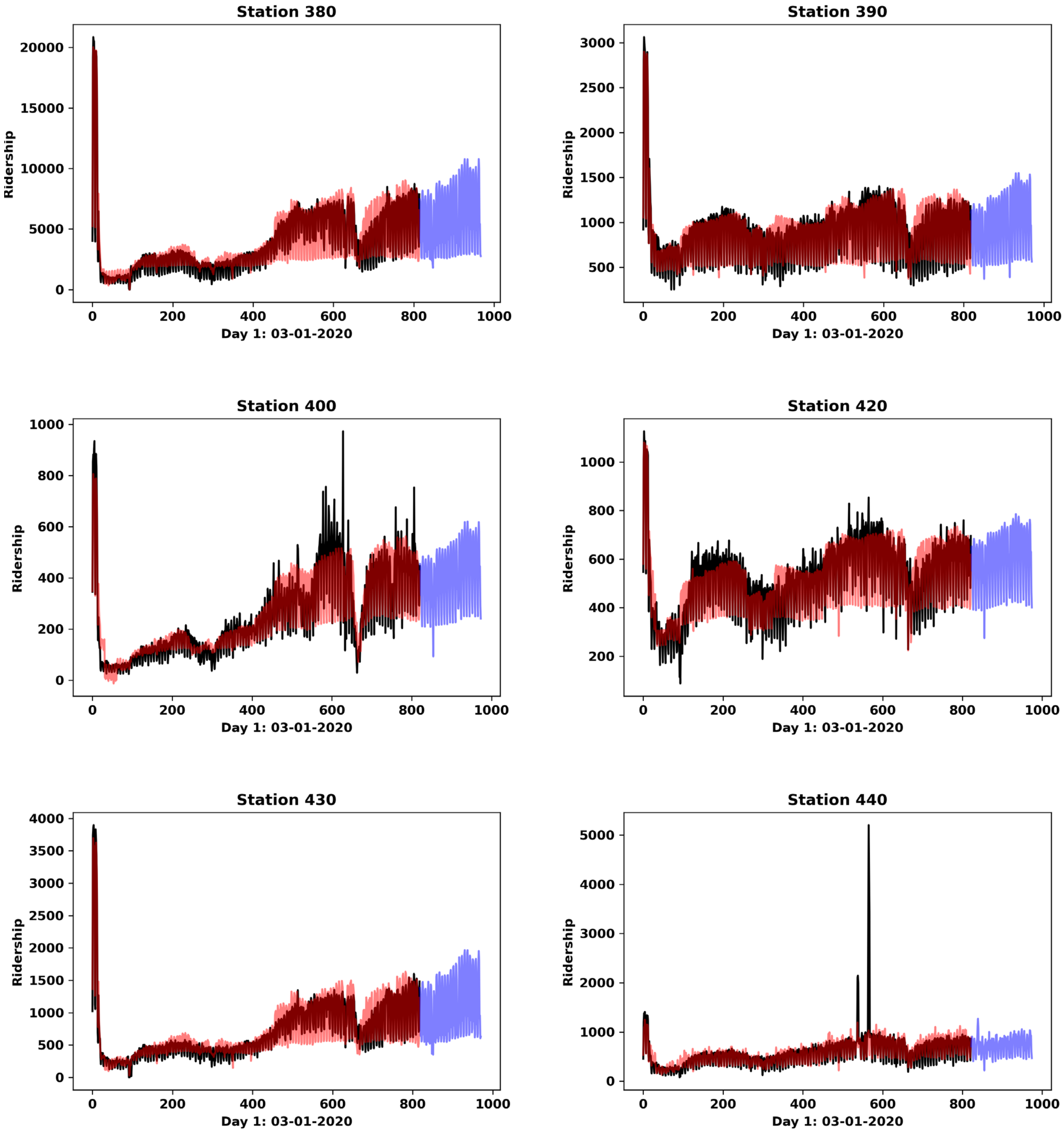
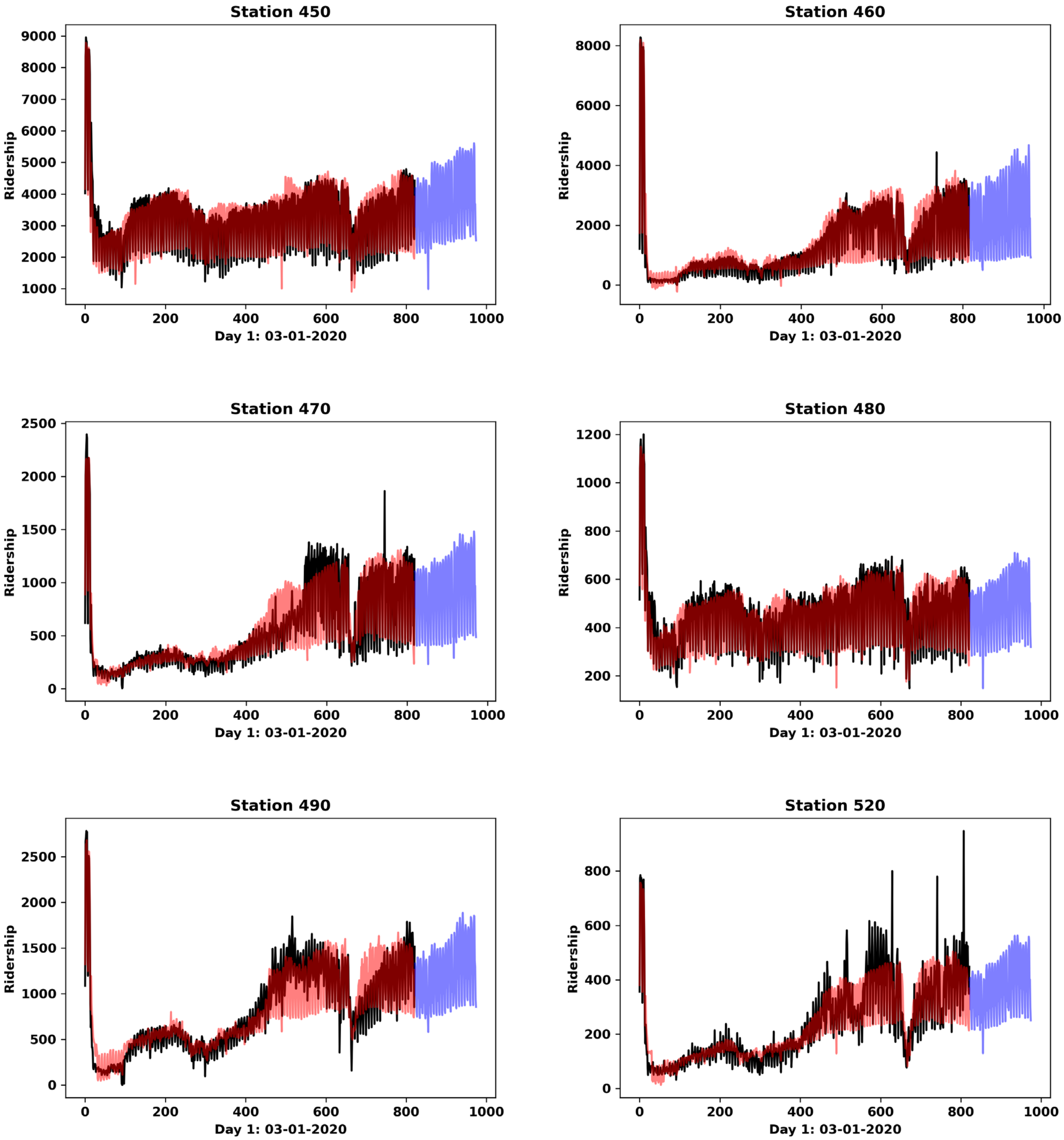
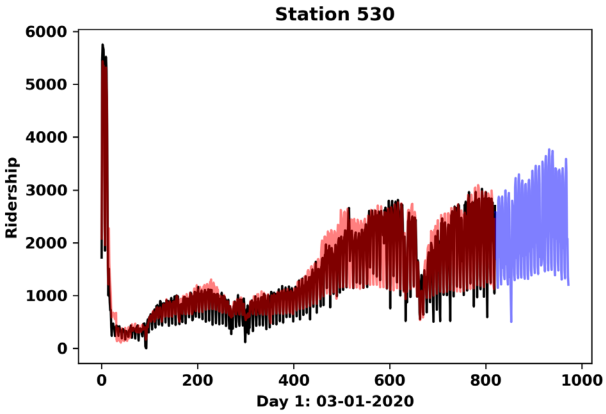
Day 1: 03-01-2020

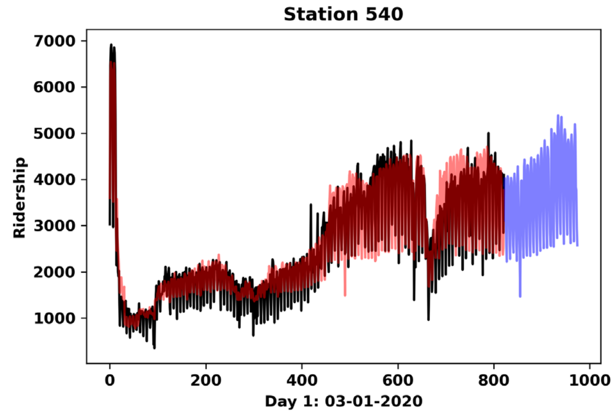

Station 360
Ridership
3500
3000
2500
2000
1500
1000
500
0
0
200
400
600
800
1000
Day 1: 03-01-2020

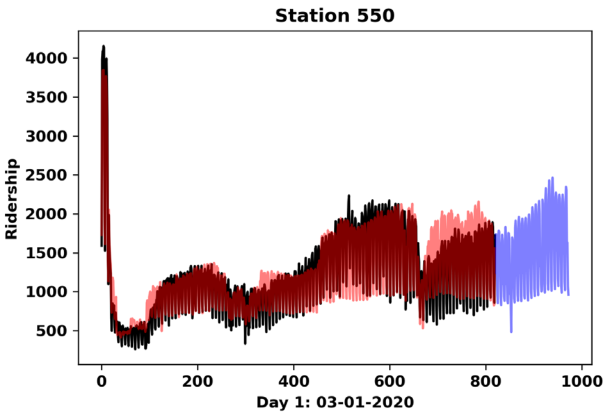

Station 370
Ridership
14000
12000
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
Day 1: 03-01-2020

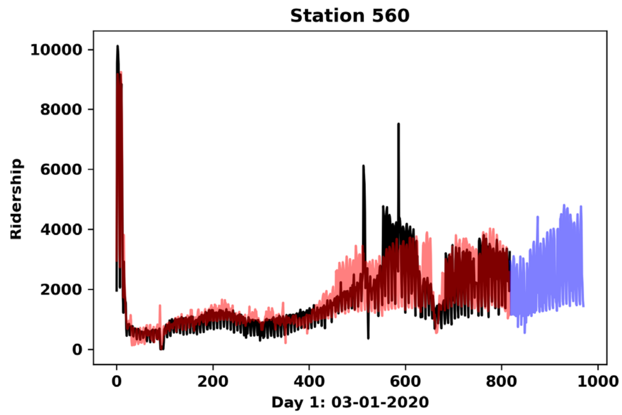

Station 380
Station 390
Station 400
Station 420
Station 430
Station 440
Ridership
Day 1: 03-01-2020

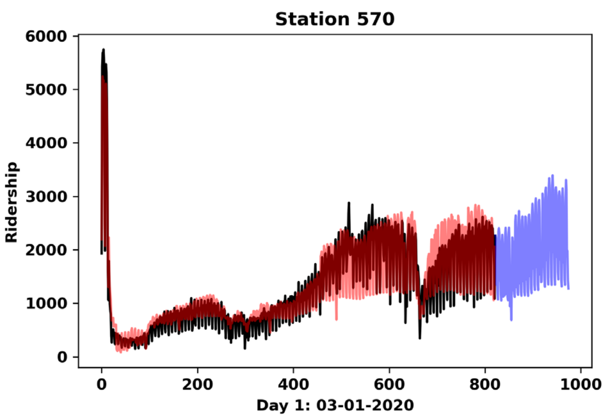

Station 450
Station 460
Station 470
Station 480
Station 490
Station 520
Ridership
Day 1: 03-01-2020

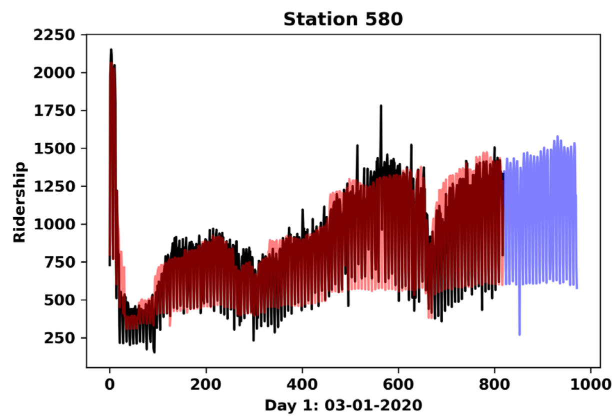

Station 530
Ridership
Day 1: 03-01-2020

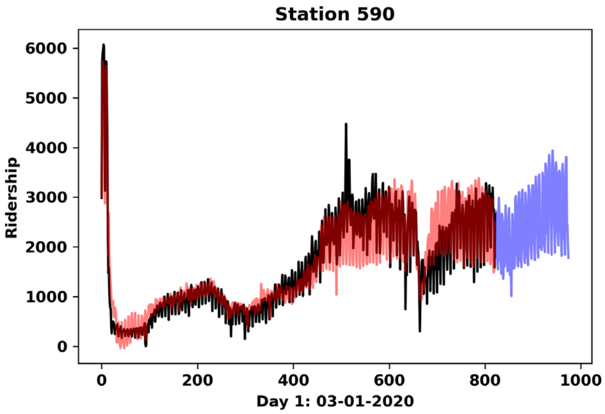

Station 540
Ridership
Day 1: 03-01-2020


Station 550
Ridership
Day 1: 03-01-2020


Station 560
Ridership
Day 1: 03-01-2020


Station 570
Ridership
Day 1: 03-01-2020


Station 580
Ridership
Day 1: 03-01-2020


Station 590
Ridership
0
1000
2000
3000
4000
5000
6000
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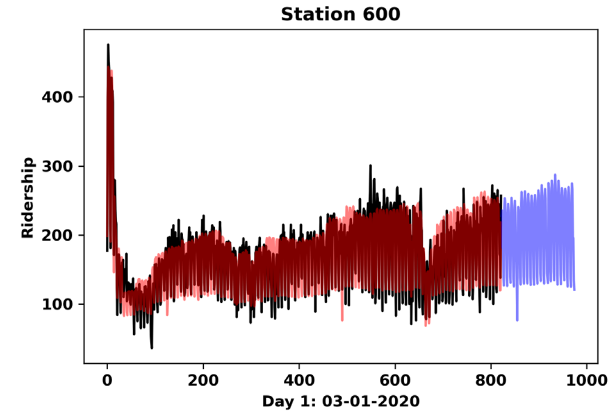
200
400
600
800
1000
Day 1: 03-01-2020


Station 600
Ridership
100
200
300
400
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200
400
600
800
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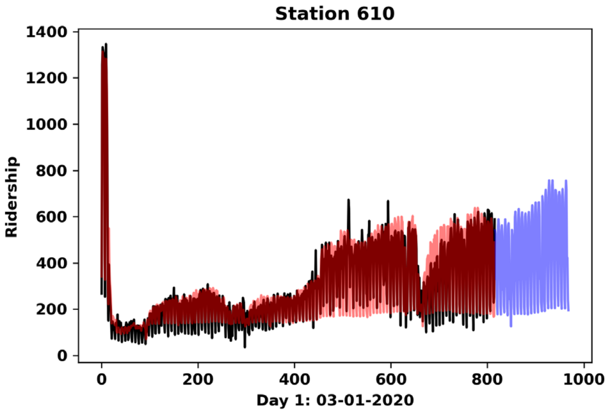
Day 1: 03-01-2020


Station 610
Ridership
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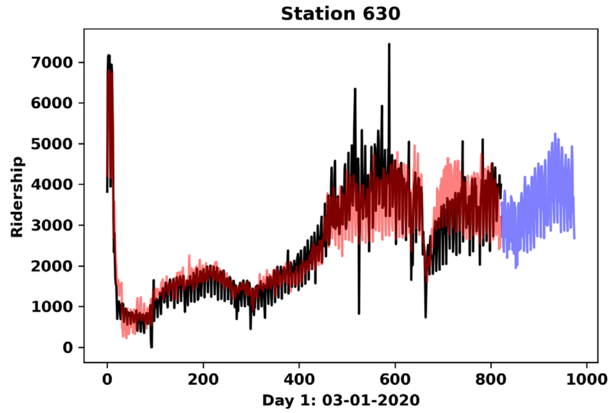
200
400
600
800
1000
1200
1400
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 630
Ridership
0
1000
2000
3000
4000
5000
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7000
0
200
400
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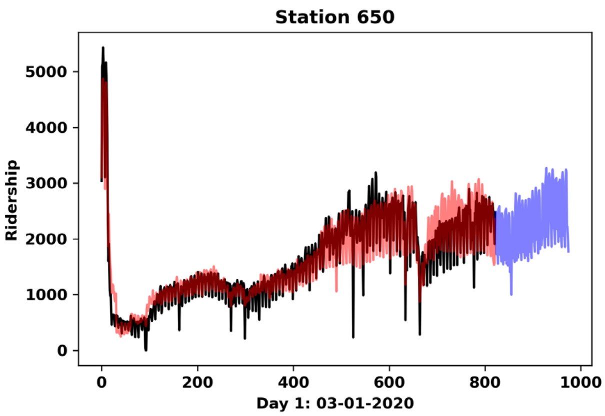
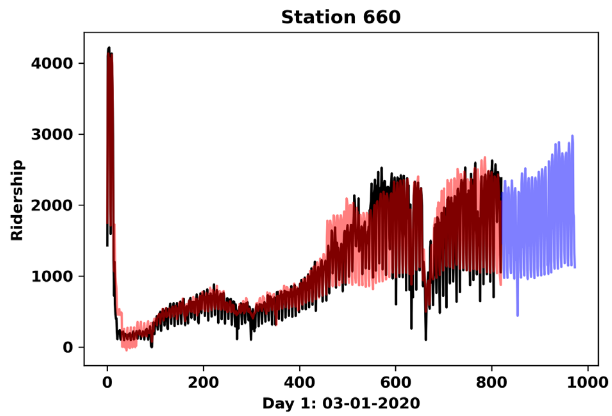
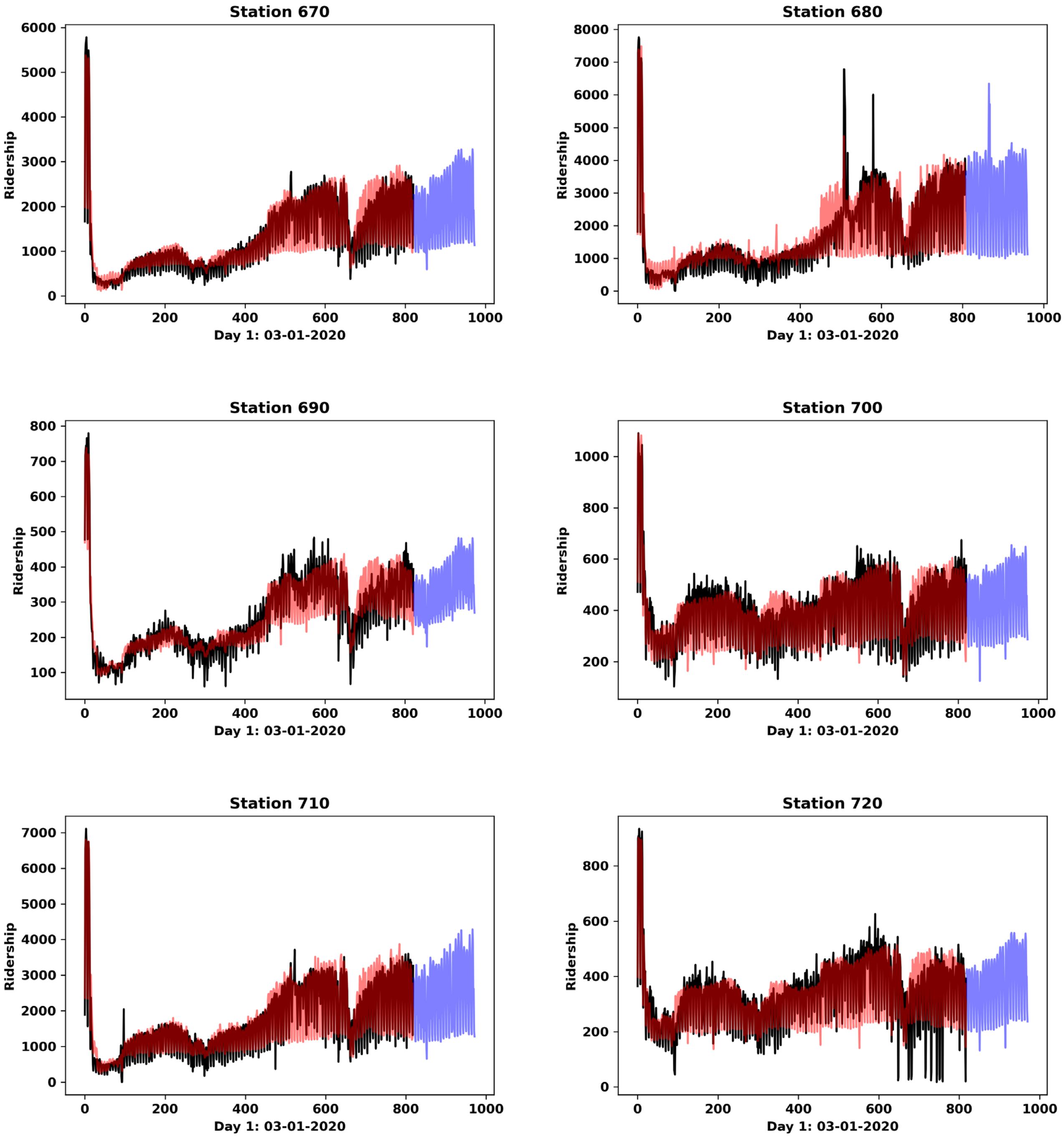
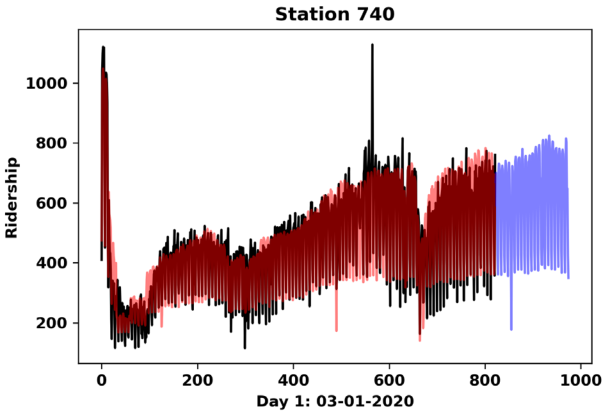
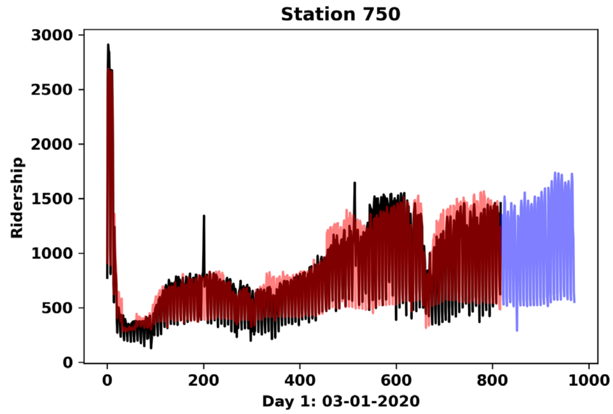
800
1000
Day 1: 03-01-2020

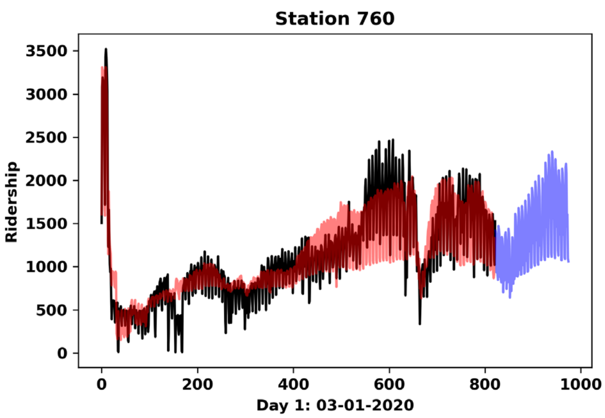

Station 650
Ridership
0
1000
2000
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020

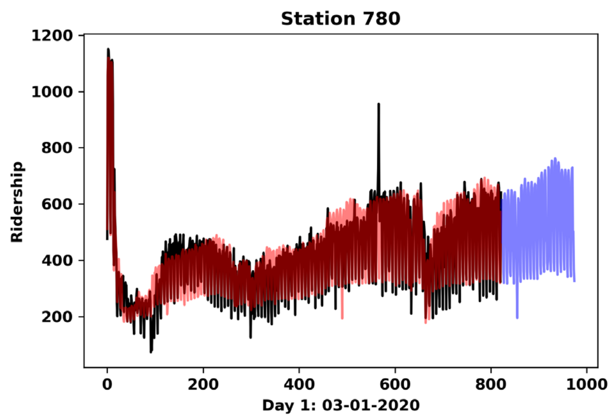

Station 660
Ridership
0
1000
2000
3000
4000
0
200
400
600
800
1000
Day 1: 03-01-2020

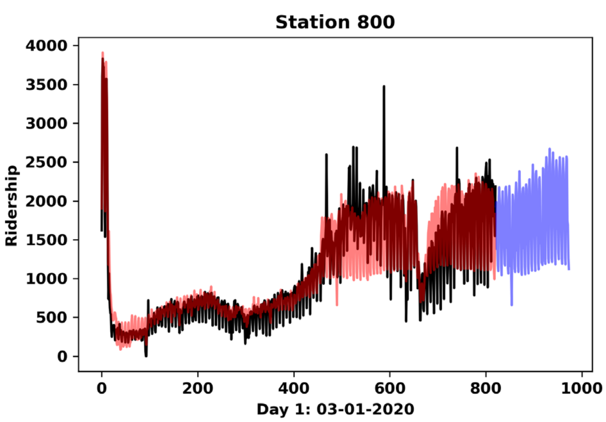

Station 670
Station 680
Station 690
Station 700
Station 710
Station 720
Ridership
Day 1: 03-01-2020

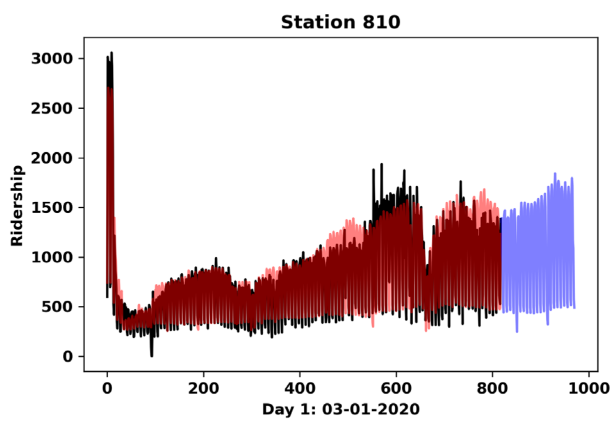

Station 740
Ridership
Day 1: 03-01-2020

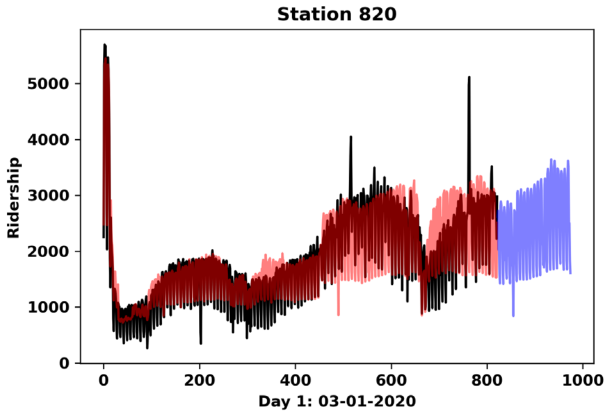

Station 750
Ridership
Day 1: 03-01-2020

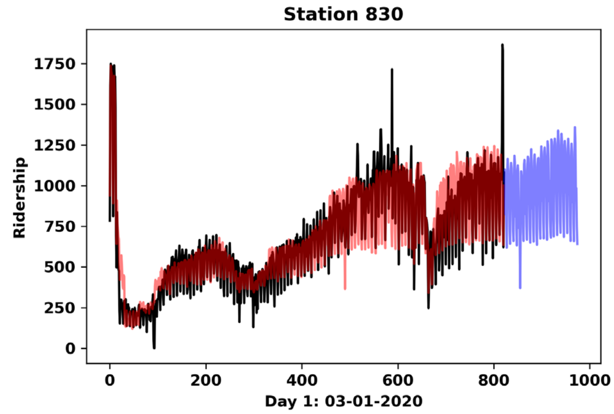

Station 760
Ridership
Day 1: 03-01-2020

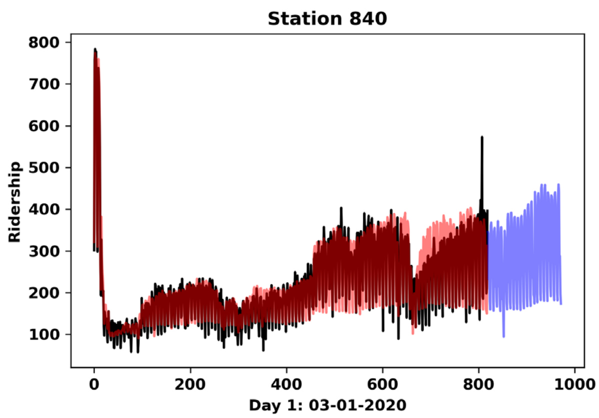

Station 780
Ridership
Day 1: 03-01-2020

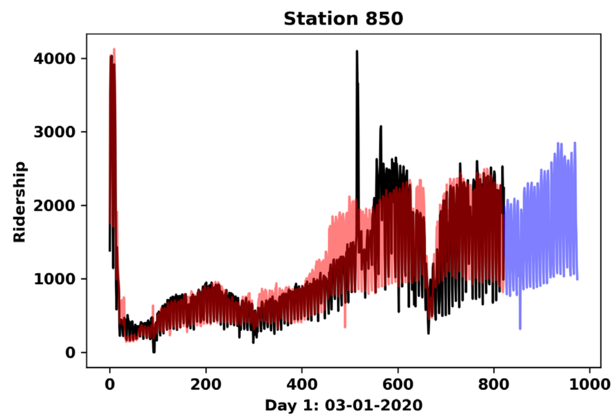

Station 800
Ridership
Day 1: 03-01-2020

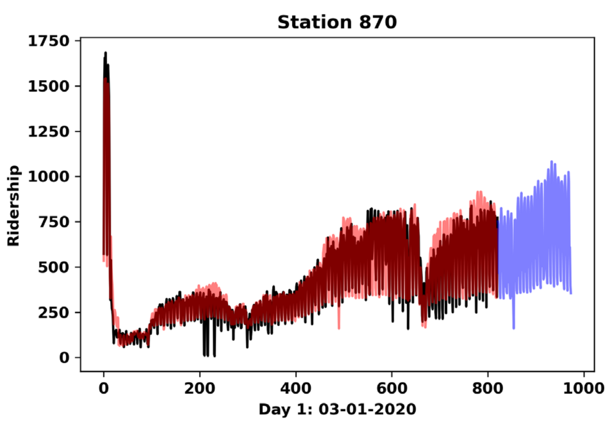

Station 810
Ridership
Day 1: 03-01-2020

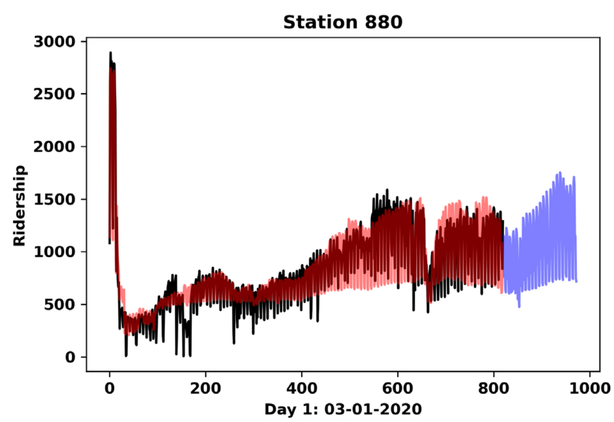

Station 820
Ridership
0
1000
2000
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020

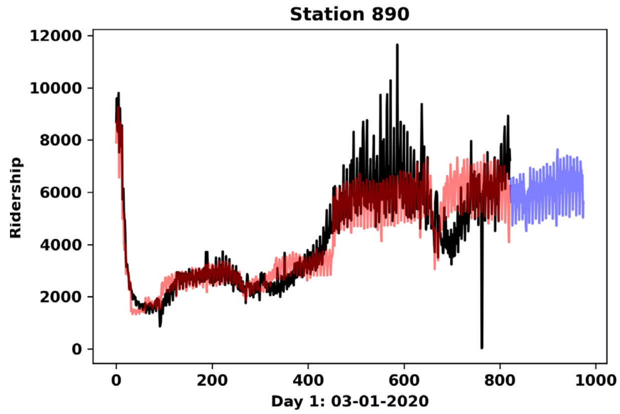

Station 830
Ridership
0
250
500
750
1000
1250
1500
1750
0
200
400
600
800
1000
Day 1: 03-01-2020

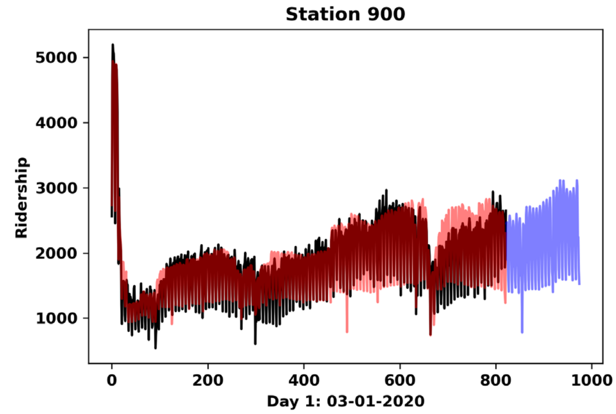

Station 840
Ridership
100
200
300
400
500
600
700
800
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 850
Ridership
0
1000
2000
3000
4000
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 870
Ridership
0
250
500
750
1000
1250
1500
1750
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 880
Ridership
0
500
1000
1500
2000
2500
3000
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 890
Ridership
12000
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 900
Ridership
5000
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3000
2000
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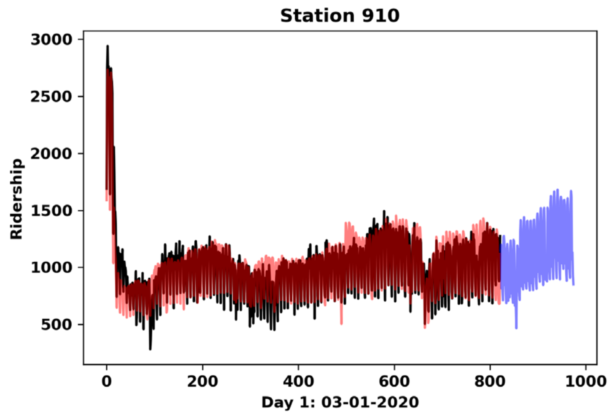
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 910
Ridership
3000
2500
2000
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500
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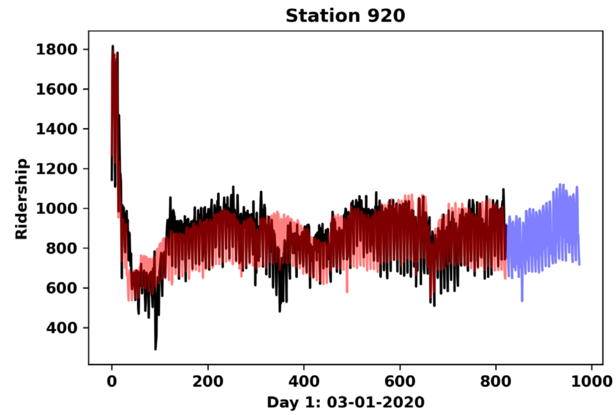
200
400
600
800
1000
Day 1: 03-01-2020


Station 920
Ridership
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1600
1400
1200
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800
600
400
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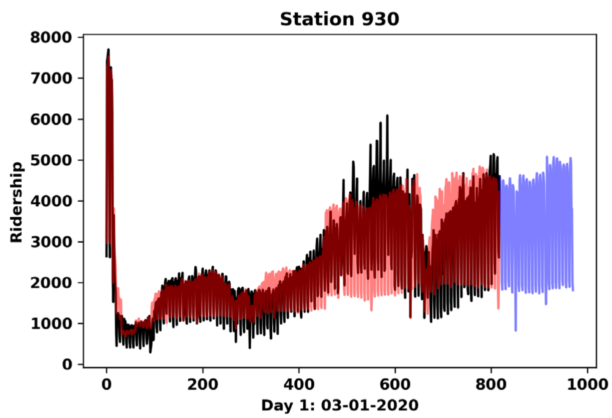
200
400
600
800
1000
Day 1: 03-01-2020


Station 930
Ridership
8000
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6000
5000
4000
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2000
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0
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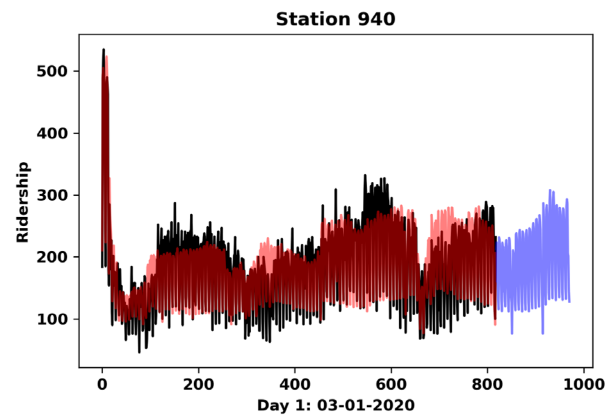
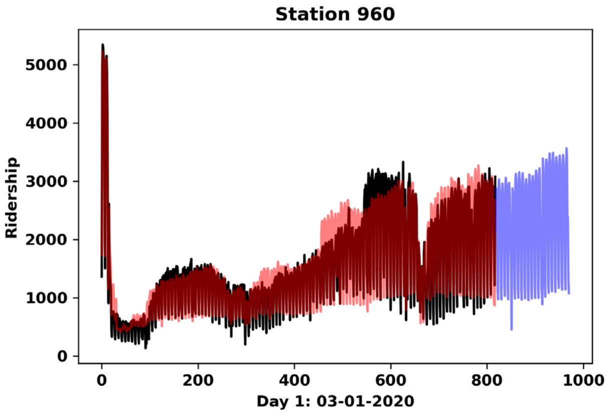
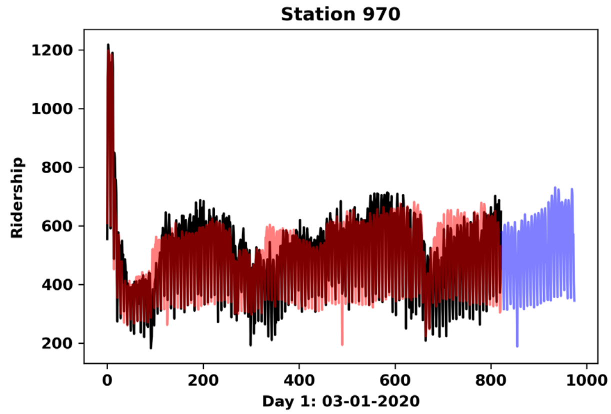
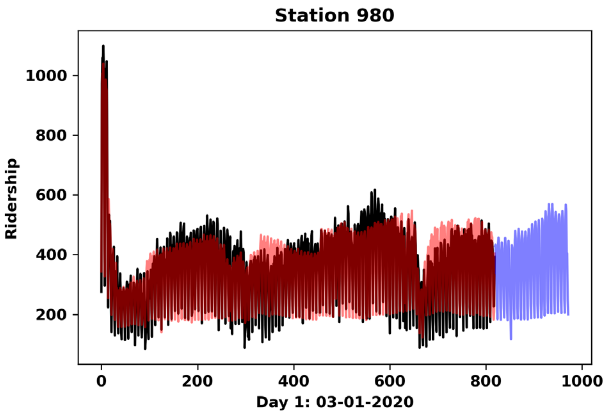
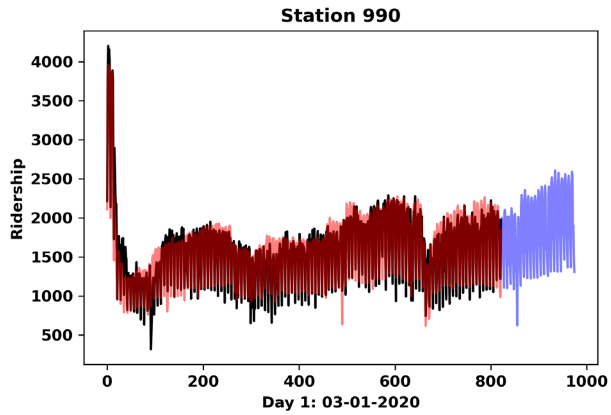
200
400
600
800
1000
Day 1: 03-01-2020

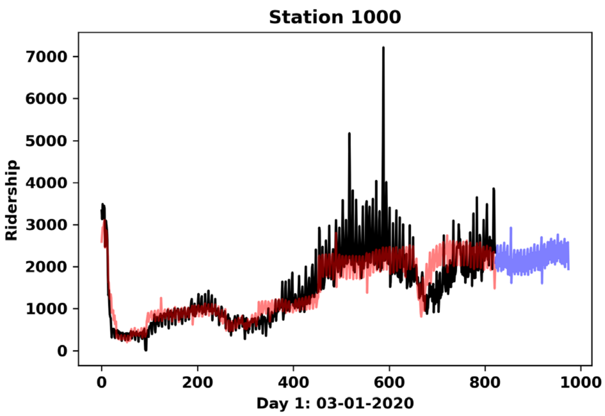

Station 940
Ridership
500
400
300
200
100
0
200
400
600
800
1000
Day 1: 03-01-2020

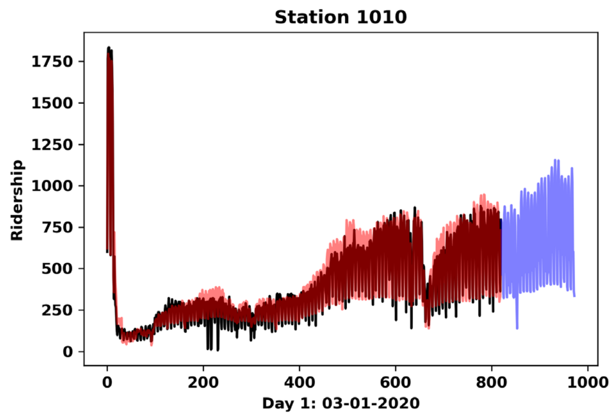

Station 960
Ridership
Day 1: 03-01-2020

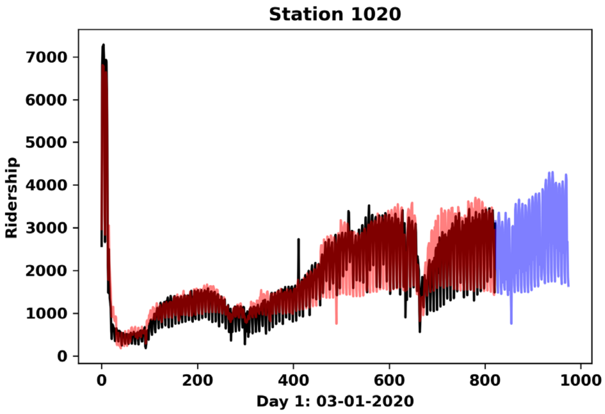

Station 970
Ridership
Day 1: 03-01-2020


Station 980
Ridership
Day 1: 03-01-2020


Station 990
Ridership
Day 1: 03-01-2020


Station 1000
Ridership
Day 1: 03-01-2020


Station 1010
Ridership
Day 1: 03-01-2020


Station 1020
Ridership
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2000
3000
4000
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6000
7000
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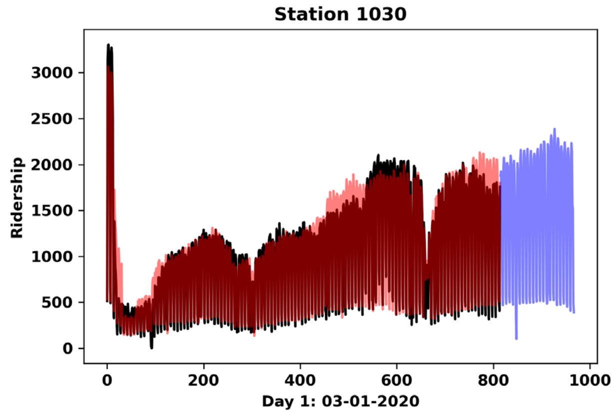
200
400
600
800
1000
Day 1: 03-01-2020


Station 1030
Ridership
0
500
1000
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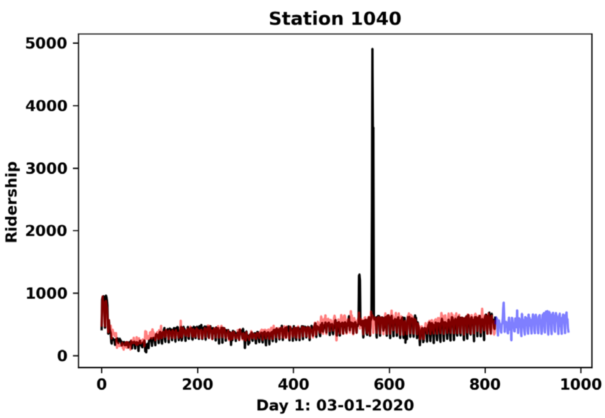
2000
2500
3000
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 1040
Ridership
0
1000
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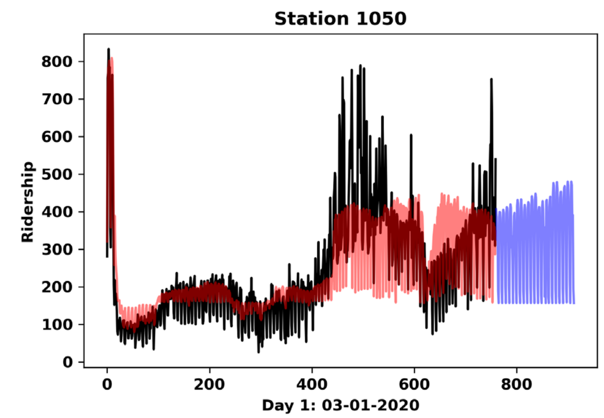
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020


Station 1050
Ridership
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300
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600
700
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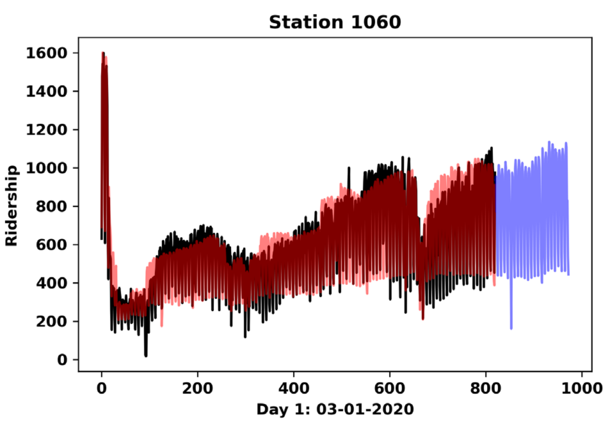
0
200
400
600
800
Day 1: 03-01-2020


Station 1060
Ridership
0
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1600
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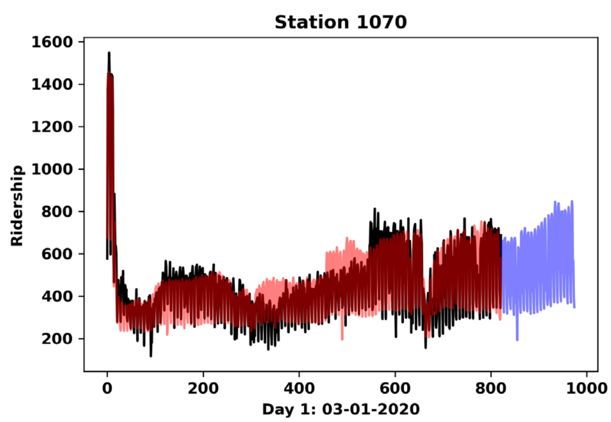
200
400
600
800
1000
Day 1: 03-01-2020


Station 1070
Ridership
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600
800
1000
1200
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1600
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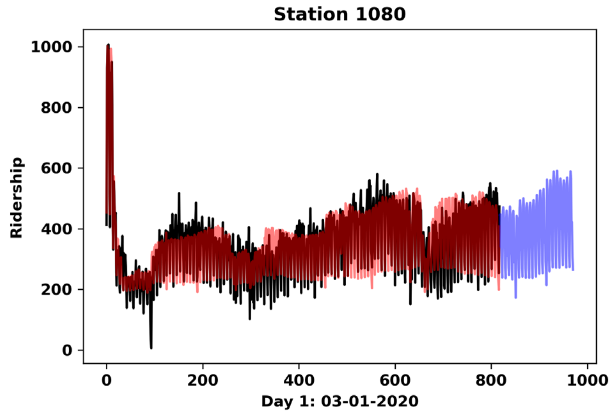
200
400
600
800
1000
Day 1: 03-01-2020


Station 1080
Ridership
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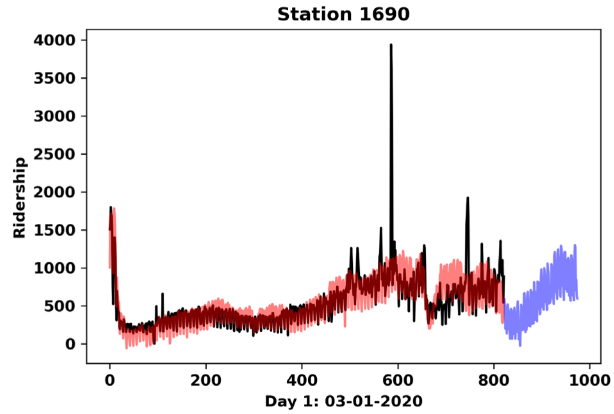
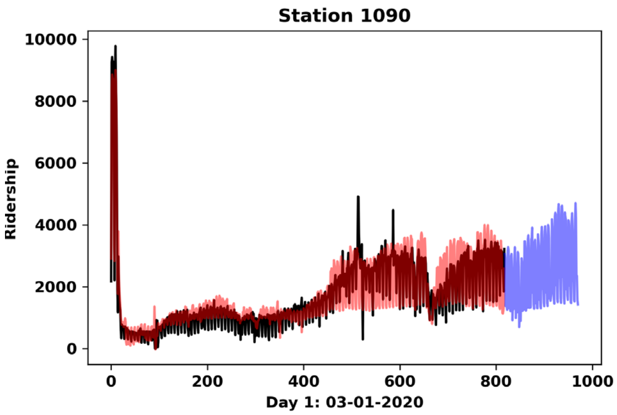
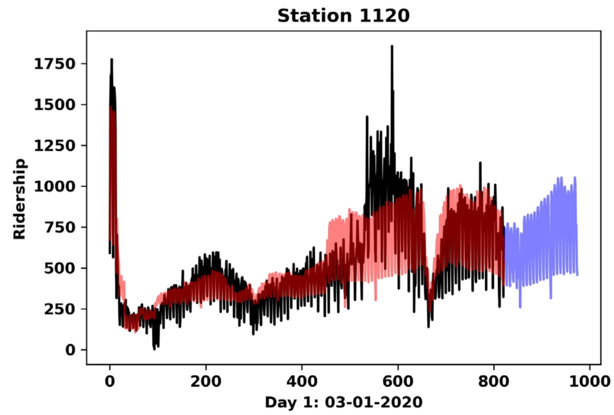
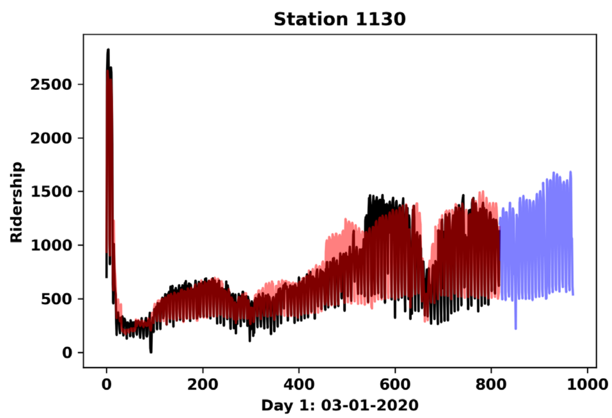
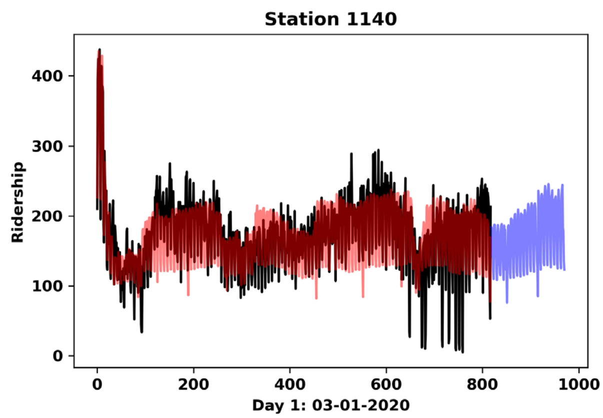
200
400
600
800
1000
Day 1: 03-01-2020

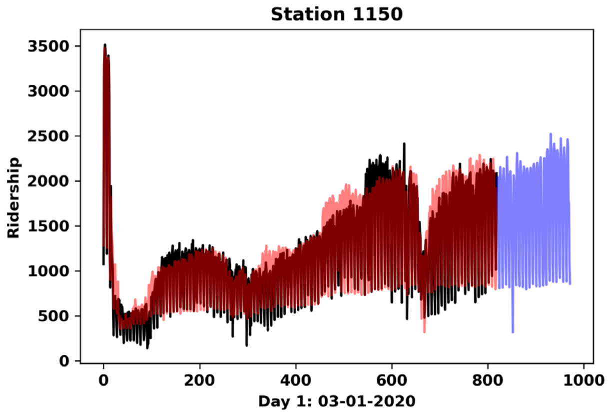

Station 1690
Ridership
0
500
1000
1500
2000
2500
3000
3500
4000
Day 1: 03-01-2020

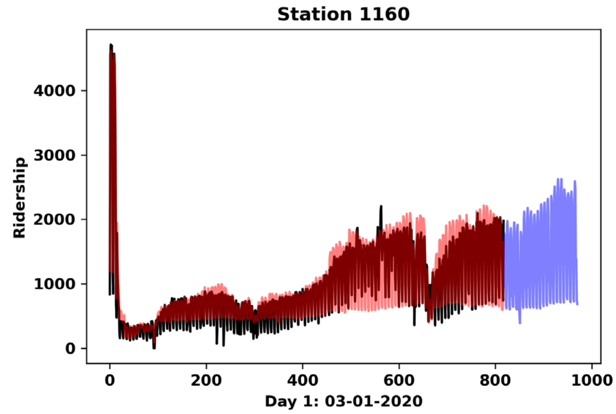

Station 1090
Ridership
0
2000
4000
6000
8000
10000
Day 1: 03-01-2020

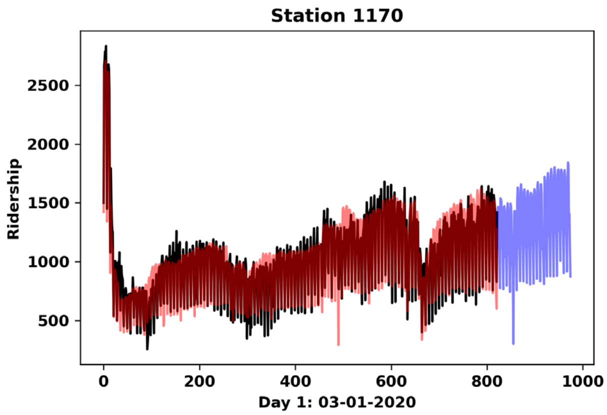

Station 1120
Ridership
0
250
500
750
1000
1250
1500
1750
Day 1: 03-01-2020

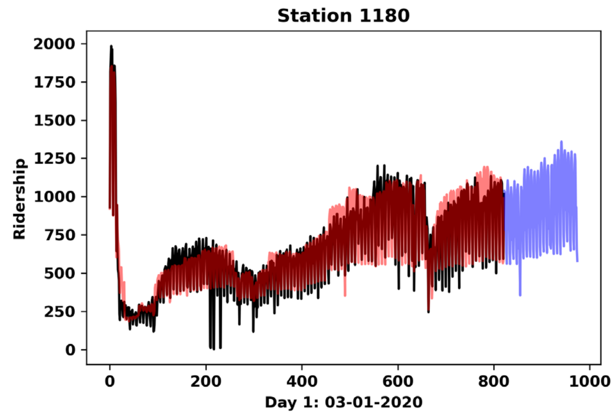

Station 1130
Ridership
0
500
1000
1500
2000
2500
Day 1: 03-01-2020

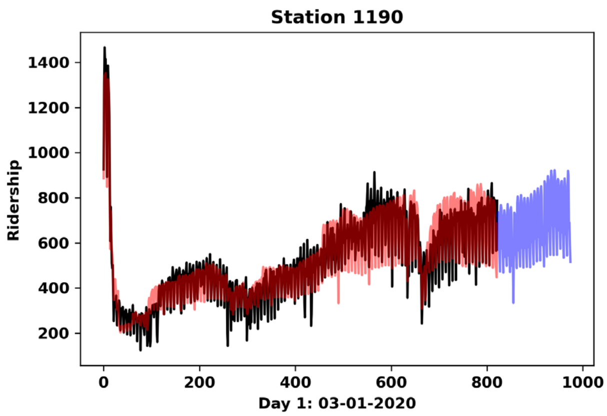

Station 1140
Ridership
0
100
200
300
400
Day 1: 03-01-2020

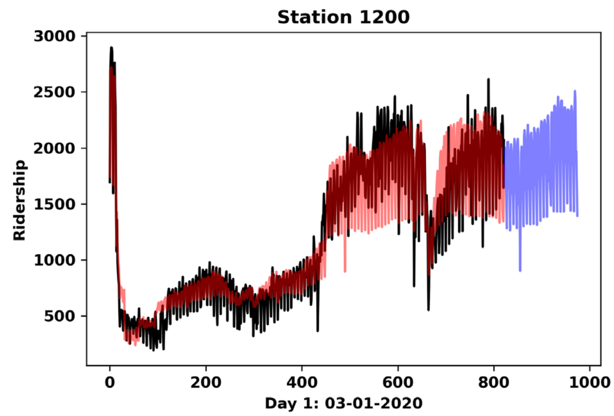

Station 1150
Ridership
Day 1: 03-01-2020

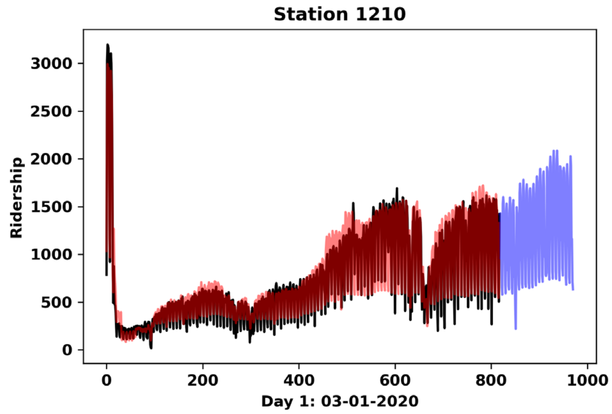

Station 1160
Ridership
Day 1: 03-01-2020

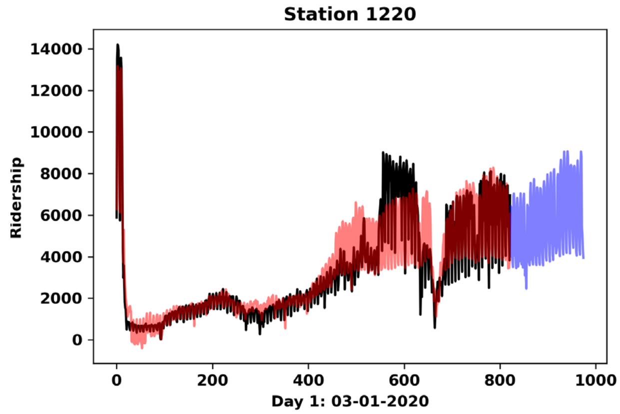

Station 1170
Ridership
Day 1: 03-01-2020

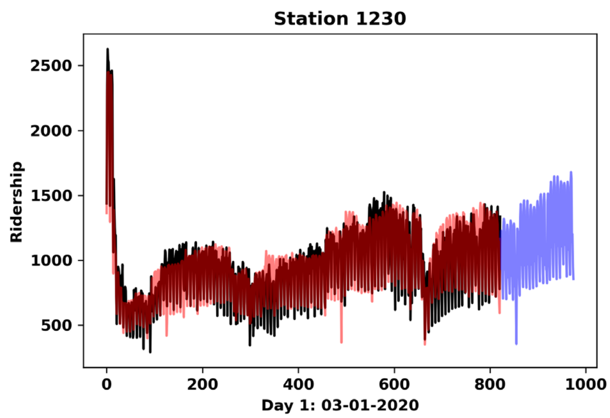

Station 1180
Ridership
Day 1: 03-01-2020

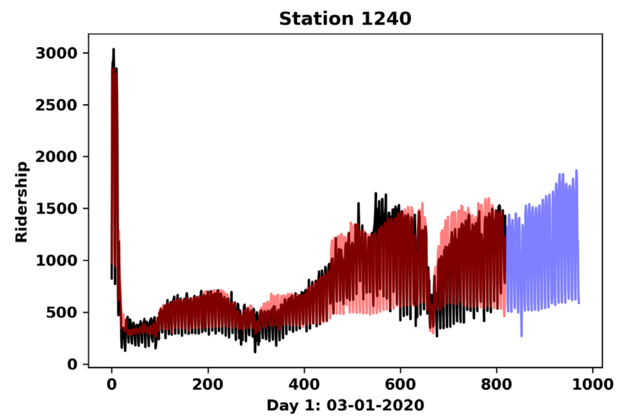

Station 1190
Ridership
Day 1: 03-01-2020

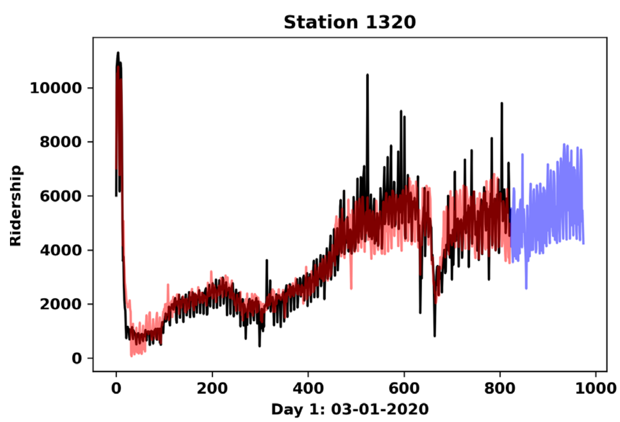

Station 1200
Ridership
Day 1: 03-01-2020

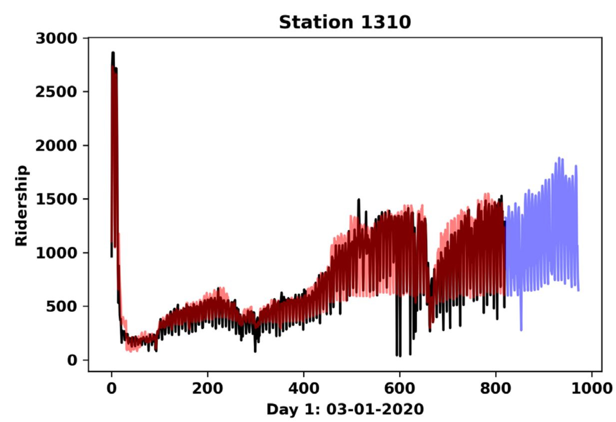

Station 1210
Ridership
Day 1: 03-01-2020

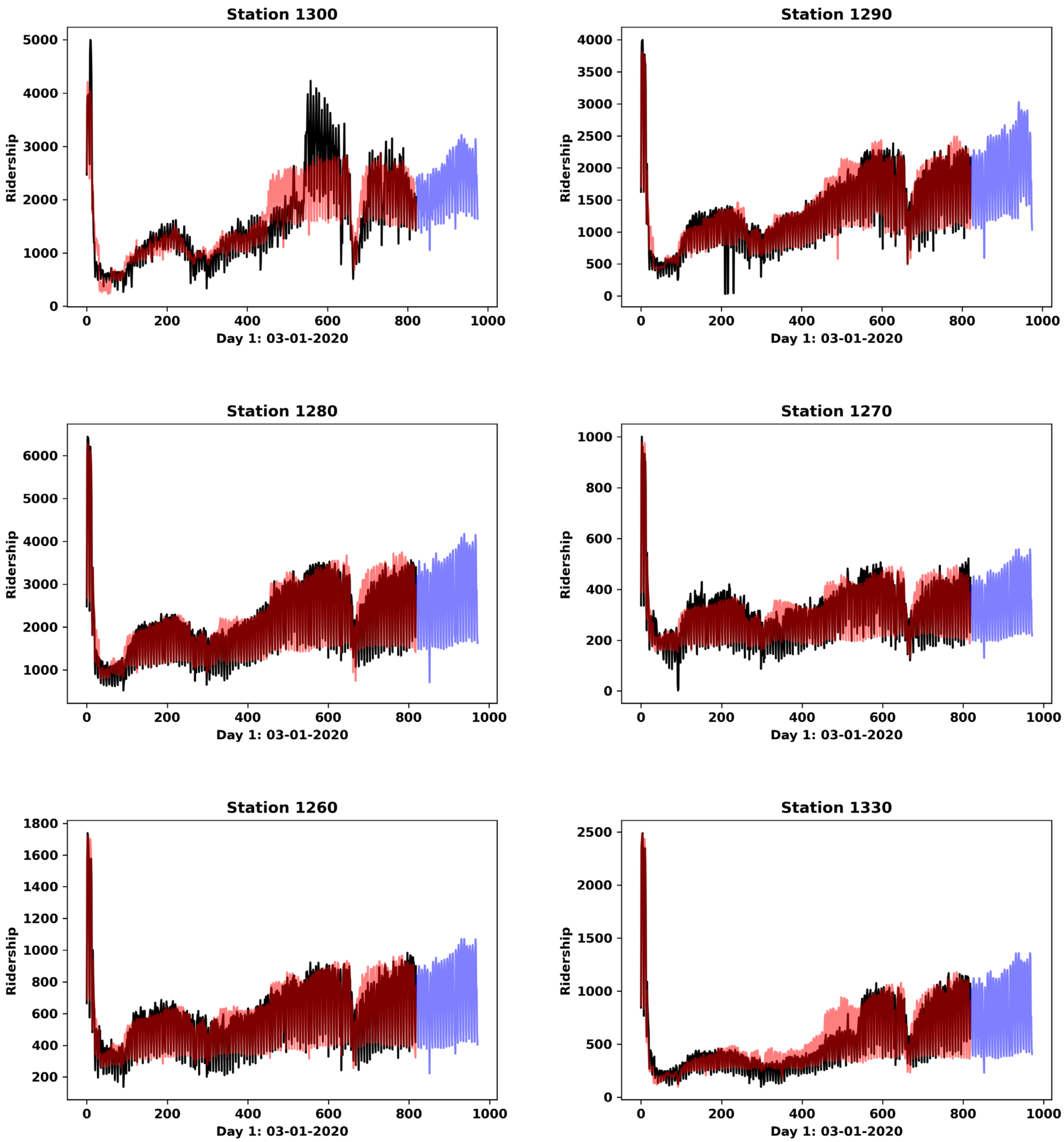

Station 1220
Ridership
Day 1: 03-01-2020

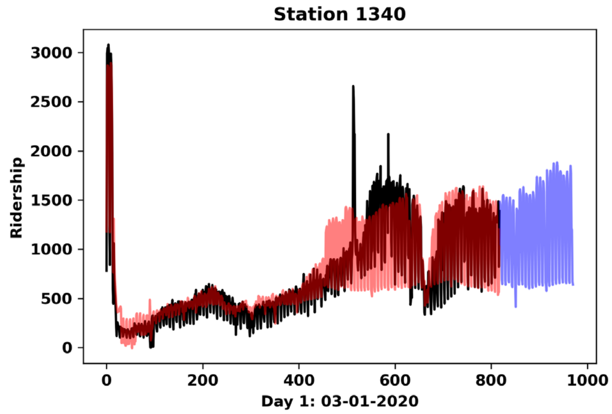

Station 1230
Ridership
Day 1: 03-01-2020

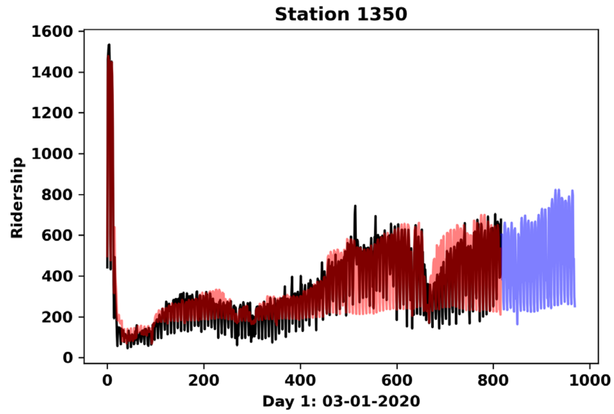

Station 1240
Ridership
Day 1: 03-01-2020

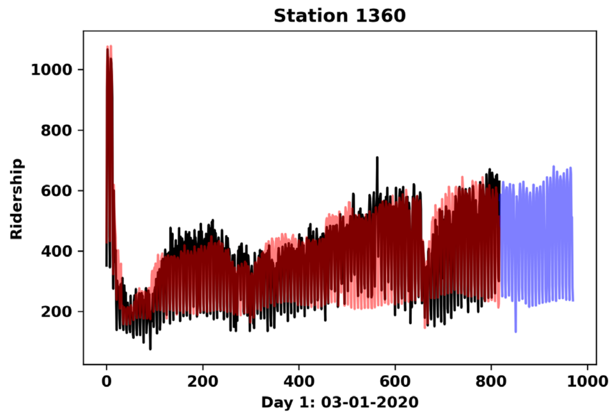

Station 1320
Ridership
Day 1: 03-01-2020

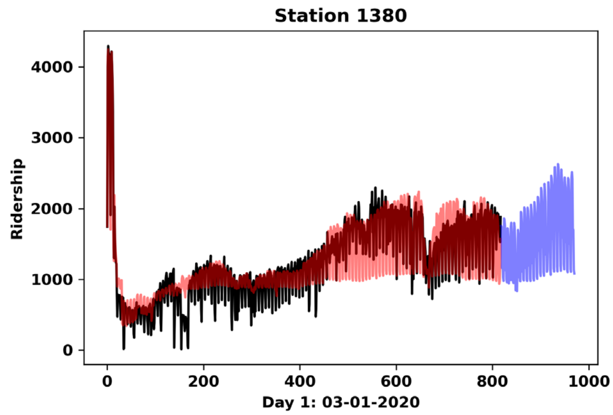

Station 1310
Ridership
Day 1: 03-01-2020

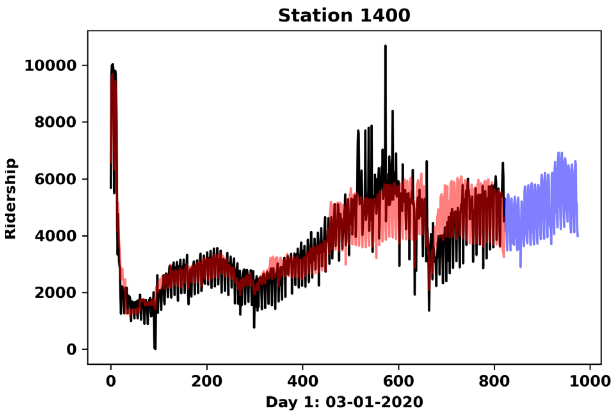

Station 1300
Ridership
0
1000
2000
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 1290
Ridership
0
500
1000
1500
2000
2500
3000
3500
4000
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 1280
Ridership
1000
2000
3000
4000
5000
6000
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 1270
Ridership
0
200
400
600
800
1000
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 1260
Ridership
200
400
600
800
1000
1200
1400
1600
1800
0
200
400
600
800
1000
Day 1: 03-01-2020
Station 1330
Ridership
0
500
1000
1500
2000
2500
0
200
400
600
800
1000
Day 1: 03-01-2020

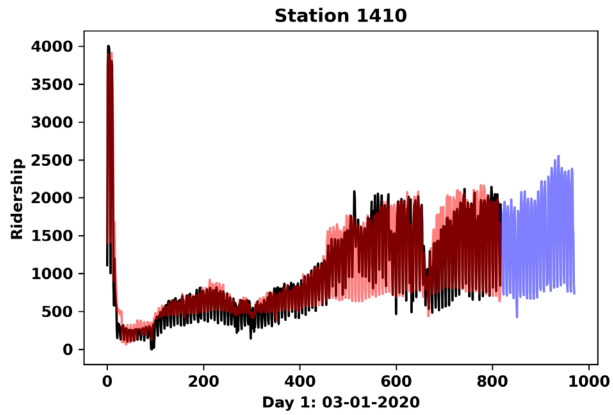

Station 1340
Ridership
0
500
1000
1500
2000
2500
3000
0
200
400
600
800
1000
Day 1: 03-01-2020

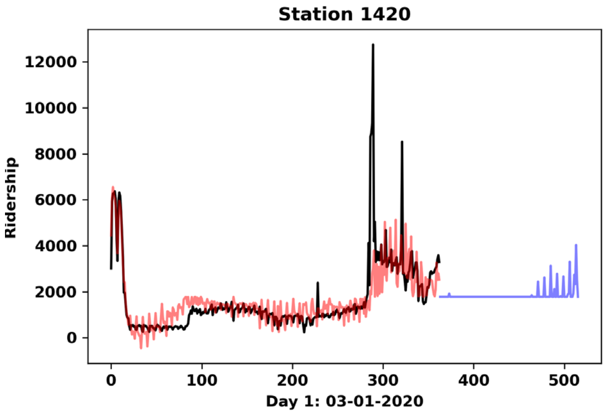

Station 1350
Ridership
0
200
400
600
800
1000
1200
1400
1600
0
200
400
600
800
1000
Day 1: 03-01-2020

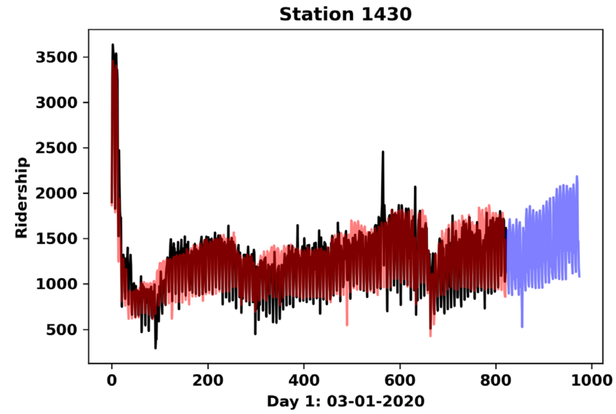

Station 1360
Ridership
200
400
600
800
1000
0
200
400
600
800
1000
Day 1: 03-01-2020

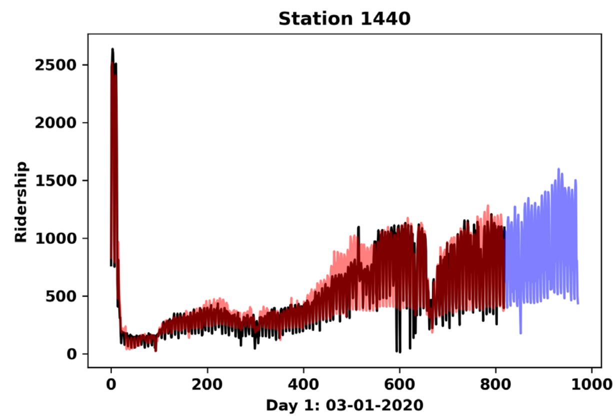

Station 1380
Ridership
0
1000
2000
3000
4000
0
200
400
600
800
1000
Day 1: 03-01-2020

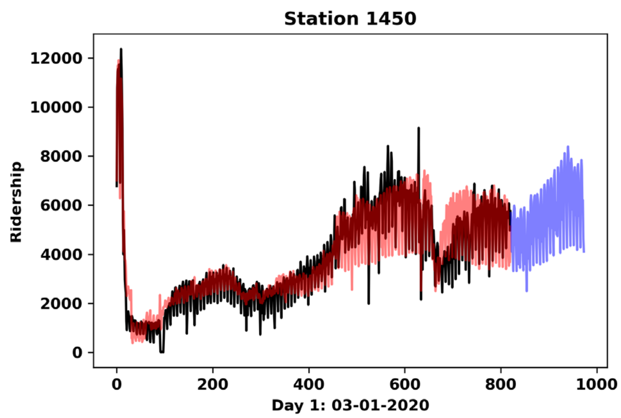

Station 1400
Ridership
0
2000
4000
6000
8000
10000
0
200
400
600
800
1000
Day 1: 03-01-2020

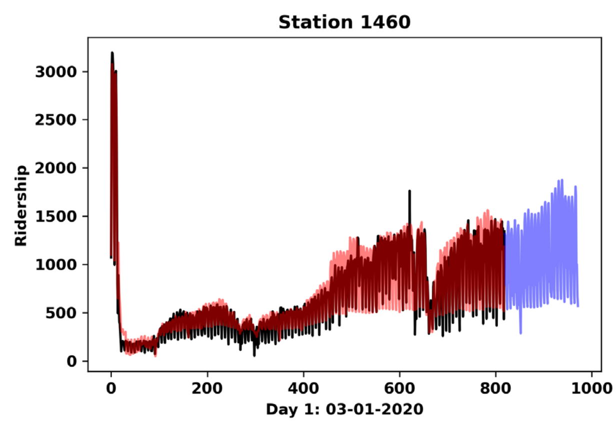

Station 1410
Ridership
0
500
1000
1500
2000
2500
3000
3500
4000
0
200
400
600
800
1000
Day 1: 03-01-2020

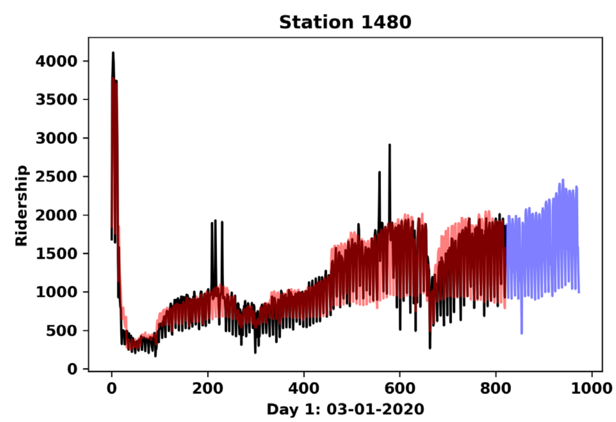

Station 1420
Ridership
Day 1: 03-01-2020

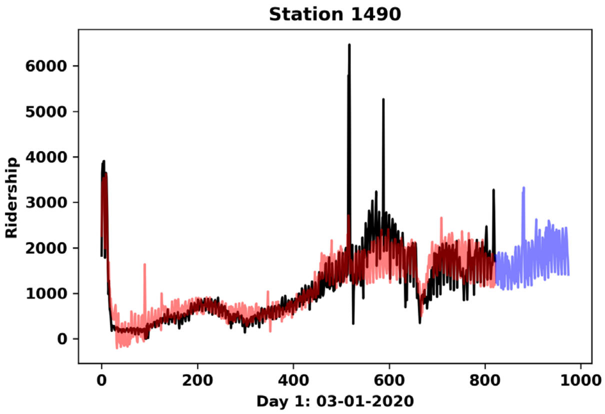

Station 1430
Ridership
Day 1: 03-01-2020

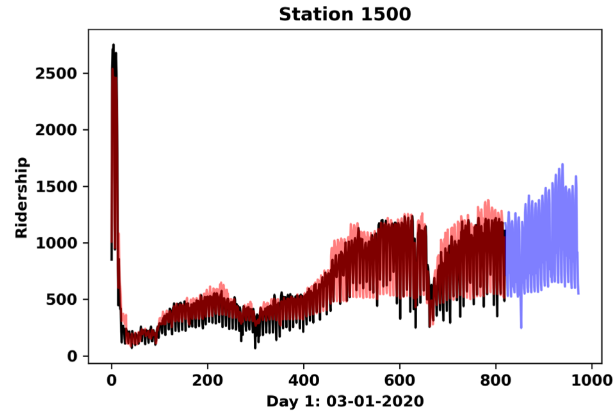

Station 1440
Ridership
Day 1: 03-01-2020

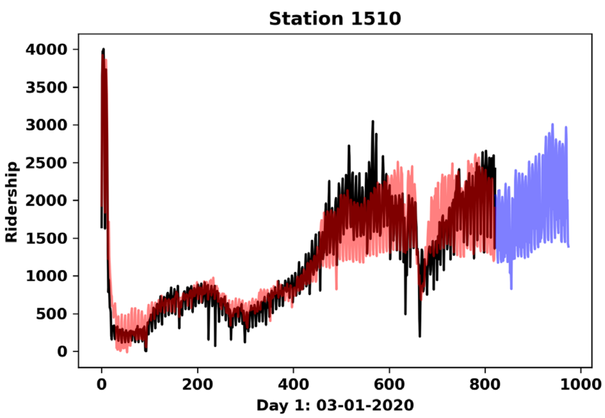

Station 1450
Ridership
Day 1: 03-01-2020

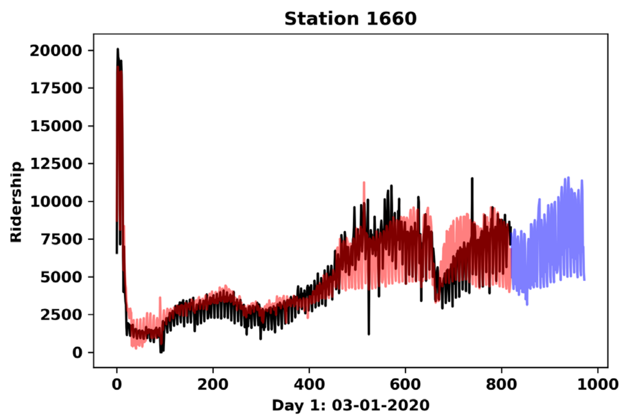

Station 1460
Ridership
Day 1: 03-01-2020

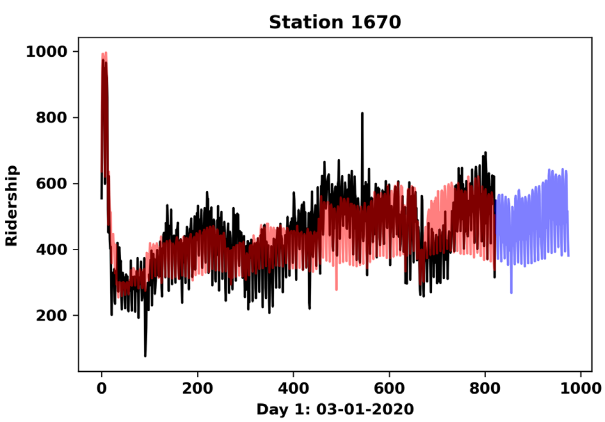

Station 1480
Ridership
Day 1: 03-01-2020

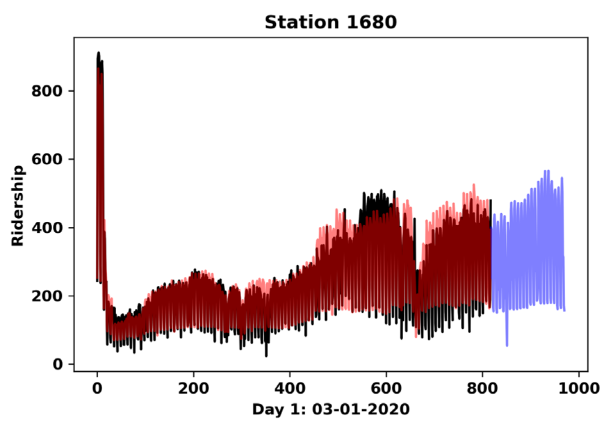

Station 1490
Ridership
Day 1: 03-01-2020


Station 1500
Ridership
Day 1: 03-01-2020

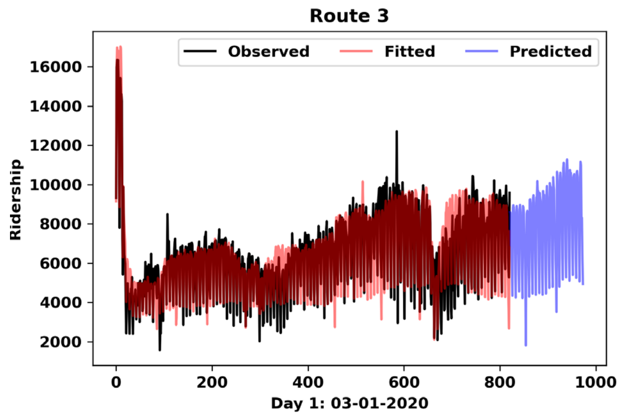

Station 1510
Ridership
Day 1: 03-01-2020

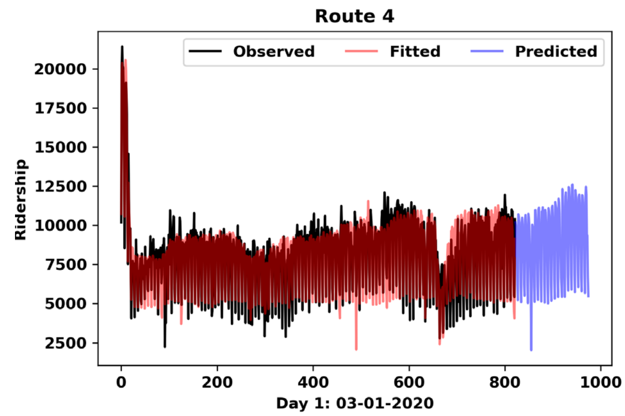

Station 1660
Ridership
Day 1: 03-01-2020

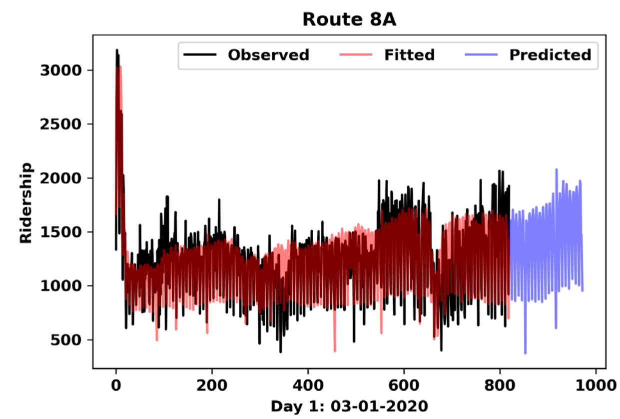

Station 1670
Ridership
Day 1: 03-01-2020

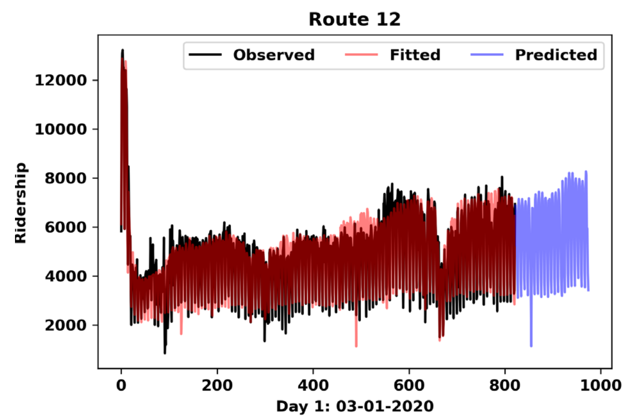

Station 1680
Ridership
Day 1: 03-01-2020

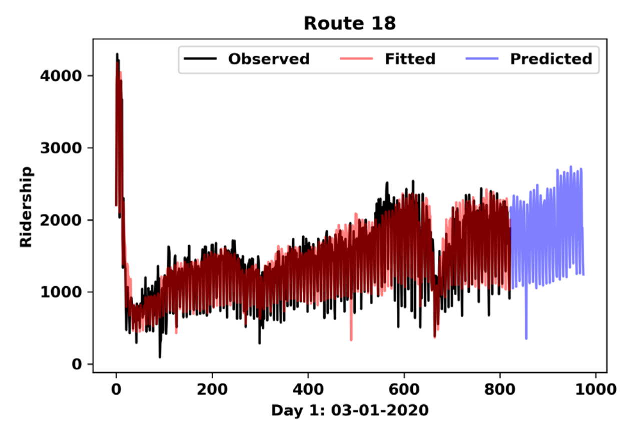
APPENDIX C: TIME-SERIES PLOTS FOR CTA BUS ROUTES

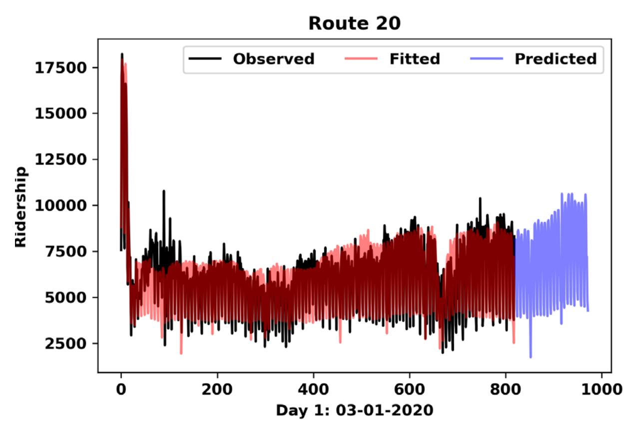


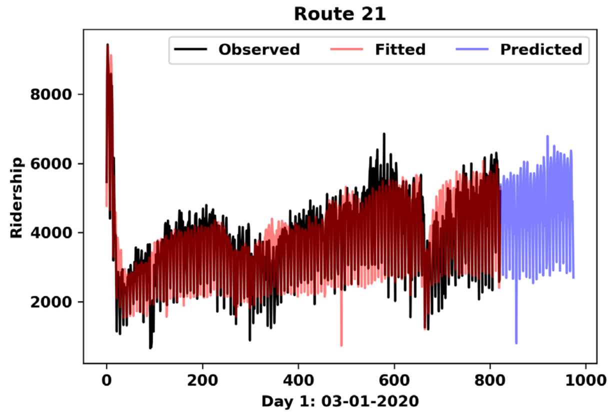


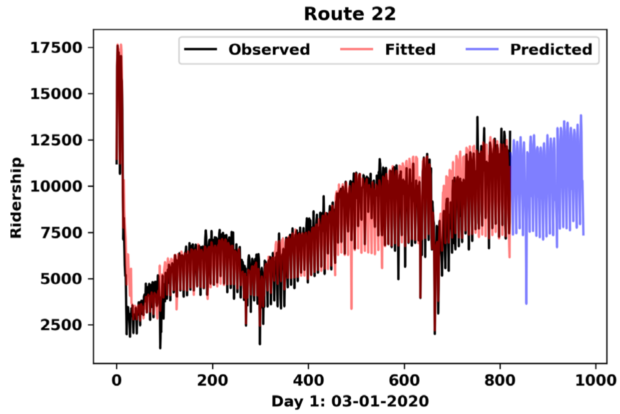


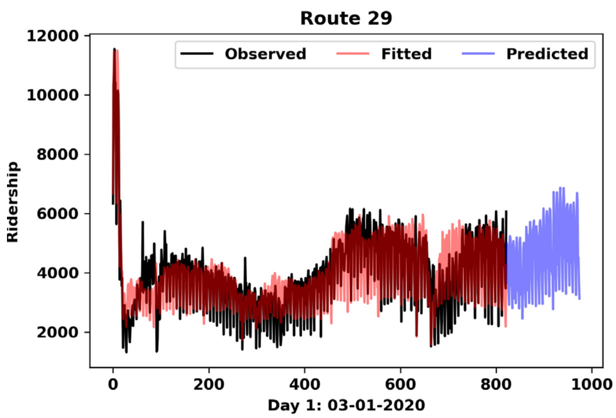


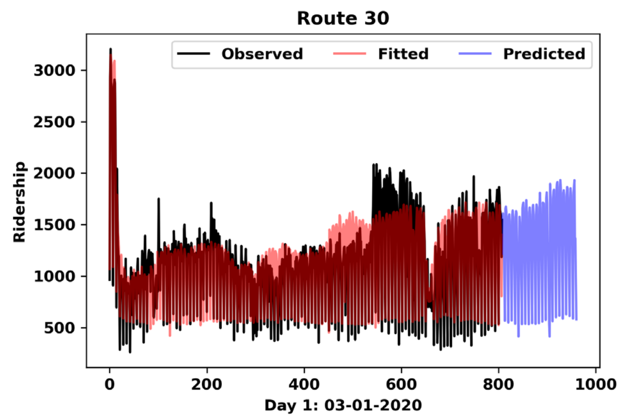


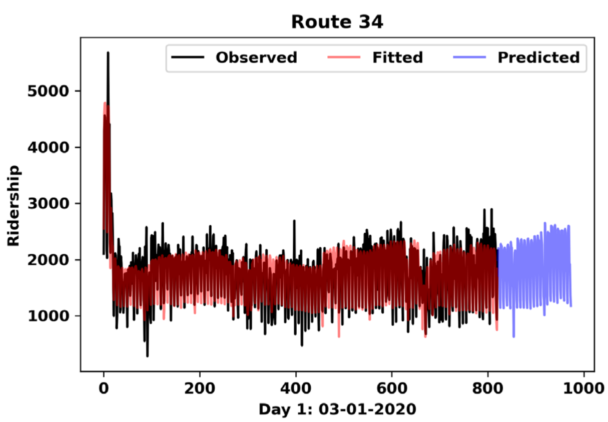


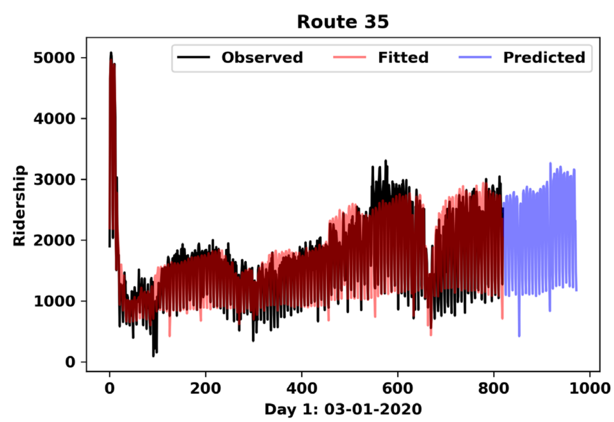

Route 21
Observed
Fitted
Predicted
Ridership
2000
4000
6000
8000
0
200
400
600
800
1000
Day 1: 03-01-2020

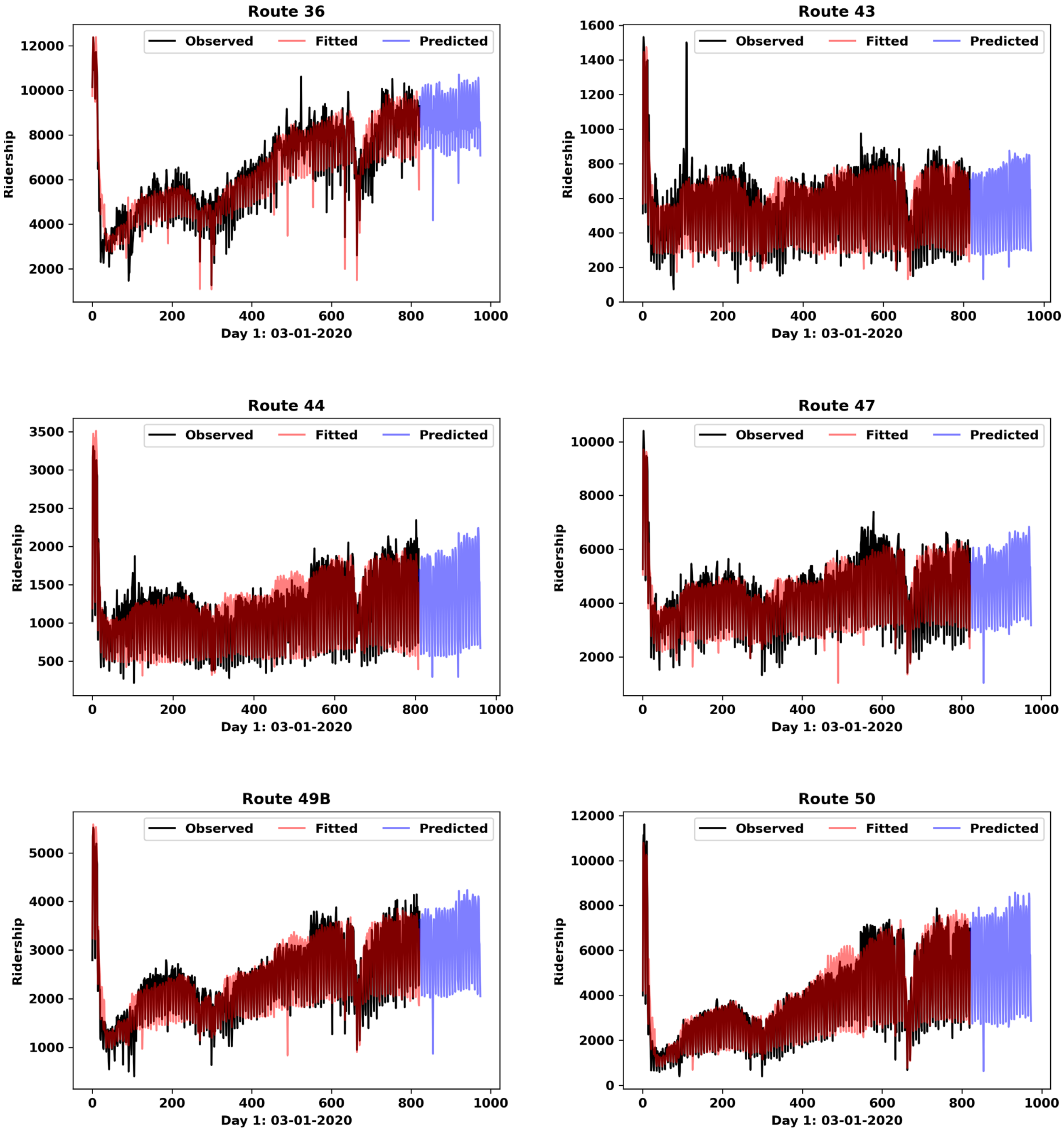

Route 22
Observed
Fitted
Predicted
Ridership
2500
5000
7500
10000
12500
15000
17500
0
200
400
600
800
1000
Day 1: 03-01-2020

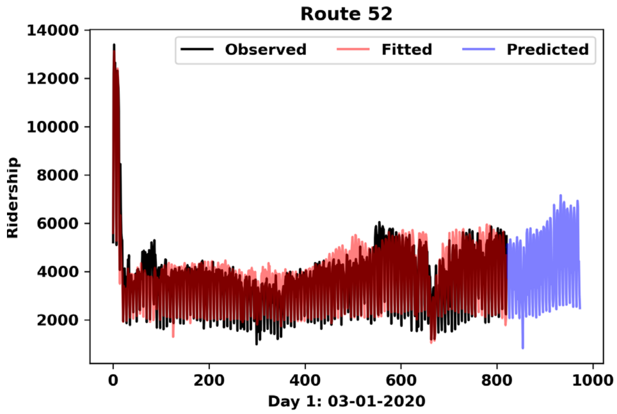

Route 29
Observed
Fitted
Predicted
Ridership
2000
4000
6000
8000
10000
12000
0
200
400
600
800
1000
Day 1: 03-01-2020

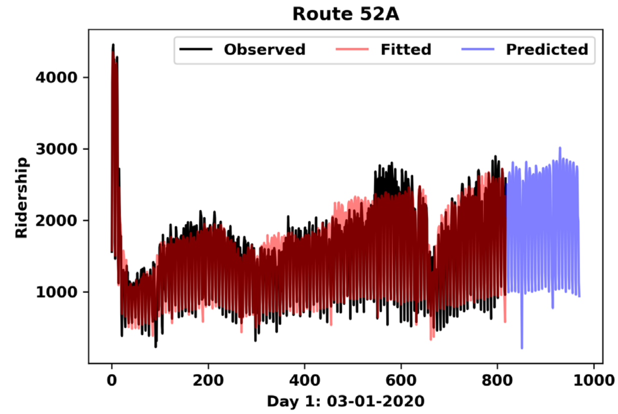

Route 30
Observed
Fitted
Predicted
Ridership
500
1000
1500
2000
2500
3000
0
200
400
600
800
1000
Day 1: 03-01-2020

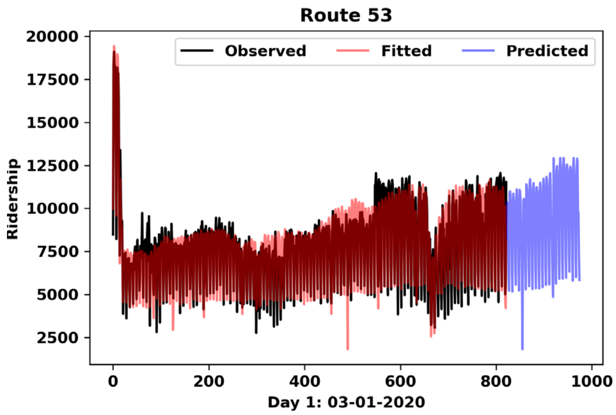

Route 34
Observed
Fitted
Predicted
Ridership
1000
2000
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020

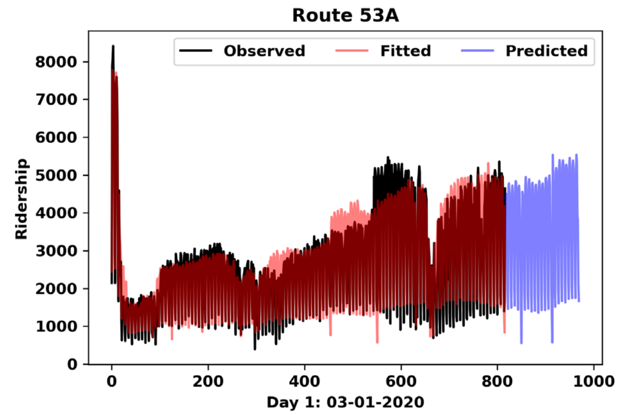

Route 35
Observed
Fitted
Predicted
Ridership
0
1000
2000
3000
4000
5000
0
200
400
600
800
1000
Day 1: 03-01-2020

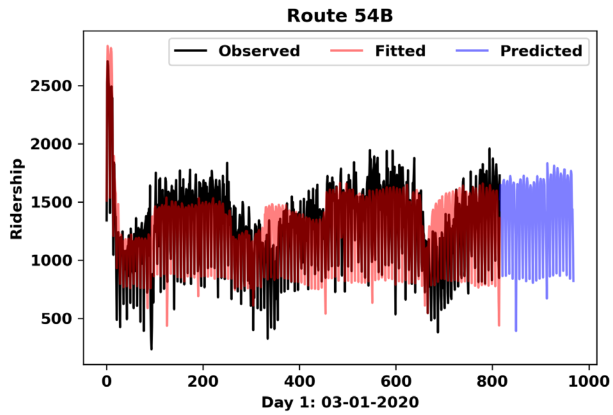

Route 36
Route 43
Route 44
Route 47
Route 49B
Route 50
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

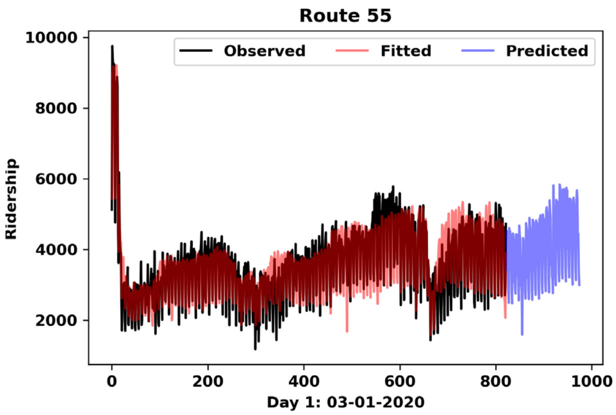

Route 52
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

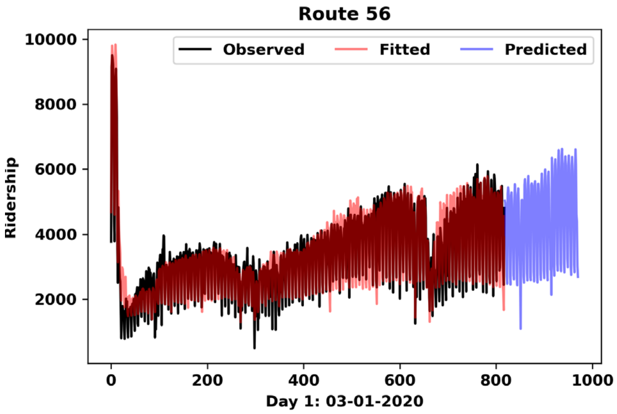

Route 52A
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

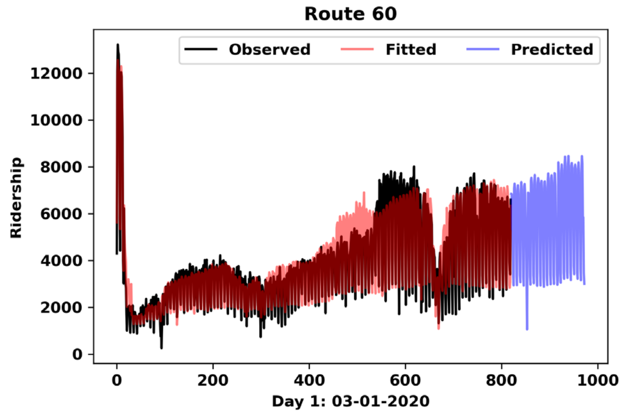

Route 53
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

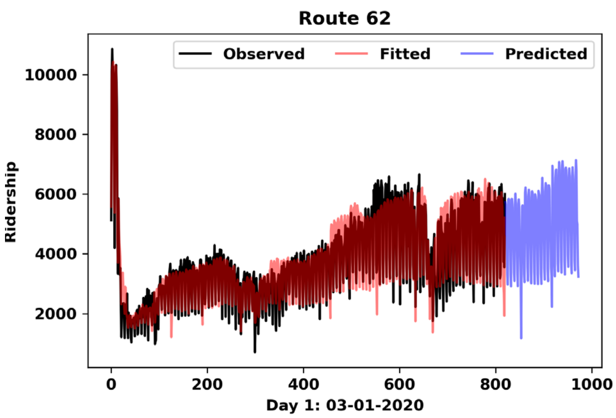

Route 53A
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

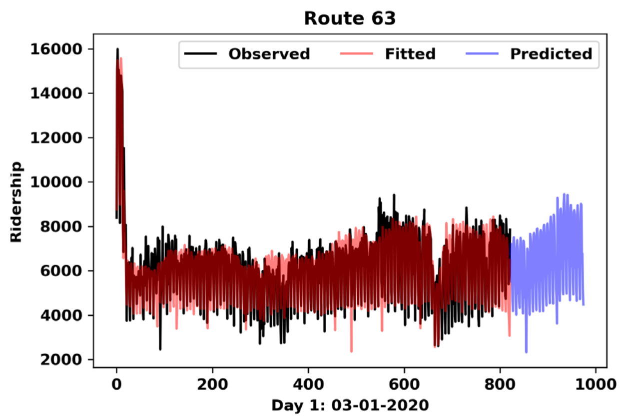

Route 54B
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

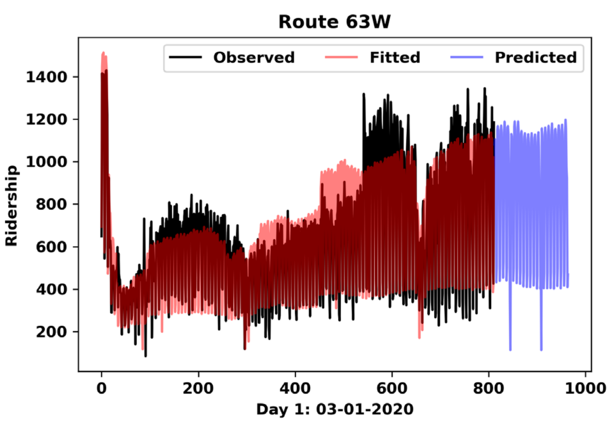

Route 55
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

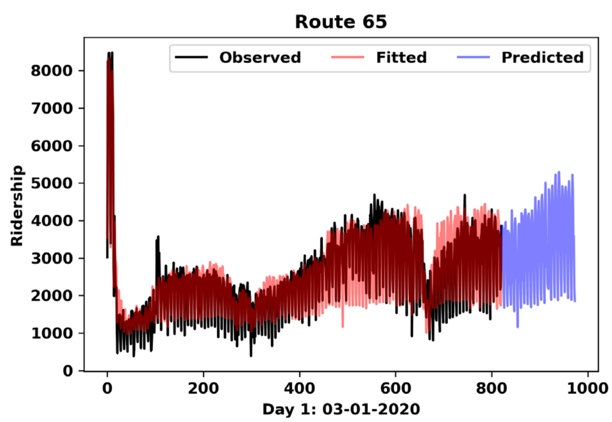

Route 56
Observed
Fitted
Predicted
Ridership
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

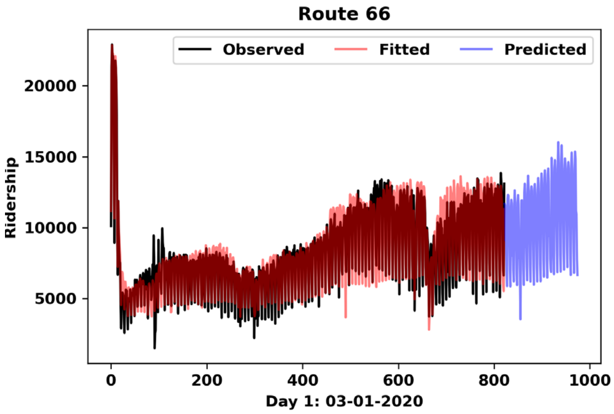

Route 60
Observed
Fitted
Predicted
Ridership
12000
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
Day 1: 03-01-2020

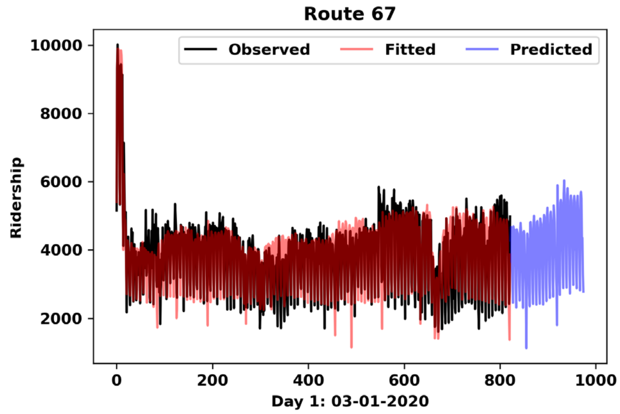

Route 62
Observed
Fitted
Predicted
Ridership
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

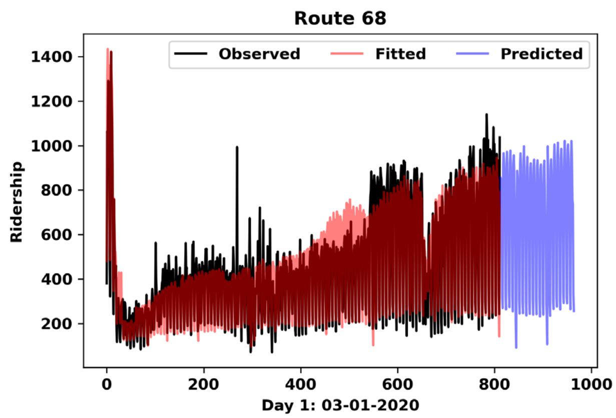

Route 63
Observed
Fitted
Predicted
Ridership
16000
14000
12000
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

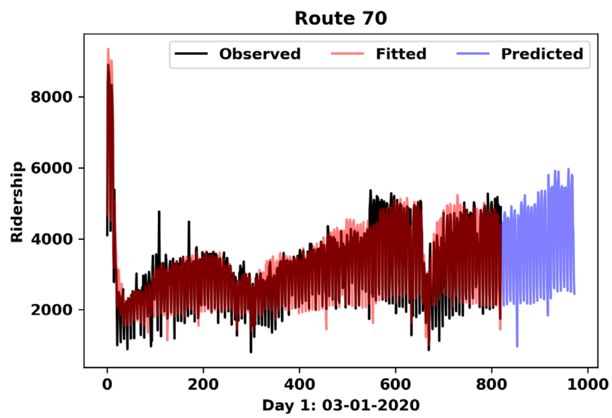

Route 63W
Observed
Fitted
Predicted
Ridership
1400
1200
1000
800
600
400
200
0
200
400
600
800
1000
Day 1: 03-01-2020

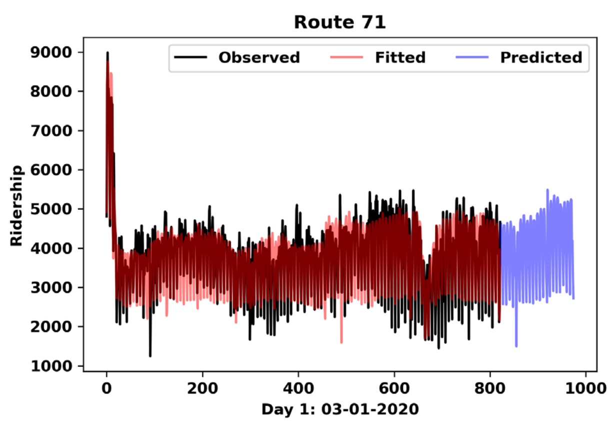

Route 65
Observed
Fitted
Predicted
Ridership
8000
7000
6000
5000
4000
3000
2000
1000
0
0
200
400
600
800
1000
Day 1: 03-01-2020

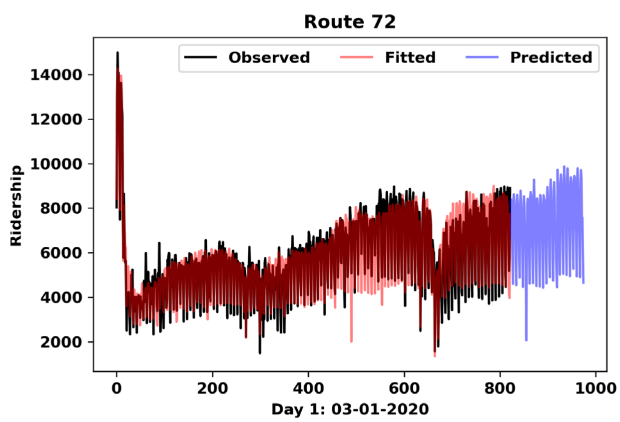

Route 66
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

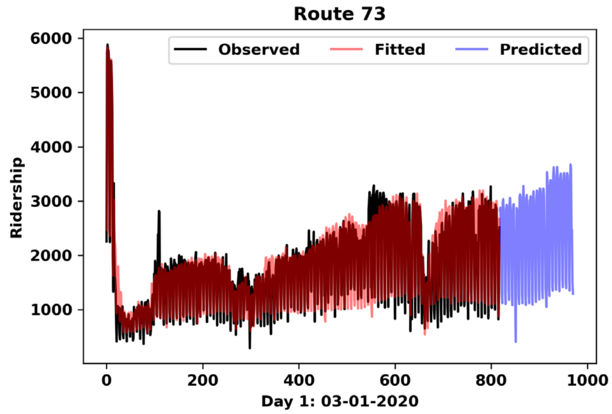

Route 67
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

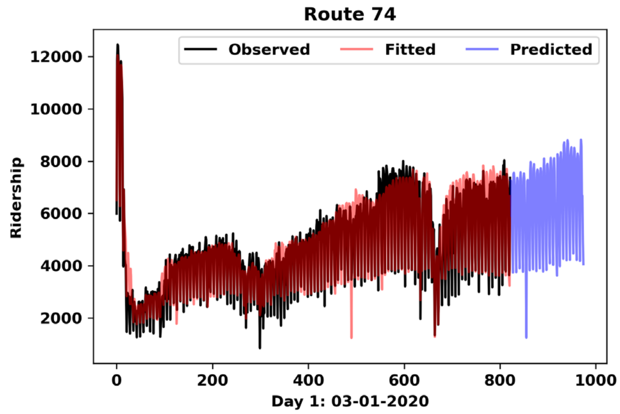

Route 68
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

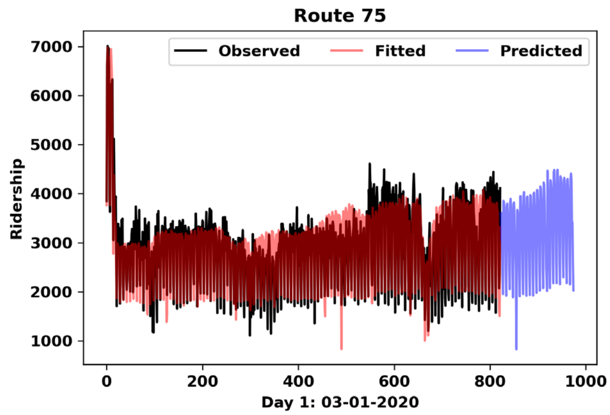

Route 70
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

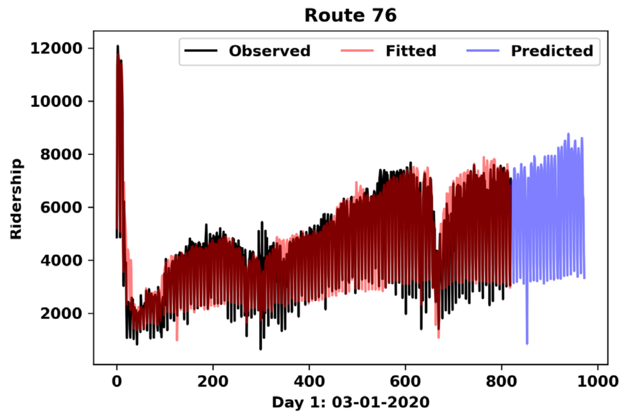

Route 71
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

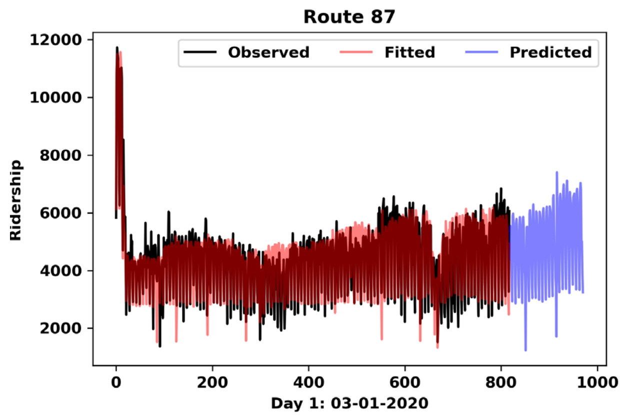

Route 72
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

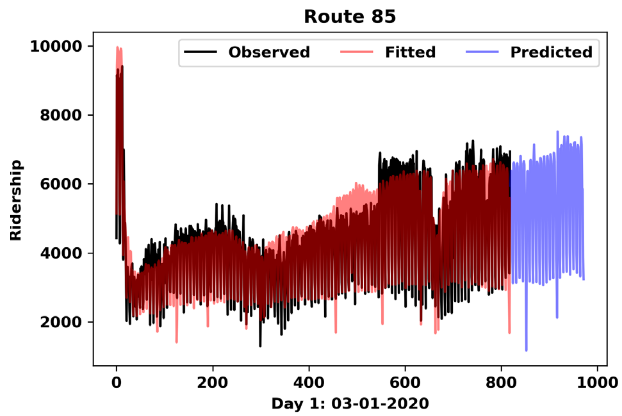

Route 73
Observed
Fitted
Predicted
Ridership
6000
5000
4000
3000
2000
1000
0
200
400
600
800
1000
Day 1: 03-01-2020

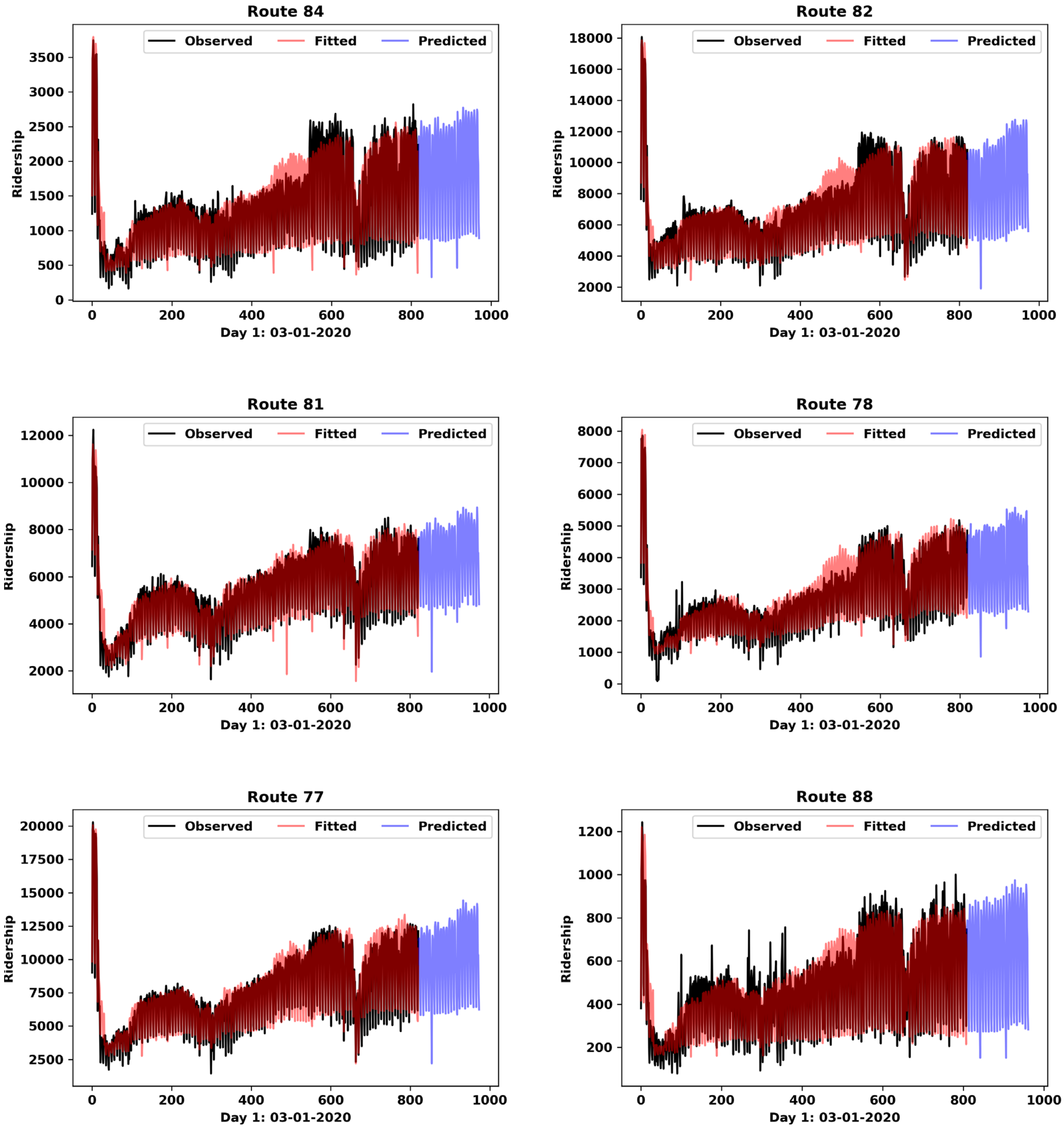

Route 74
Observed
Fitted
Predicted
Ridership
12000
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

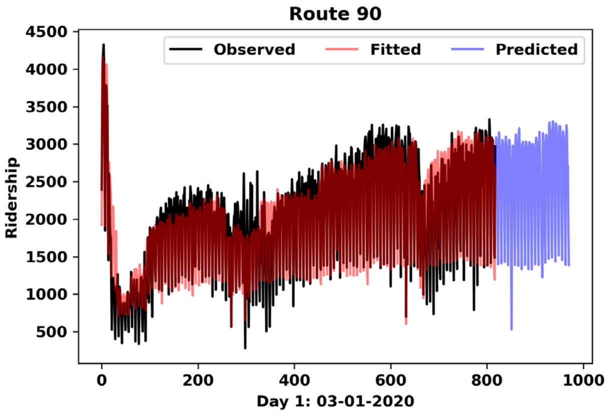

Route 75
Observed
Fitted
Predicted
Ridership
7000
6000
5000
4000
3000
2000
1000
0
200
400
600
800
1000
Day 1: 03-01-2020

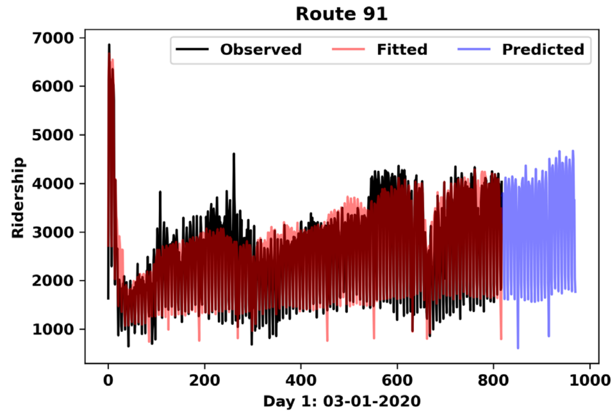

Route 76
Observed
Fitted
Predicted
Ridership
12000
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

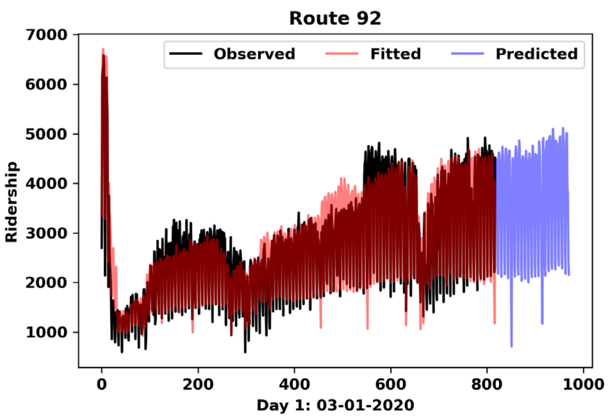

Route 87
Observed
Fitted
Predicted
Ridership
12000
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

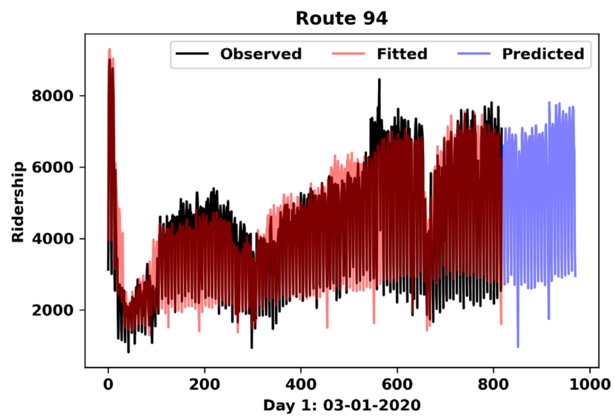

Route 85
Observed
Fitted
Predicted
Ridership
10000
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020

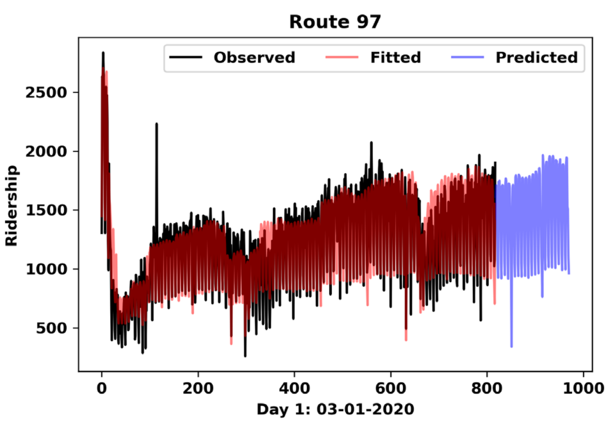

Route 84
Route 82
Route 81
Route 78
Route 77
Route 88
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020

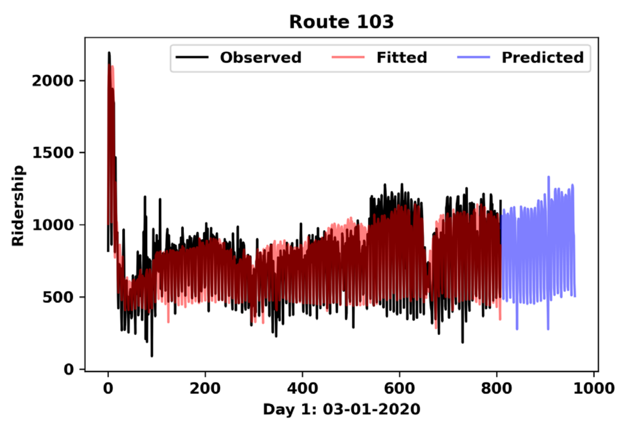

Route 90
Observed
Fitted
Predicted
Ridership
4500
4000
3500
3000
2500
2000
1500
1000
500
0
200
400
600
800
1000
Day 1: 03-01-2020

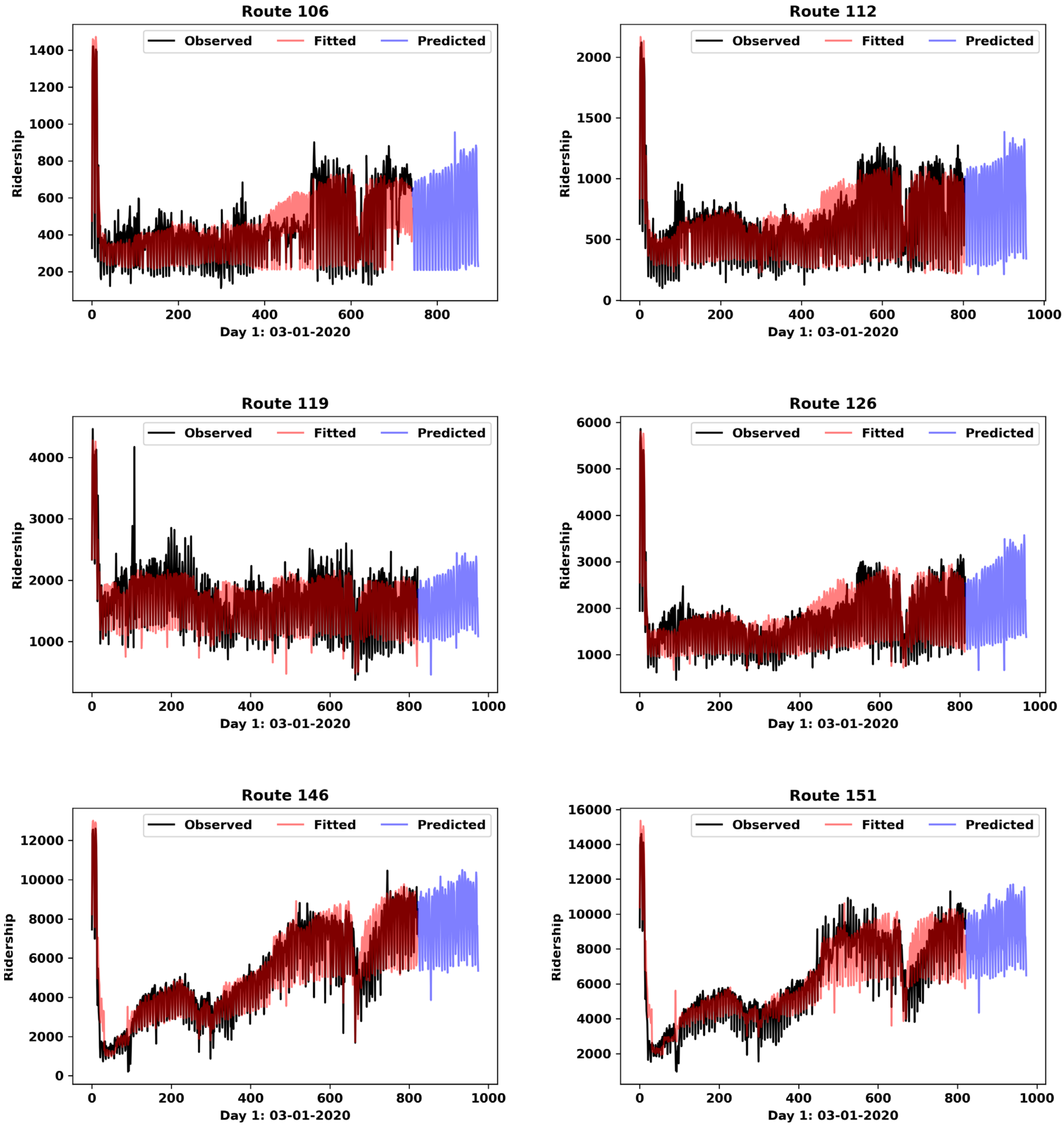

Route 91
Observed
Fitted
Predicted
Ridership
7000
6000
5000
4000
3000
2000
1000
0
200
400
600
800
1000
Day 1: 03-01-2020

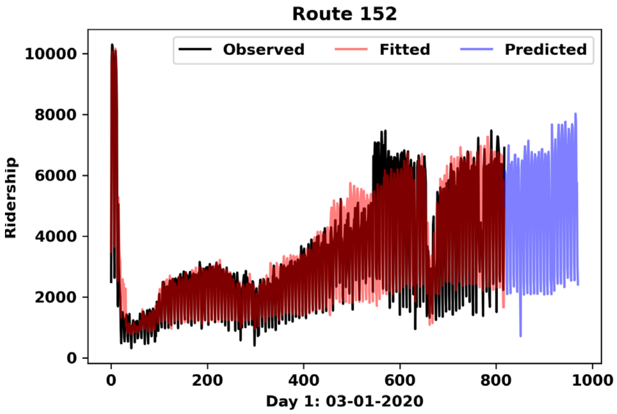

Route 92
Observed
Fitted
Predicted
Ridership
7000
6000
5000
4000
3000
2000
1000
0
200
400
600
800
1000
Day 1: 03-01-2020

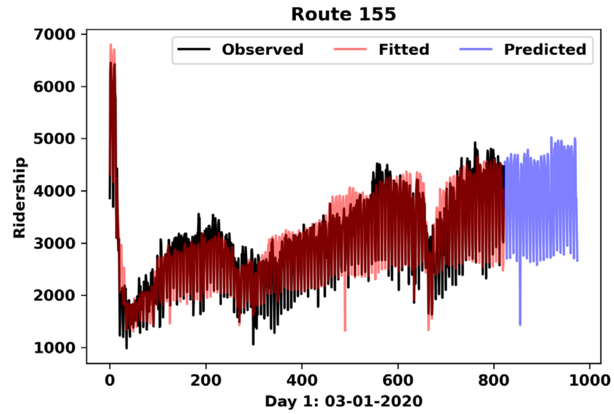

Route 94
Observed
Fitted
Predicted
Ridership
8000
6000
4000
2000
0
200
400
600
800
1000
Day 1: 03-01-2020


Route 97
Observed
Fitted
Predicted
Ridership
2500
2000
1500
1000
500
0
200
400
600
800
1000
Day 1: 03-01-2020


Route 103
Observed
Fitted
Predicted
Ridership
2000
1500
1000
500
0
0
200
400
600
800
1000
Day 1: 03-01-2020


Route 106
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
Route 112
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
Route 119
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
Route 126
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
Route 146
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
Route 151
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020


Route 152
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
0
2000
4000
6000
8000
10000
0
200
400
600
800
1000


Route 155
Observed
Fitted
Predicted
Ridership
Day 1: 03-01-2020
1000
2000
3000
4000
5000
6000
7000
0
200
400
600
800
1000

APPENDIX D: SPATIAL REGRESSION ANALYSIS RESULTS

The fitted ordinary least squares (OLS) model parameters along with their p-values for all rail station and bus lines are presented in Tables 7–12.

Table 7. Results of Module 3 Linear Regression Model: Pandemic-related Factors' Impacts on CTA Rail Ridership vs. Sociodemographic Variables

Variables	COVID-19 Cases		Cumulative Vaccinations		Stay-at-home Orders	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
(Intercept)	1.56E-04	0.18	1.64E-06	0.00	-9.08E-03	0.87
prop_male	-7.21E-04	0.12	-	-	-	-
I(prop_male^2)	7.39E-04	0.10	-	-	-	-
prop_poverty	-	-	-1.99E-07	0.00	-	-
I(prop_poverty^2)	**1.59E-04**	**0.00**	-	-	1.43E-01	0.04
prop_age_0_24	-	-	-	-	-	-
I(prop_age_0_24^2)	**-1.69E-04**	**0.00**	-	-	-	-
prop_age_25_39	-1.05E-04	0.03	-	-	-	-
I(prop_age_25_39^2)	7.45E-05	0.19	-	-	-	-
prop_age_40_64	4.07E-04	0.03	-	-	9.94E-01	0.00
I(prop_age_40_64^2)	-8.29E-04	0.01	-	-	-1.60E+00	0.01
prop_edu	-	-	-	-	-	-
I(prop_edu^2)	**2.01E-03**	**0.00**	-	-	-	-
prop_employ	-	-	-4.04E-06	0.00	-	-
I(prop_employ^2)	-	-	2.32E-06	0.00	-	-
prop_white	-	-	-	-	-4.36E-02	0.03
I(prop_white^2)	-	-	-	-	-	-
prop_black	**-1.85E-05**	**0.00**	1.25E-07	0.00	-4.62E-02	0.01
I(prop_black^2)	-	-	-	-	-	-
prop_asian	-4.03E-05	0.04	-	-	-1.83E-01	0.00
I(prop_asian^2)	8.75E-05	0.01	-	-	2.83E-01	0.00
prop_R_Manuf	-	-	1.50E-06	0.00	-	-
I(prop_R_Manuf^2)	-	-	-5.67E-06	0.01	-	-
prop_R_Trade	-3.31E-04	0.14	-	-	-1.62E+00	0.00
I(prop_R_Trade^2)	1.20E-03	0.18	-	-	6.55E+00	0.00
prop_R_Edu	2.28E-04	0.01	-	-	1.39E-01	0.00
I(prop_R_Edu^2)	-7.49E-04	0.02	-	-	-	-
prop_R_Health	4.68E-04	0.00	-	-	-	-
I(prop_R_Health^2)	-1.75E-03	0.00	9.66E-07	0.02	-	-
prop_W_Manuf	-	-	-	-	-	-
I(prop_W_Manuf^2)	-	-	-	-	-	-
prop_W_Trade	-	-	-	-	-	-

Variables	COVID-19 Cases		Cumulative Vaccinations		Stay-at-home Orders	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
I(prop_W_Trade^2)	-	-	-	-	-	-
prop_W_Edu	-4.04E-05	0.00	1.22E-07	0.02	-	-
I(prop_W_Edu^2)	6.19E-05	0.00	-1.84E-07	0.02	-	-
prop_W_Health	-	-	-	-	5.90E-02	0.02
I(prop_W_Health^2)	-	-	-	-	-7.39E-02	0.03
prop_LU_residential	6.35E-05	0.02	-	-	-	-
I(prop_LU_residential^2)	-7.47E-05	0.09	-	-	-	-
prop_LU_commerical	8.64E-05	0.00	-	-	-	-
I(prop_LU_commerical^2)	-1.56E-04	0.00	-	-	-	-
prop_LU_medical	-4.81E-05	0.12	-	-	-	-
I(prop_LU_medical^2)	-	-	2.37E-06	0.01	1.43E+00	0.02
prop_LU_education	-	-	-5.14E-07	0.00	-	-
I(prop_LU_education^2)	8.88E-05	0.03	9.79E-07	0.00	-	-
prop_LU_industrial	-	-	-	-	-	-
I(prop_LU_industrial^2)	6.80E-05	0.07	-	-	2.74E-01	0.00
prop_LU_transport	2.33E-05	0.04	-	-	-	-
I(prop_LU_transport^2)	-	-	-	-	-	-
prop_LU_openspace	2.36E-05	0.00	-	-	-	-
I(prop_LU_openspace^2)	-	-	-	-	-	-
LUM	-6.05E-05	0.06	-	-	-	-
I(LUM^2)	4.45E-05	0.07	-	-	-	-
R^2	0.5343		0.7765		0.5448	

Table 8. Results of Module 3 Linear Regression Model: Socioeconomic Changes' Impacts on CTA Rail Ridership vs. Sociodemographic Variables

Variables	Workplace Occup. Reduction		Unemployment Rate		Gas Price		Crime		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
(Intercept)	-7.69E-01	0.64	-3.07E-03	0.76	-6.66E-02	0.00	-2.09E+00	0.00	-2.92E-01	0.00
prop_male	-	-	5.80E-02	0.00	-	-	8.92E+00	0.00	-	-
I(prop_male^2)	-7.40E-01	0.06	-	-	-	-	-8.82E+00	0.00	-	-
prop_poverty	-2.95E-01	0.14	2.02E-02	0.00	-	-	-5.18E-01	0.00	-	-
I(prop_poverty^2)	-	-	-	-	2.58E-01	0.00	6.30E-01	0.02	-5.90E-01	0.00
prop_age_0_24	1.72E+00	0.02	-9.33E-02	0.00	-	-	-	-	-	-
I(prop_age_0_24^2)	-2.17E+00	0.06	9.51E-02	0.00	-	-	-	-	3.20E-01	0.00
prop_age_25_39	-1.68E+00	0.01	-	-	-	-	-	-	2.03E-01	0.00
I(prop_age_25_39^2)	2.52E+00	0.00	-3.92E-02	0.00	-	-	-	-	-	-
prop_age_40_64	-	-	-	-	-	-	-	-	-	-
I(prop_age_40_64^2)	-	-	-8.38E-02	0.00	-	-	-	-	-	-
prop_edu	-	-	-	-	-	-	-	-	-	-
I(prop_edu^2)	-	-	-	-	-	-	-	-	-	-
prop_employ	5.68E+00	0.16	-	-	-	-	-	-	-	-
I(prop_employ^2)	-3.68E+00	0.12	-	-	9.79E-02	0.00	-	-	-	-
prop_white	7.06E-01	0.09	-1.85E-02	0.03	-	-	-	-	-6.52E-02	0.02
I(prop_white^2)	-6.70E-01	0.05	1.37E-02	0.03	-	-	-1.69E-01	0.00	-	-
prop_black	-4.58E-01	0.02	-8.98E-03	0.04	-	-	-4.50E-02	0.17	-	-
I(prop_black^2)	5.29E-01	0.01	-	-	-2.71E-02	0.01	-	-	-	-
prop_asian	6.80E-01	0.02	-6.70E-03	0.11	-	-	-7.98E-02	0.06	-	-
I(prop_asian^2)	-1.21E+00	0.02	-	-	-9.97E-02	0.00	-	-	-3.54E-01	0.00
prop_R_Manuf	-1.28E+00	0.10	3.71E-02	0.05	-	-	-1.32E+00	0.00	-	-
I(prop_R_Manuf^2)	-	-	-	-	-	-	4.46E+00	0.08	-	-
prop_R_Trade	-	-	-	-	-	-	-	-	2.97E+00	0.01
I(prop_R_Trade^2)	-9.47E+00	0.00	-	-	-	-	-	-	-1.24E+01	0.01
prop_R_Edu	-2.79E+00	0.05	9.91E-02	0.01	5.47E-01	0.00	-4.99E-01	0.11	-	-

Variables	Workplace Occup. Reduction		Unemployment Rate		Gas Price		Crime		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
I(prop_R_Edu^2)	6.28E+00	0.19	-2.65E-01	0.03	-1.82E+00	0.00	2.09E+00	0.03	-	-
prop_R_Health	-	-	1.03E-01	0.07	-	-	4.55E-01	0.00	-	-
I(prop_R_Health^2)	-5.54E+00	0.01	-3.85E-01	0.05	-	-	-	-	1.72E+00	0.01
prop_W_Manuf	2.27E-01	0.15	-1.35E-02	0.01	-	-	-	-	-	-
I(prop_W_Manuf^2)	-	-	-	-	-	-	-	-	-	-
prop_W_Trade	-	-	3.87E-03	0.15	-	-	-	-	-	-
I(prop_W_Trade^2)	-	-	-	-	-	-	-	-	-	-
prop_W_Edu	-	-	-	-	-	-	-	-	-	-
I(prop_W_Edu^2)	-	-	-	-	-	-	-	-	-	-
prop_W_Health	-3.56E-01	0.02	-	-	-	-	9.99E-02	0.03	-	-
I(prop_W_Health^2)	4.95E-01	0.02	-	-	-	-	-1.57E-01	0.01	-	-
prop_LU_residential	-	-	-	-	-	-	-	-	-	-
I(prop_LU_residential^2)	-	-	-	-	-	-	-	-	-	-
prop_LU_commerical	-9.36E-01	0.01	1.61E-02	0.09	1.61E-01	0.00	-	-	-	-
I(prop_LU_commerical^2)	1.50E+00	0.01	-3.43E-02	0.04	-3.27E-01	0.00	-	-	-	-
prop_LU_medical	-	-	-	-	-	-	-	-	-	-
I(prop_LU_medical^2)	-	-	-	-	-1.85E+00	0.00	-	-	-	-
prop_LU_education	-	-	-	-	-	-	-	-	-	-
I(prop_LU_education^2)	-1.06E+00	0.06	-	-	3.02E-01	0.00	-	-	-	-
prop_LU_industrial	-	-	-	-	-	-	-	-	-	-
I(prop_LU_industrial^2)	-1.79E+00	0.00	3.35E-02	0.04	-	-	-	-	-	-
prop_LU_transport.	-4.62E-01	0.00	-	-	-	-	-2.03E-01	0.11	-	-
I(prop_LU_transport.^2)	-	-	-	-	-	-	9.84E-01	0.04	-	-
prop_LU_openspace	-3.16E-01	0.15	4.73E-03	0.08	1.06E-01	0.00	-1.77E-01	0.00	-1.17E-01	0.00
I(prop_LU_openspace^2)	8.30E-01	0.05	-	-	-2.34E-01	0.00	2.19E-01	0.04	-	-
LUM	1.59E-01	0.07	-	-	-	-	-	-	-	-
I(LUM^2)	-	-	-	-	-	-	-	-	-	-
R^2	0.6631		0.4905		0.4399		0.3634		0.3103	

Table 9. Results of Module 3 Linear Regression Model: Pandemic-related Factors' Impacts on CTA Bus Ridership vs. Sociodemographic Variables

Variables	COVID-19 Cases		Cumulative Vaccinations		Stay-at-home Orders	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
(Intercept)	-2.42E-04	0.00	3.46E-07	0.32	3.59E+00	0.00
prop_male	-	-	-	-	-2.36E+01	0.00
I(prop_male^2)	4.51E-05	0.08	-	-	2.40E+01	0.00
prop_poverty	-	-	-2.17E-07	0.08	-	-
I(prop_poverty^2)	-	-	-	-	-	-
prop_age_0_24	6.07E-04	0.00	-2.49E-06	0.00	-	-
I(prop_age_0_24^2)	-9.09E-04	0.00	4.84E-06	0.00	-	-
prop_age_25_39	1.12E-04	0.02	-2.41E-06	0.00	-2.49E+00	0.00
I(prop_age_25_39^2)	-3.51E-04	0.00	4.66E-06	0.00	5.08E+00	0.00
prop_age_40_64	-	-	5.16E-06	0.02	-	-
I(prop_age_40_64^2)	-2.05E-04	0.00	-8.09E-06	0.04	1.02E+00	0.07
prop_edu	-	-	-3.59E-06	0.12	-	-
I(prop_edu^2)	-3.82E-03	0.00	7.32E-05	0.06	4.98E+01	0.00
prop_employ	6.51E-04	0.00	-	-	7.38E+00	0.01
I(prop_employ^2)	-3.49E-04	0.00	-2.24E-07	0.09	-4.95E+00	0.01
prop_white	-	-	-	-	9.10E-01	0.00
I(prop_white^2)	-	-	-	-	-6.36E-01	0.00
prop_black	-3.02E-05	0.00	1.87E-07	0.01	-2.29E-01	0.08
I(prop_black^2)	-	-	-6.86E-08	0.19	5.92E-01	0.00
prop_asian	-6.58E-05	0.00	2.55E-07	0.01	7.99E-01	0.04
I(prop_asian^2)	-	-	-	-	-2.38E+00	0.11
prop_R_Manuf	-	-	4.05E-06	0.00	6.30E+00	0.00
I(prop_R_Manuf^2)	-1.54E-03	0.00	-2.25E-05	0.00	-3.24E+01	0.01
prop_R_Trade	-7.65E-04	0.00	-	-	-8.74E+00	0.01
I(prop_R_Trade^2)	2.87E-03	0.00	-3.67E-06	0.01	3.37E+01	0.01
prop_R_Edu	-	-	2.07E-06	0.17	-4.37E+00	0.01
I(prop_R_Edu^2)	3.98E-04	0.01	-1.31E-05	0.08	1.96E+01	0.02
prop_R_Health	-5.01E-04	0.00	-	-	2.89E+00	0.22
I(prop_R_Health^2)	1.93E-03	0.00	-2.61E-06	0.01	-9.11E+00	0.21
prop_W_Manuf	-4.84E-05	0.03	-	-	5.60E-01	0.01
I(prop_W_Manuf^2)	2.61E-04	0.01	-	-	-5.51E+00	0.00
prop_W_Trade	-7.84E-05	0.00	1.24E-06	0.00	-4.14E-01	0.04
I(prop_W_Trade^2)	1.48E-04	0.00	-2.65E-06	0.00	9.92E-01	0.02
prop_W_Edu	-4.97E-05	0.03	-	-	-	-
I(prop_W_Edu^2)	1.97E-04	0.09	1.38E-06	0.01	1.60E+00	0.00
prop_W_Health	-	-	-	-	-	-
I(prop_W_Health^2)	-3.57E-05	0.00	5.56E-07	0.00	4.33E-01	0.00
prop_LU_residential	7.26E-05	0.01	-8.84E-07	0.03	1.63E+00	0.00

Variables	COVID-19 Cases		Cumulative Vaccinations		Stay-at-home Orders	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
I(prop_LU_residential^2)	-1.87E-04	0.00	1.47E-06	0.01	-2.06E+00	0.01
prop_LU_commerical	-	-	4.29E-07	0.04	2.02E+00	0.01
I(prop_LU_commerical^2)	-	-	-	-	-1.00E+01	0.02
prop_LU_medical	-4.73E-04	0.00	7.81E-06	0.00	5.54E+00	0.00
I(prop_LU_medical^2)	1.34E-02	0.02	-3.30E-04	0.00	-2.09E+02	0.00
prop_LU_education	-	-	-2.51E-06	0.00	-	-
I(prop_LU_education^2)	-	-	2.62E-05	0.00	-	-
prop_LU_industrial	-	-	-	-	-	-
I(prop_LU_industrial^2)	-	-	2.24E-06	0.01	6.77E+00	0.00
prop_LU_transport.	-	-	-	-	1.59E+00	0.00
I(prop_LU_transport.^2)	-	-	2.59E-06	0.00	-6.94E+00	0.00
prop_LU_openspace	-	-	5.19E-07	0.00	1.03E+00	0.00
I(prop_LU_openspace^2)	-	-	-9.92E-07	0.03	-1.36E+00	0.00
LUM	-3.97E-05	0.00	-2.33E-06	0.02	-2.93E+00	0.00
I(LUM^2)	-	-	2.04E-06	0.01	2.27E+00	0.01
R^2	0.8528		0.8772		0.7261	

Table 10. Results of Module 3 Linear Regression Model: Socioeconomic Changes' Impacts on CTA Bus Ridership vs. Sociodemographic Variables

Variables	Workplace Occup. Reduction		Unemployment Rate		Gas Price		Crime		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
(Intercept)	-4.25E+00	0.19	8.43E-02	0.68	-2.15E-01	0.02	-5.80E+00	0.00	-4.57E+00	0.00
prop_male	5.76E+01	0.00	-1.27E+00	0.17	-	-	2.10E+01	0.00	1.58E+01	0.00
I(prop_male^2)	-5.88E+01	0.00	1.39E+00	0.14	-5.98E-01	0.00	-2.33E+01	0.00	-1.64E+01	0.00
prop_poverty	5.04E+00	0.00	-	-	-	-	1.96E+00	0.00	-	-
I(prop_poverty^2)	-1.26E+01	0.00	-	-	-7.12E-01	0.00	-3.90E+00	0.00	6.56E-01	0.01
prop_age_0_24	3.21E+00	0.10	6.92E-02	0.03	2.48E-01	0.02	-2.04E+00	0.00	1.09E+00	0.12
I(prop_age_0_24^2)	-5.24E+00	0.09	-	-	-	-	2.81E+00	0.01	-2.02E+00	0.08
prop_age_25_39	6.86E+00	0.00	-	-	-	-	2.36E+00	0.00	-	-
I(prop_age_25_39^2)	-1.33E+01	0.00	-7.20E-02	0.25	-	-	-3.82E+00	0.00	9.44E-01	0.00
prop_age_40_64	-	-	-5.06E-01	0.23	-3.13E-01	0.00	-7.40E+00	0.00	-	-
I(prop_age_40_64^2)	-	-	7.89E-01	0.27	-	-	1.31E+01	0.00	1.27E+00	0.02
prop_edu	2.42E+01	0.00	-	-	-	-	-5.46E+00	0.02	-1.23E+01	0.00
I(prop_edu^2)	-5.32E+02	0.00	-	-	-	-	9.04E+01	0.02	1.97E+02	0.00
prop_employ	-2.85E+01	0.00	1.31E+00	0.02	-	-	-	-	-4.54E-01	0.05
I(prop_employ^2)	1.83E+01	0.00	-8.09E-01	0.02	1.80E-01	0.00	-	-	-	-
prop_white	-4.42E+00	0.00	7.01E-02	0.14	-	-	3.20E-01	0.00	-	-
I(prop_white^2)	3.95E+00	0.00	-6.84E-02	0.04	5.09E-02	0.02	-	-	-	-
prop_black	5.89E-01	0.06	-5.83E-02	0.01	-	-	-	-	-	-
I(prop_black^2)	-2.43E+00	0.00	6.77E-02	0.02	-	-	3.06E-01	0.00	1.13E-01	0.00
prop_asian	-6.14E+00	0.00	8.68E-02	0.20	-2.38E-01	0.09	-6.49E-01	0.02	6.48E-01	0.02
I(prop_asian^2)	2.30E+01	0.00	-4.17E-01	0.12	1.26E+00	0.08	5.30E+00	0.00	-3.50E+00	0.01
prop_R_Manuf	-3.60E+01	0.00	1.14E+00	0.00	-2.93E+00	0.00	-	-	-	-
I(prop_R_Manuf^2)	2.10E+02	0.00	-8.81E+00	0.00	1.78E+01	0.00	-	-	-	-
prop_R_Trade	7.06E+01	0.00	-1.79E+00	0.02	6.57E+00	0.00	1.57E+00	0.00	-	-
I(prop_R_Trade^2)	-2.80E+02	0.00	6.76E+00	0.02	-2.40E+01	0.00	-	-	7.78E+00	0.00
prop_R_Edu	-	-	-	-	-5.69E+00	0.00	-	-	1.25E+00	0.00

Variables	Workplace Occup. Reduction		Unemployment Rate		Gas Price		Crime		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
I(prop_R_Edu^2)	-1.03E+01	0.02	5.89E-01	0.05	2.41E+01	0.00	-	-	-	-
prop_R_Health	-7.11E+00	0.16	-4.94E-01	0.30	3.94E+00	0.00	6.47E+00	0.00	-3.39E+00	0.06
I(prop_R_Health^2)	3.15E+01	0.06	1.31E+00	0.38	-1.11E+01	0.00	-2.24E+01	0.00	1.18E+01	0.05
prop_W_Manuf	-9.89E-01	0.08	7.48E-02	0.07	-	-	-	-	-	-
I(prop_W_Manuf^2)	1.23E+01	0.00	-4.75E-01	0.03	1.13E+00	0.00	1.48E+00	0.01	-	-
prop_W_Trade	-	-	-1.39E-01	0.00	-6.52E-02	0.04	5.73E-01	0.00	-	-
I(prop_W_Trade^2)	-2.39E+00	0.00	3.89E-01	0.00	-	-	-2.18E+00	0.00	-6.04E-01	0.00
prop_W_Edu	-1.48E+00	0.01	3.69E-02	0.03	-	-	-2.44E-01	0.01	4.20E-01	0.09
I(prop_W_Edu^2)	5.27E+00	0.07	-	-	-5.94E-01	0.02	-	-	-3.56E+00	0.01
prop_W_Health	2.42E+00	0.00	-	-	-	-	-6.34E-01	0.00	-2.94E-01	0.00
I(prop_W_Health^2)	-6.78E+00	0.00	3.52E-02	0.16	-	-	9.69E-01	0.01	-	-
prop_LU_residential	-1.86E+00	0.00	9.84E-02	0.30	4.35E-01	0.00	-	-	-	-
I(prop_LU_residential^2)	-	-	-1.08E-01	0.40	-7.72E-01	0.00	-	-	-2.66E-01	0.07
prop_LU_commerical	-4.74E+00	0.02	3.51E-01	0.02	-	-	-2.16E+00	0.00	-1.30E+00	0.11
I(prop_LU_commerical^2)	1.91E+01	0.08	-1.80E+00	0.03	-	-	1.40E+01	0.00	7.93E+00	0.08
prop_LU_medical	-3.75E+01	0.00	1.37E+00	0.00	-	-	8.31E-01	0.03	9.85E-01	0.03
I(prop_LU_medical^2)	1.45E+03	0.00	-5.07E+01	0.00	-	-	-	-	-	-
prop_LU_education	3.27E+00	0.00	-1.62E-01	0.00	-	-	1.47E+00	0.00	7.37E-01	0.01
I(prop_LU_education^2)	-	-	-	-	-	-	-	-	-	-
prop_LU_industrial	4.94E-01	0.47	-	-	-1.64E-01	0.02	-	-	-6.11E-01	0.00
I(prop_LU_industrial^2)	-1.97E+01	0.00	4.62E-01	0.02	-	-	-1.17E+00	0.10	-	-
prop_LU_transport.	-4.89E+00	0.00	1.13E-01	0.11	9.94E-01	0.00	-	-	-7.32E-01	0.00
I(prop_LU_transport.^2)	2.53E+01	0.00	-3.41E-01	0.35	-3.10E+00	0.00	1.51E+00	0.01	-	-
prop_LU_openspace	-2.90E+00	0.00	1.46E-01	0.00	-	-	-7.97E-01	0.00	-6.71E-01	0.00
I(prop_LU_openspace^2)	4.62E+00	0.00	-2.23E-01	0.02	-	-	2.06E+00	0.00	1.79E+00	0.00
LUM	1.51E+00	0.48	-6.16E-01	0.00	-2.29E-01	0.00	4.23E+00	0.00	3.65E+00	0.00
I(LUM^2)	-1.93E+00	0.27	5.00E-01	0.00	-	-	-3.59E+00	0.00	-2.97E+00	0.00
R^2	0.9048		0.8468		0.7550		0.8267		0.7719	

APPENDIX E: TEMPORAL REGRESSION ANALYSIS RESULTS

Table 11. Temporal Regression for the CTA Bus System: Constant, Cases, Total Vaccinations, and Workplace Occupancy Reduction

Route ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
3	9.05E-01	-1.79E+03	1.34E-42	1.47E-05	2.31E-12	-5.94E-08	3.56E-06	7.18E-01	1.77E-180
4	8.93E-01	-1.66E+03	5.35E-32	1.27E-05	4.60E-12	-1.54E-08	1.58E-01	6.61E-01	9.73E-190
8A	7.61E-01	-3.72E+02	1.25E-32	6.47E-06	2.91E-02	-3.76E-08	3.60E-02	7.27E-01	4.33E-115
12	9.07E-01	-6.95E+02	5.22E-17	4.36E-06	8.22E-03	2.26E-08	2.57E-02	6.94E-01	1.07E-212
18	8.93E-01	-1.06E+02	2.45E-03	1.05E-05	3.03E-09	-8.58E-09	4.31E-01	7.07E-01	5.34E-199
20	9.13E-01	-1.74E+03	4.60E-52	7.48E-06	1.30E-04	-6.86E-08	9.95E-09	8.18E-01	1.02E-223
21	8.19E-01	-2.08E+02	2.59E-02	8.11E-06	1.08E-04	-4.13E-11	9.97E-01	6.44E-01	1.30E-144
22	9.00E-01	-1.36E+03	2.50E-13	1.23E-05	8.11E-11	-5.76E-08	4.07E-07	7.16E-01	2.48E-188
29	8.81E-01	-1.55E+03	9.58E-49	1.13E-05	3.72E-06	-2.52E-08	8.13E-02	8.44E-01	1.53E-184
30	8.86E-01	-4.13E+02	1.20E-75	1.61E-05	2.47E-08	-1.86E-09	9.14E-01	7.92E-01	4.30E-136
34	8.70E-01	-6.19E+02	1.23E-67	3.61E-06	1.42E-01	4.06E-08	5.43E-03	7.21E-01	2.99E-152
35	9.28E-01	-4.21E+02	4.34E-39	1.37E-05	3.79E-11	-1.50E-08	2.28E-01	7.62E-01	2.44E-194
36	8.75E-01	4.22E+02	5.26E-02	1.04E-05	6.02E-07	-7.27E-08	5.11E-09	5.94E-01	6.83E-130
43	8.49E-01	-1.31E+02	8.91E-33	1.16E-05	1.75E-05	3.98E-08	1.55E-02	6.20E-01	1.76E-100
44	9.17E-01	-2.93E+02	2.70E-51	5.32E-06	1.50E-02	-3.75E-09	7.87E-01	8.12E-01	3.35E-188
47	8.26E-01	-7.53E+02	1.02E-18	6.96E-06	5.96E-04	2.59E-08	3.78E-02	6.10E-01	4.60E-139
49B	9.04E-01	-6.19E+02	1.09E-40	9.66E-06	8.71E-07	-4.21E-08	3.67E-04	6.98E-01	1.66E-180
50	9.35E-01	-6.16E+02	1.84E-20	1.32E-05	1.23E-11	-8.62E-08	1.17E-12	8.02E-01	2.30E-210
52	9.33E-01	-8.32E+02	4.53E-28	6.13E-06	4.11E-04	-3.43E-08	1.41E-03	8.27E-01	5.14E-251
52A	9.19E-01	-2.14E+02	7.99E-18	1.00E-05	2.03E-07	1.79E-08	1.24E-01	7.29E-01	1.92E-192
53	8.94E-01	-1.72E+03	9.46E-41	6.36E-06	3.52E-04	-2.05E-08	6.30E-02	7.28E-01	1.77E-210
53A	9.16E-01	-5.47E+02	1.01E-28	1.28E-05	2.63E-08	-1.26E-08	3.82E-01	7.60E-01	2.94E-159
54B	7.22E-01	-3.90E+02	4.40E-38	1.15E-05	8.75E-04	4.66E-08	1.87E-02	6.18E-01	5.90E-76
55	8.93E-01	-9.88E+02	1.23E-35	1.34E-05	5.03E-13	-1.14E-08	3.15E-01	6.82E-01	1.26E-189
56	9.45E-01	-1.08E+03	9.65E-75	9.97E-06	1.10E-08	-5.84E-08	3.16E-08	8.03E-01	2.49E-245
60	9.39E-01	-1.05E+03	1.70E-38	1.66E-05	1.85E-15	-7.18E-08	1.19E-08	8.23E-01	1.31E-210
62	9.30E-01	-1.16E+03	1.27E-54	8.51E-06	3.58E-06	-2.82E-08	1.20E-02	7.65E-01	5.33E-215
63	9.04E-01	-2.00E+03	1.42E-69	7.73E-06	2.32E-05	-2.65E-08	1.60E-02	6.87E-01	2.48E-200
63W	8.07E-01	-1.13E+02	6.37E-17	1.23E-05	2.74E-04	-1.18E-08	5.64E-01	7.20E-01	4.15E-88
65	9.42E-01	-8.22E+02	1.21E-51	1.11E-05	7.34E-09	-2.52E-08	3.15E-02	8.30E-01	6.57E-225
66	9.39E-01	-2.33E+03	7.41E-56	7.75E-06	1.14E-06	-5.74E-08	7.65E-09	7.77E-01	1.96E-253
67	8.84E-01	-9.74E+02	2.87E-42	8.23E-06	1.81E-05	-6.11E-09	6.00E-01	6.70E-01	3.32E-183
68	9.04E-01	-9.11E+01	6.21E-23	1.12E-05	1.28E-04	-8.47E-08	2.00E-06	8.42E-01	1.89E-144
70	9.33E-01	-9.63E+02	3.16E-68	1.21E-05	1.36E-10	-5.76E-08	6.02E-07	7.63E-01	2.17E-220
71	8.34E-01	-1.14E+03	4.17E-55	1.23E-05	5.79E-09	1.42E-08	2.66E-01	6.40E-01	7.92E-148
72	8.98E-01	-1.05E+03	1.44E-20	1.05E-05	5.29E-09	-3.98E-08	2.08E-04	7.03E-01	2.35E-206

Route ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
73	9.45E-01	-3.98E+02	3.88E-35	1.37E-05	1.10E-13	-4.26E-08	1.95E-04	7.79E-01	6.68E-225
74	9.26E-01	-1.17E+03	5.87E-40	1.33E-05	1.12E-12	-7.00E-08	5.23E-10	7.14E-01	8.31E-203
75	8.38E-01	-5.50E+02	6.01E-21	6.75E-06	1.19E-03	-2.72E-08	2.96E-02	6.68E-01	1.27E-160
76	9.30E-01	-8.50E+02	6.13E-29	1.16E-05	7.76E-11	-3.01E-08	5.47E-03	6.79E-01	1.25E-194
77	9.42E-01	-2.18E+03	1.69E-65	9.06E-06	2.39E-08	-4.07E-08	5.10E-05	7.40E-01	1.22E-236
78	9.34E-01	-8.58E+02	3.07E-53	3.59E-06	7.28E-02	-6.19E-08	3.20E-07	8.25E-01	2.00E-214
81	9.10E-01	-1.09E+03	4.17E-30	5.48E-06	1.93E-03	-3.68E-08	4.12E-04	5.97E-01	1.26E-169
82	9.20E-01	-1.90E+03	1.03E-53	1.15E-05	5.07E-10	-6.23E-08	7.87E-08	7.48E-01	2.48E-207
84	9.17E-01	-3.24E+02	9.06E-38	1.19E-05	1.47E-06	-5.68E-08	1.60E-04	7.48E-01	2.36E-151
85	8.83E-01	-1.17E+03	1.59E-54	7.64E-06	1.14E-03	-7.46E-08	2.15E-07	7.15E-01	1.55E-155
87	8.91E-01	-1.23E+03	1.07E-50	6.97E-06	3.45E-04	-2.42E-08	4.09E-02	7.31E-01	5.64E-198
88	9.20E-01	-1.51E+02	5.63E-79	1.00E-05	1.82E-04	-7.86E-08	1.15E-06	6.72E-01	1.63E-118
90	8.60E-01	-5.27E+02	3.04E-46	4.82E-06	6.95E-02	3.02E-09	8.49E-01	5.46E-01	1.62E-84
91	8.93E-01	-6.05E+02	1.24E-43	4.42E-06	4.15E-02	-7.04E-09	6.04E-01	6.76E-01	6.01E-149
92	9.03E-01	-7.02E+02	4.09E-45	1.07E-05	7.28E-06	-6.04E-08	3.19E-05	7.17E-01	2.68E-148
94	8.53E-01	-9.70E+02	6.72E-39	1.64E-05	3.63E-09	-3.82E-08	2.76E-02	5.82E-01	1.50E-84
97	8.64E-01	-3.36E+02	1.66E-43	6.99E-06	1.75E-03	8.23E-10	9.51E-01	5.72E-01	2.77E-113
103	8.96E-01	-2.75E+02	4.39E-75	1.30E-05	1.45E-06	-2.68E-08	8.79E-02	7.14E-01	3.54E-136
106	9.16E-01	-2.08E+02	1.95E-10	1.32E-05	1.34E-04	-1.15E-07	7.81E-08	9.14E-01	7.70E-139
112	9.13E-01	-2.13E+02	2.11E-62	1.08E-05	3.11E-04	-5.40E-08	3.28E-03	8.74E-01	5.11E-159
119	7.63E-01	-3.67E+02	2.87E-18	1.89E-06	4.77E-01	3.64E-08	2.11E-02	6.71E-01	1.08E-118
126	9.40E-01	-6.65E+02	1.46E-81	8.75E-06	7.48E-06	-7.25E-08	1.04E-08	8.75E-01	4.80E-233
146	8.88E-01	-6.85E+02	2.05E-05	9.02E-06	1.48E-05	-3.94E-08	1.87E-03	7.57E-01	2.99E-172
151	8.89E-01	-2.65E+03	4.00E-37	1.61E-05	2.21E-09	-8.79E-08	2.01E-08	7.73E-01	7.35E-141
152	9.26E-01	-7.15E+02	1.14E-26	1.47E-05	5.55E-10	-9.45E-08	7.13E-10	8.54E-01	6.70E-180
155	8.79E-01	-5.82E+02	3.82E-19	1.04E-05	1.13E-07	-3.04E-08	9.29E-03	6.61E-01	5.05E-168

Table 12. Temporal Regression for the CTA Bus System: Stay at Home, Crime, Gas Price, Unemployment, and Discount

Route ID	Stay at Home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
3	3.88E-02	8.80E-07	-3.67E-02	9.86E-06	4.96E-02	1.25E-18	2.00E-03	6.23E-02	-2.10E-02	2.00E-01
4	3.04E-02	9.70E-06	-3.95E-02	3.10E-06	3.99E-02	1.13E-15	-1.20E-04	8.99E-01	5.39E-03	6.93E-01
8A	3.20E-02	3.37E-03	-3.28E-02	1.38E-02	2.60E-02	9.87E-04	-2.22E-03	1.42E-01	1.71E-02	4.49E-01
12	3.20E-02	1.32E-06	-2.39E-02	1.16E-05	2.04E-02	5.50E-06	3.22E-03	5.27E-04	-2.53E-02	4.13E-02
18	3.23E-02	4.00E-06	-3.24E-02	3.48E-06	2.33E-02	1.99E-06	7.55E-03	5.71E-14	-9.41E-03	4.80E-01
20	-2.60E-03	7.26E-01	-6.59E-03	1.52E-01	4.48E-02	2.07E-17	-7.85E-03	6.17E-14	4.37E-02	3.52E-03
21	3.60E-02	9.68E-06	-6.08E-02	1.40E-05	1.66E-02	3.20E-03	4.71E-03	3.59E-05	-2.59E-02	1.02E-01
22	4.79E-02	3.45E-11	-2.65E-02	1.65E-04	1.77E-02	6.74E-04	8.47E-03	7.03E-17	-3.90E-02	4.86E-03
29	4.06E-02	6.83E-06	-5.53E-02	1.82E-07	7.21E-02	2.55E-25	-6.28E-03	4.53E-07	-9.18E-02	5.88E-07
30	3.55E-02	1.04E-03	-4.02E-02	4.54E-04	3.03E-02	2.54E-05	-9.98E-04	5.01E-01	-6.31E-02	4.06E-03
34	1.84E-02	3.90E-02	-1.13E-02	1.32E-01	3.03E-02	1.57E-06	-3.31E-04	7.89E-01	-5.85E-02	1.59E-03
35	3.28E-02	2.90E-05	-2.94E-02	6.03E-02	2.58E-02	1.87E-06	5.74E-03	1.50E-07	-7.51E-02	1.59E-06
36	3.68E-02	9.10E-07	-1.39E-02	1.34E-02	-1.04E-02	1.07E-01	7.33E-03	5.64E-12	-3.59E-02	1.58E-02
43	6.78E-02	1.29E-10	-2.82E-02	3.35E-03	3.44E-02	6.74E-07	3.90E-04	7.85E-01	-6.41E-02	1.90E-03
44	2.50E-02	5.44E-03	-2.96E-02	6.76E-03	1.34E-02	2.00E-02	-8.09E-04	5.05E-01	-3.16E-02	6.93E-02
47	5.15E-02	2.18E-10	-5.20E-02	5.85E-06	2.64E-02	1.42E-06	2.26E-03	4.73E-02	-5.58E-02	2.59E-04
49B	5.28E-02	4.46E-12	-2.96E-02	2.82E-03	1.47E-02	4.62E-03	8.73E-03	1.62E-16	-3.59E-02	1.35E-02
50	3.08E-02	7.86E-05	-9.16E-02	5.44E-10	1.19E-02	2.07E-02	9.54E-03	8.36E-18	-1.21E-02	4.09E-01
52	-5.77E-03	3.92E-01	-5.60E-02	8.45E-07	5.38E-02	6.68E-28	-4.61E-03	1.47E-06	3.95E-03	7.67E-01
52A	2.43E-02	1.21E-03	-6.90E-02	7.56E-05	1.38E-03	7.87E-01	6.11E-03	2.62E-08	-2.46E-02	8.27E-02
53	8.46E-03	2.29E-01	-4.87E-02	9.18E-05	2.78E-02	2.06E-08	-1.01E-03	3.03E-01	-1.14E-02	3.97E-01
53A	4.71E-02	5.01E-07	-6.29E-02	8.97E-03	1.78E-02	3.81E-03	5.66E-03	1.55E-05	-7.44E-02	3.13E-05
54B	9.19E-02	1.04E-13	-5.01E-02	1.06E-01	9.90E-03	2.46E-01	-1.29E-04	9.38E-01	-9.15E-02	2.67E-04
55	4.65E-02	1.24E-10	-6.18E-02	3.05E-05	5.44E-02	6.49E-26	2.55E-03	9.80E-03	-4.77E-02	6.67E-04
56	3.35E-02	7.50E-07	-2.92E-02	1.88E-04	3.88E-02	4.35E-16	3.47E-03	2.05E-04	-5.52E-03	6.71E-01
60	1.99E-02	1.18E-02	-1.05E-02	2.75E-02	3.01E-02	1.52E-08	6.46E-03	6.56E-09	-4.18E-02	7.87E-03
62	4.31E-02	2.55E-09	-3.03E-02	3.20E-04	3.88E-02	6.27E-14	6.78E-03	2.68E-11	-6.90E-02	9.30E-07
63	1.58E-02	2.02E-02	-5.27E-02	1.52E-06	6.24E-02	1.48E-33	9.94E-05	9.16E-01	-1.80E-02	1.88E-01
63W	5.42E-02	4.80E-05	8.09E-03	7.10E-01	-1.81E-02	3.28E-02	4.55E-03	1.36E-02	-1.07E-01	2.56E-05
65	4.13E-02	1.28E-07	-7.99E-02	4.69E-12	5.74E-02	7.40E-28	3.47E-03	1.11E-03	-5.36E-02	2.10E-04
66	2.91E-02	6.27E-06	-3.65E-02	2.42E-06	5.40E-02	2.13E-33	1.35E-03	1.27E-01	-3.52E-02	3.79E-03
67	3.63E-02	4.97E-07	-3.75E-02	1.31E-06	4.98E-02	8.83E-21	-1.75E-03	8.29E-02	-2.10E-02	1.48E-01
68	-2.11E-02	5.67E-02	-2.47E-02	9.47E-02	-1.16E-02	1.04E-01	9.68E-03	3.82E-10	-1.11E-02	6.22E-01
70	4.00E-02	2.98E-08	-5.46E-02	7.49E-09	3.90E-02	1.35E-14	2.89E-03	3.49E-03	-4.08E-03	7.80E-01
71	3.06E-02	1.37E-04	-4.15E-02	2.31E-05	4.44E-02	1.97E-14	-1.35E-03	2.24E-01	-4.91E-02	1.93E-03
72	2.06E-02	2.09E-03	-6.91E-02	1.07E-09	2.77E-02	1.43E-08	4.21E-03	6.47E-06	-2.54E-02	5.47E-02
73	5.80E-02	1.11E-15	-5.64E-02	9.71E-05	2.80E-02	6.36E-09	5.40E-03	5.97E-08	-6.72E-03	6.37E-01
74	4.54E-02	1.18E-10	-5.95E-02	5.74E-05	2.64E-02	1.27E-07	8.74E-03	2.36E-18	-1.24E-02	3.70E-01

Route ID	Stay at Home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
75	1.31E-02	9.79E-02	-1.21E-02	1.27E-01	3.37E-02	2.51E-09	-2.24E-03	4.10E-02	-3.63E-03	8.13E-01
76	3.65E-02	1.83E-07	-7.34E-02	5.30E-06	2.39E-02	9.78E-07	1.16E-02	5.46E-30	-3.73E-02	4.84E-03
77	4.40E-02	1.15E-11	-8.88E-02	1.44E-07	3.11E-02	1.51E-12	9.36E-03	3.14E-24	-3.32E-02	6.88E-03
78	2.70E-02	4.66E-04	-4.82E-02	5.70E-03	2.86E-02	3.64E-08	7.51E-03	2.50E-12	-3.56E-02	1.73E-02
81	6.81E-02	1.43E-23	-9.46E-02	8.19E-11	1.89E-02	6.68E-05	1.14E-02	7.34E-33	-3.80E-02	3.01E-03
82	2.60E-02	4.28E-04	-2.15E-02	1.16E-01	3.65E-02	1.39E-12	2.79E-03	7.12E-03	-2.11E-02	1.34E-01
84	2.15E-02	2.25E-02	-4.30E-02	3.81E-03	8.97E-03	1.60E-01	1.19E-02	6.31E-19	-3.96E-02	3.46E-02
85	2.36E-02	6.88E-03	-4.10E-02	5.24E-03	1.62E-02	9.29E-03	3.09E-03	1.07E-02	-1.06E-02	5.49E-01
87	1.51E-02	4.09E-02	-4.66E-02	4.75E-04	3.86E-02	5.62E-13	-1.81E-03	7.58E-02	8.39E-03	5.68E-01
88	2.53E-02	1.15E-02	-3.84E-02	1.12E-03	1.70E-02	1.11E-02	1.58E-02	1.03E-27	-2.73E-02	1.74E-01
90	9.78E-02	3.48E-21	-1.41E-01	1.04E-05	4.98E-03	4.62E-01	1.64E-02	4.24E-29	-7.69E-02	1.05E-04
91	2.85E-02	1.13E-03	-8.09E-02	7.38E-06	1.70E-02	3.54E-03	7.81E-03	1.73E-10	-2.00E-02	2.31E-01
92	6.28E-02	1.27E-11	-4.08E-02	2.48E-03	4.78E-03	4.32E-01	9.67E-03	3.63E-14	-3.21E-02	7.61E-02
94	8.23E-02	5.40E-13	-1.27E-01	1.25E-09	1.68E-02	2.99E-02	1.41E-02	2.61E-18	-6.58E-02	2.06E-03
97	7.62E-02	6.39E-18	-4.12E-02	3.82E-01	2.55E-02	1.29E-05	1.13E-02	5.23E-20	-5.13E-02	1.92E-03
103	3.77E-02	9.14E-05	-4.67E-02	6.19E-03	3.32E-02	5.43E-07	4.63E-03	4.27E-04	-2.86E-02	1.55E-01
106	-1.12E-02	3.58E-01	-1.56E-03	8.52E-01	3.02E-02	2.76E-04	-4.60E-04	7.80E-01	2.04E-02	4.69E-01
112	2.62E-02	1.39E-02	-4.90E-02	7.85E-04	1.98E-02	6.78E-03	-2.50E-04	8.64E-01	-6.10E-02	1.22E-02
119	5.10E-02	2.16E-07	-2.46E-02	1.39E-02	4.11E-02	5.90E-09	-6.61E-03	1.48E-06	-4.36E-02	2.60E-02
126	8.29E-03	2.86E-01	-2.04E-02	7.04E-03	5.36E-02	4.21E-20	-3.37E-03	2.08E-03	2.07E-02	1.85E-01
146	3.98E-02	1.05E-06	-2.52E-02	1.88E-06	1.29E-02	2.42E-02	1.22E-02	3.62E-25	-6.55E-02	2.15E-05
151	2.83E-02	3.57E-03	-4.75E-02	5.30E-07	4.83E-02	2.52E-11	1.26E-02	8.56E-20	-7.96E-02	4.63E-05
152	2.35E-02	1.48E-02	-1.26E-01	8.21E-08	2.41E-02	1.44E-04	7.84E-03	5.43E-09	-3.07E-02	1.05E-01
155	5.19E-02	2.96E-12	-2.87E-02	3.41E-03	7.54E-03	1.54E-01	7.67E-03	1.07E-13	-3.16E-02	2.77E-02

Table 13. Temporal Regression for the CTA Rail System: Constant, Cases, Total Vaccinations, and Workplace Occupancy Reduction

Station ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
10	9.78E-01	-1.93E+02	7.8E-134	7.32E-06	1.95E-07	8.06E-09	3.59E-01	8.32E-01	5.03E-307
20	9.57E-01	-4.88E+02	9.6E-126	8.03E-06	1.58E-06	7.36E-09	4.66E-01	7.31E-01	8.25E-233
30	8.91E-01	-2.40E+02	5.36E-104	8.95E-06	2.26E-05	4.00E-08	1.98E-03	5.66E-01	6.38E-122
40	9.90E-01	-3.94E+02	1.17E-64	9.74E-07	4.00E-01	-2.85E-08	9.46E-05	1.08E+00	0.00E+00
50	9.37E-01	-4.20E+02	4.46E-61	1.18E-05	1.73E-10	-4.58E-08	6.36E-05	8.00E-01	1.52E-223
60	9.61E-01	-5.42E+02	7.67E-80	1.08E-05	2.03E-11	-4.67E-08	2.79E-06	7.91E-01	3.61E-258
70	9.58E-01	-6.04E+02	3.35E-43	1.05E-05	5.37E-08	-4.81E-08	9.94E-05	9.19E-01	6.13E-240
80	9.32E-01	-6.93E+02	2.21E-64	1.34E-05	1.92E-10	-6.24E-08	1.28E-06	8.49E-01	5.47E-205
90	9.57E-01	-1.94E+02	2.74E-27	7.14E-06	2.67E-05	-9.10E-08	1.49E-17	8.92E-01	3.46E-266
100	9.31E-01	-4.02E+02	6.62E-32	1.04E-05	4.38E-12	-3.30E-08	3.59E-04	7.46E-01	3.00E-252
120	9.55E-01	-2.75E+02	3.19E-61	9.29E-06	5.57E-07	-3.04E-08	8.27E-03	8.79E-01	4.95E-244
130	9.34E-01	-1.46E+02	1.3E-109	4.30E-06	3.10E-02	-3.34E-08	5.06E-03	7.81E-01	3.11E-205
140	9.28E-01	-2.48E+02	2.79E-89	1.11E-05	1.61E-04	-3.21E-08	6.11E-02	8.28E-01	4.04E-141
150	9.26E-01	-1.55E+02	3.14E-99	3.68E-06	3.11E-02	2.19E-08	3.20E-02	6.12E-01	5.52E-178
160	9.89E-01	-1.72E+02	2.04E-75	1.41E-06	2.69E-01	-3.07E-08	8.64E-05	1.00E+00	0.00E+00
170	8.34E-01	-4.25E+02	1.91E-38	6.79E-06	1.76E-01	-8.85E-08	5.61E-04	8.87E-01	1.93E-79
180	9.85E-01	-1.46E+02	4.8E-126	6.05E-06	2.69E-05	-2.09E-08	1.80E-02	9.75E-01	0.00E+00
190	6.79E-01	-1.00E+03	2.83E-32	4.15E-05	9.48E-05	-1.06E-07	3.06E-02	1.07E+00	4.46E-34
240	9.20E-01	-4.78E+02	3.77E-28	2.06E-07	8.81E-01	2.69E-08	1.64E-03	6.57E-01	1.24E-238
250	9.10E-01	-2.40E+02	5.52E-68	6.41E-06	4.77E-04	4.70E-08	3.31E-05	6.46E-01	4.01E-173
260	9.19E-01	-2.53E+03	1.46E-113	1.06E-05	1.88E-03	-6.03E-08	3.96E-03	1.04E+00	7.42E-146
270	9.39E-01	-1.31E+02	3.27E-58	1.31E-05	2.17E-12	-5.49E-08	1.69E-06	7.75E-01	2.04E-215
280	9.30E-01	-2.46E+02	5.30E-88	4.64E-06	7.25E-03	2.16E-08	3.98E-02	6.47E-01	6.49E-196
290	9.36E-01	-1.77E+02	6.3E-167	1.25E-05	8.57E-10	-1.03E-11	9.99E-01	6.58E-01	1.34E-163
300	9.47E-01	-9.76E+01	2.32E-97	6.67E-06	4.47E-04	3.25E-09	7.84E-01	7.90E-01	9.89E-211
320	9.50E-01	-7.69E+02	1.55E-76	1.44E-05	4.68E-12	-8.94E-08	6.01E-12	9.04E-01	5.18E-224
330	7.77E-01	-2.54E+03	1.25E-36	2.93E-05	1.83E-07	-9.47E-08	3.95E-03	9.32E-01	1.45E-62
350	9.02E-01	-4.69E+02	5.29E-11	2.65E-05	9.33E-16	-1.21E-07	4.09E-09	8.32E-01	4.76E-108
360	9.23E-01	-4.70E+02	5.60E-44	1.29E-05	1.47E-07	-9.30E-08	4.17E-10	9.63E-01	2.42E-197

Station ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
370	9.61E-01	-1.59E+03	2.74E-75	4.93E-06	8.29E-03	-6.17E-08	1.06E-07	9.34E-01	8.66E-257
380	9.81E-01	-1.78E+03	2.30E-96	3.72E-06	1.67E-02	-2.55E-08	8.61E-03	9.93E-01	0.00E+00
390	9.74E-01	-3.73E+02	3.6E-160	6.77E-06	3.03E-06	2.19E-08	1.45E-02	7.28E-01	4.74E-264
400	8.91E-01	-9.35E+01	2.32E-23	3.05E-05	2.01E-24	-1.14E-07	3.50E-10	8.20E-01	3.79E-126
420	8.82E-01	-1.93E+02	2.20E-79	8.75E-06	3.46E-05	2.74E-08	2.92E-02	5.63E-01	1.51E-119
430	9.80E-01	-3.51E+02	1.68E-92	7.66E-07	5.88E-01	-3.42E-08	1.08E-04	9.89E-01	0.00E+00
440	4.65E-01	-1.48E+02	1.20E-05	1.36E-05	3.70E-02	-3.98E-09	9.22E-01	5.37E-01	1.27E-15
450	9.40E-01	-6.07E+02	9.07E-29	1.35E-07	9.20E-01	3.74E-08	8.94E-06	7.16E-01	9.98E-266
460	9.84E-01	-4.94E+02	8.69E-57	5.61E-06	9.57E-05	-4.65E-08	3.50E-07	1.02E+00	0.00E+00
470	9.33E-01	-2.30E+02	1.79E-41	1.79E-05	4.12E-10	-1.43E-07	1.42E-15	9.81E-01	3.65E-180
480	9.13E-01	-1.31E+02	6.43E-57	3.32E-06	5.60E-02	2.71E-08	1.08E-02	6.27E-01	1.36E-179
490	9.20E-01	-4.89E+02	4.96E-77	1.67E-05	4.41E-10	-6.69E-08	5.29E-05	9.22E-01	1.63E-168
520	8.59E-01	-1.20E+02	2.28E-29	2.80E-05	2.79E-16	-1.30E-07	4.82E-10	8.88E-01	1.86E-116
530	9.65E-01	-5.01E+02	9.71E-52	6.96E-06	3.04E-05	-6.82E-08	2.20E-11	9.43E-01	2.34E-295
540	9.24E-01	-1.17E+03	2.23E-69	1.78E-05	5.91E-15	-9.82E-08	1.11E-12	7.84E-01	7.62E-172
550	9.57E-01	-4.85E+02	1.73E-84	8.89E-06	9.72E-08	-7.88E-09	4.40E-01	7.27E-01	9.46E-225
560	9.60E-01	-8.90E+02	1.32E-51	1.13E-05	5.95E-08	-7.16E-08	1.03E-07	9.04E-01	2.30E-214
570	9.54E-01	-6.12E+02	1.96E-56	1.05E-05	1.96E-08	-6.46E-08	2.54E-08	9.00E-01	7.77E-248
580	9.40E-01	-2.75E+02	2.03E-92	9.09E-06	2.53E-06	-1.60E-08	1.65E-01	6.88E-01	1.37E-179
590	9.11E-01	-8.88E+02	7.62E-43	1.61E-05	3.26E-11	-8.94E-08	3.64E-09	8.83E-01	5.48E-180
600	9.29E-01	-6.40E+01	5.75E-96	6.66E-06	3.68E-04	1.78E-08	1.11E-01	6.79E-01	1.01E-180
610	9.80E-01	-1.25E+02	4.7E-112	7.94E-06	2.05E-07	-3.23E-08	7.11E-04	9.48E-01	3.66e-322
630	8.79E-01	-1.49E+03	1.06E-45	2.30E-05	7.68E-14	-1.18E-07	1.38E-10	8.00E-01	4.10E-120
650	8.93E-01	-6.80E+02	7.86E-30	1.01E-05	4.54E-07	-5.96E-08	1.20E-06	8.01E-01	1.26E-195
660	9.41E-01	-4.46E+02	6.82E-43	1.34E-05	8.47E-10	-9.13E-08	5.75E-11	9.62E-01	1.19E-222
670	9.67E-01	-5.93E+02	9.96E-76	9.52E-06	1.98E-08	-5.68E-08	1.36E-07	9.14E-01	4.43E-279
680	9.33E-01	-9.95E+02	1.69E-102	1.17E-05	1.38E-03	-3.97E-08	7.95E-02	1.17E+00	2.29E-163
690	9.02E-01	-1.29E+02	6.32E-52	1.62E-05	8.30E-14	-3.36E-08	1.09E-02	8.20E-01	2.02E-190
700	9.11E-01	-1.27E+02	6.38E-62	8.47E-06	1.52E-05	5.56E-08	7.31E-06	6.83E-01	2.69E-173
710	9.69E-01	-6.47E+02	2.54E-69	7.68E-06	4.87E-06	-4.02E-08	1.44E-04	8.82E-01	4.90E-271
720	9.05E-01	-1.33E+02	4.34E-78	1.37E-05	3.33E-08	6.76E-09	6.62E-01	6.70E-01	1.02E-124

Station ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
740	9.22E-01	-1.38E+02	3.05E-67	7.78E-06	6.48E-05	-4.90E-08	2.45E-05	6.29E-01	3.73E-158
750	9.67E-01	-2.93E+02	6.1E-100	7.83E-06	3.83E-06	-2.84E-08	6.67E-03	8.20E-01	2.78E-254
760	9.33E-01	-6.61E+02	3.65E-79	1.87E-05	5.47E-15	-1.32E-07	8.13E-19	7.06E-01	4.14E-142
780	9.30E-01	-1.55E+02	2.78E-76	3.54E-06	5.73E-02	-8.50E-09	4.46E-01	7.43E-01	2.76E-200
800	9.12E-01	-6.39E+02	1.28E-62	1.87E-05	1.11E-09	-9.96E-08	9.39E-08	9.91E-01	4.11E-162
810	9.56E-01	-2.49E+02	1.20E-66	8.01E-06	4.32E-05	-5.33E-08	1.74E-05	7.69E-01	2.96E-195
820	9.05E-01	-7.18E+02	1.24E-46	9.53E-06	2.81E-05	-3.86E-09	7.85E-01	7.59E-01	3.56E-158
830	8.82E-01	-2.86E+02	3.99E-46	1.49E-05	2.08E-08	-5.86E-08	2.38E-04	7.74E-01	1.00E-134
840	9.65E-01	-9.43E+01	6.3E-105	6.39E-06	7.95E-05	-1.38E-08	1.63E-01	8.59E-01	4.01E-278
850	8.94E-01	-9.41E+01	3.37E-02	1.65E-05	6.90E-13	-8.41E-08	7.48E-09	7.96E-01	1.08E-159
870	9.69E-01	-1.45E+02	1.75E-57	6.78E-06	5.85E-06	-6.06E-08	5.46E-11	8.75E-01	2.19E-296
880	9.62E-01	-4.74E+02	4.78E-128	1.04E-05	6.15E-08	-9.08E-08	8.30E-14	7.79E-01	1.12E-208
890	7.74E-01	-7.67E+02	7.64E-04	1.69E-05	1.17E-06	-2.31E-08	2.77E-01	6.88E-01	7.62E-79
900	9.38E-01	-6.77E+02	1.51E-85	7.71E-06	7.00E-07	-1.34E-09	8.87E-01	6.90E-01	1.26E-231
910	9.09E-01	-2.40E+02	5.70E-25	7.65E-07	5.89E-01	6.55E-09	4.54E-01	7.13E-01	7.48E-252
920	8.19E-01	-2.71E+02	1.59E-37	-6.96E-07	6.77E-01	8.41E-08	1.02E-15	5.34E-01	1.55E-145
930	9.38E-01	-8.34E+02	1.20E-59	1.31E-05	1.29E-08	-3.29E-08	1.98E-02	8.42E-01	1.35E-186
940	9.11E-01	-7.89E+01	1.46E-79	1.03E-05	1.54E-05	4.83E-08	1.06E-03	6.48E-01	3.73E-122
960	9.52E-01	-4.55E+02	4.18E-57	1.06E-05	1.33E-07	-2.20E-08	8.03E-02	8.73E-01	2.47E-224
970	9.00E-01	-1.55E+02	8.10E-66	6.09E-06	8.16E-04	6.13E-08	4.98E-08	6.00E-01	1.31E-159
980	9.47E-01	-1.19E+02	7.84E-88	1.11E-05	2.52E-09	4.73E-08	4.00E-05	6.23E-01	1.01E-163
990	9.19E-01	-3.45E+02	7.25E-33	2.44E-06	8.45E-02	3.07E-08	4.11E-04	6.76E-01	3.17E-241
1000	7.28E-01	1.82E+02	1.55E-01	3.41E-05	1.58E-12	-3.82E-08	1.72E-01	6.26E-01	1.45E-44
1010	9.75E-01	-1.38E+02	4.82E-53	5.49E-06	1.55E-04	-6.28E-08	1.58E-12	9.39E-01	0.00E+00
1020	9.61E-01	-7.36E+02	5.88E-61	1.01E-05	1.73E-09	-5.77E-08	2.94E-08	8.86E-01	2.18E-275
1030	9.67E-01	-1.07E+02	1.36E-15	1.22E-05	5.32E-13	-3.10E-08	2.02E-03	6.71E-01	3.81E-206
1040	3.81E-01	-2.01E+02	9.13E-11	1.21E-05	2.27E-01	-5.56E-08	3.42E-01	5.85E-01	5.26E-10
1060	9.23E-01	-1.62E+02	6.01E-51	7.55E-06	1.46E-04	4.35E-10	9.72E-01	7.40E-01	4.31E-185
1070	9.23E-01	-1.56E+02	4.06E-51	4.46E-06	2.10E-02	1.19E-08	3.23E-01	8.63E-01	3.42E-227
1080	9.39E-01	-1.74E+02	9.1E-140	8.27E-06	4.30E-05	1.05E-08	4.07E-01	7.38E-01	6.22E-184
1090	9.69E-01	-8.95E+02	4.69E-65	5.55E-06	2.02E-03	-4.19E-08	1.74E-04	9.25E-01	1.59E-262

Station ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
1120	8.70E-01	-2.51E+02	7.28E-43	2.59E-05	1.08E-15	-6.33E-08	2.18E-03	7.23E-01	3.40E-89
1130	9.58E-01	-2.21E+02	3.39E-49	1.16E-05	2.36E-10	-4.71E-08	4.95E-05	8.83E-01	3.09E-249
1140	8.55E-01	-7.93E+01	1.14E-74	1.15E-05	6.17E-05	6.59E-08	1.83E-04	6.13E-01	1.84E-88
1150	9.43E-01	-3.22E+02	8.62E-54	1.12E-05	6.92E-09	-2.25E-08	5.76E-02	7.75E-01	6.29E-204
1160	9.80E-01	-3.89E+02	1.31E-80	5.80E-06	9.08E-05	-4.29E-08	4.31E-06	9.10E-01	1.55E-204
1170	9.06E-01	-8.67E+01	8.05E-05	5.45E-06	3.53E-04	1.29E-08	1.61E-01	7.10E-01	1.64E-239
1180	9.29E-01	-2.18E+02	7.00E-44	4.59E-06	1.36E-02	-4.15E-08	2.19E-04	7.69E-01	3.26E-207
1190	8.91E-01	-1.57E+02	2.00E-24	9.78E-06	7.34E-08	-3.64E-08	9.58E-04	7.30E-01	5.51E-200
1200	8.85E-01	-4.65E+02	3.50E-26	2.41E-05	2.80E-18	-9.58E-08	1.01E-08	7.89E-01	2.93E-129
1210	9.67E-01	-2.21E+02	3.08E-39	1.02E-05	3.87E-10	-6.10E-08	7.89E-10	9.10E-01	4.54E-290
1220	9.01E-01	-1.85E+03	1.08E-35	1.90E-05	1.37E-12	-1.14E-07	1.44E-11	1.00E+00	2.30E-177
1230	9.11E-01	-1.85E+02	4.66E-20	5.78E-06	7.14E-05	1.52E-08	8.85E-02	6.90E-01	6.46E-237
1240	9.64E-01	-2.71E+02	2.26E-68	1.35E-05	2.05E-14	-5.36E-08	1.57E-06	9.08E-01	9.76E-268
1260	9.65E-01	-2.24E+02	1.4E-138	5.59E-06	2.09E-04	-5.58E-09	5.49E-01	7.70E-01	2.41E-268
1270	9.51E-01	-1.32E+02	1.6E-114	7.04E-06	1.10E-04	3.15E-08	6.32E-03	7.79E-01	9.92E-218
1280	9.67E-01	-7.26E+02	1.7E-109	8.52E-06	2.49E-09	-1.62E-08	6.40E-02	7.58E-01	1.77E-277
1290	9.51E-01	-4.55E+02	6.24E-67	3.76E-06	2.60E-02	-4.91E-08	1.36E-06	7.92E-01	1.06E-244
1300	8.38E-01	-6.51E+02	5.99E-18	3.23E-05	3.31E-22	-1.03E-07	5.46E-08	7.13E-01	5.10E-95
1310	9.56E-01	-2.76E+02	8.08E-50	9.11E-06	5.93E-07	-6.61E-08	1.68E-09	9.01E-01	1.91E-258
1320	8.79E-01	-2.25E+03	1.20E-43	2.25E-05	3.95E-14	-1.09E-07	9.37E-10	8.94E-01	7.68E-147
1330	9.66E-01	-2.31E+02	2.06E-69	5.21E-07	7.82E-01	-4.44E-08	1.35E-04	1.02E+00	5.79E-287
1340	9.36E-01	-4.12E+02	1.11E-68	1.95E-05	1.42E-10	-9.81E-08	4.07E-08	9.55E-01	3.48E-160
1350	9.73E-01	-1.62E+02	2.8E-108	7.72E-06	1.16E-05	-3.44E-08	1.47E-03	9.48E-01	1.68E-289
1360	9.39E-01	-1.35E+02	1.3E-102	7.50E-06	3.42E-04	2.35E-08	6.26E-02	7.43E-01	2.44E-183
1380	9.62E-01	-8.30E+02	1.3E-161	8.13E-06	1.74E-04	-8.40E-08	2.54E-10	8.00E-01	2.58E-194
1400	8.37E-01	-1.51E+03	6.15E-22	1.52E-05	2.76E-08	-5.61E-08	6.93E-04	7.62E-01	7.63E-128
1410	9.69E-01	-4.25E+02	8.50E-86	8.42E-06	6.08E-06	-7.73E-08	6.42E-12	9.17E-01	1.47E-266
1430	9.15E-01	-3.04E+02	1.67E-28	1.04E-06	4.97E-01	3.11E-08	1.24E-03	7.01E-01	4.73E-228
1440	9.73E-01	-1.78E+02	1.43E-45	5.06E-06	1.49E-03	-7.23E-08	1.11E-13	9.85E-01	1e-323
1450	9.16E-01	-1.79E+03	2.59E-41	1.87E-05	4.46E-15	-8.88E-08	1.35E-09	7.72E-01	9.37E-165
1460	9.66E-01	-2.87E+02	1.02E-60	6.54E-06	2.32E-04	-6.21E-08	6.47E-09	9.63E-01	1.47E-287

Station ID	R-Squared	Constant		Cases		Total Vaccination		Work Occup. Reduction	
		Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
1480	9.40E-01	-4.62E+02	1.15E-58	7.76E-06	1.16E-04	-2.79E-08	2.25E-02	8.91E-01	9.52E-233
1490	8.33E-01	-8.85E+02	2.43E-38	3.25E-05	6.22E-11	-1.56E-07	7.89E-08	8.91E-01	1.61E-71
1500	9.67E-01	-2.48E+02	1.69E-61	7.56E-06	1.93E-06	-5.54E-08	4.49E-09	9.00E-01	8.37E-299
1510	8.84E-01	-7.45E+02	4.79E-51	1.69E-05	3.44E-09	-8.38E-08	3.68E-06	9.39E-01	2.76E-147
1660	9.40E-01	-3.13E+03	1.53E-82	1.03E-05	1.38E-05	-6.83E-08	3.40E-06	8.97E-01	4.28E-193
1670	7.98E-01	-2.15E+02	2.61E-61	7.23E-06	1.21E-02	3.20E-08	6.49E-02	6.74E-01	1.51E-99
1680	9.61E-01	-5.52E+01	5.96E-29	7.99E-06	5.74E-07	-3.21E-08	1.59E-03	7.78E-01	1.54E-238
1690	6.58E-01	4.89E+02	3.65E-14	1.45E-05	1.27E-09	-5.15E-08	1.12E-03	5.39E-01	1.61E-76

Table 14. Temporal Regression for the CTA Rail System: Stay at Home, Crime, Gas Price, Unemployment, and Discount

Station ID	Stay at home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
10	3.57E-02	6.07E-10	-2.50E-02	2.41E-03	5.21E-02	1.85E-42	3.99E-03	7.38E-07	-4.74E-02	1.41E-05
20	4.27E-02	6.82E-11	-6.51E-02	2.70E-01	4.91E-02	2.87E-29	7.40E-03	5.61E-16	-6.87E-02	6.68E-08
30	6.28E-02	2.46E-13	-1.26E-02	1.24E-02	6.33E-02	1.31E-28	7.41E-03	4.32E-10	-7.29E-02	5.08E-06
40	-1.49E-02	1.73E-03	5.34E-04	4.52E-01	2.65E-02	1.29E-16	7.97E-04	2.33E-01	-4.37E-02	1.33E-06
50	3.41E-02	3.67E-06	3.70E-11	4.46E-61	6.40E-02	9.53E-38	7.27E-03	2.09E-12	-6.44E-02	5.28E-06
60	3.67E-02	9.74E-09	-1.25E-02	1.72E-01	4.54E-02	2.62E-25	9.69E-03	1.12E-25	-6.34E-02	2.03E-07
70	-3.46E-03	6.65E-01	-4.18E-04	6.72E-01	6.36E-02	5.91E-32	4.42E-03	8.82E-05	-5.36E-02	4.43E-04
80	2.08E-02	1.30E-02	-1.54E-02	4.12E-02	6.97E-02	6.95E-35	9.90E-03	6.08E-17	-7.42E-02	2.83E-06
90	6.17E-04	9.28E-01	-9.24E-03	1.96E-01	5.23E-02	5.22E-30	7.34E-03	3.26E-13	-1.59E-02	2.06E-01
100	4.22E-02	9.05E-13	-2.40E-03	7.17E-01	5.35E-02	3.95E-35	7.30E-03	2.61E-17	-4.38E-02	8.88E-05
120	3.28E-02	1.35E-05	-3.62E-02	3.17E-04	2.80E-02	9.24E-09	7.05E-03	4.81E-11	-7.93E-02	2.67E-08
130	4.02E-02	1.56E-07	-2.19E-02	1.76E-02	4.27E-02	2.52E-16	6.27E-03	5.09E-09	-8.51E-03	5.64E-01
140	1.86E-02	9.76E-02	-5.99E-12	2.75E-89	6.68E-02	1.35E-20	7.39E-03	3.02E-06	-1.18E-01	2.81E-08
150	4.82E-02	7.20E-13	-9.43E-03	1.57E-01	3.62E-02	2.16E-15	1.19E-02	1.22E-32	-6.75E-02	6.40E-08
160	-8.54E-03	9.14E-02	-2.99E-04	6.64E-01	3.32E-02	9.87E-22	2.98E-03	2.10E-05	-2.70E-02	5.67E-03
170	1.70E-02	3.27E-01	-3.99E-02	4.88E-03	5.41E-02	5.43E-06	8.08E-03	5.19E-04	-3.03E-02	3.30E-01
180	1.40E-03	8.07E-01	2.93E-12	4.67E-126	4.90E-02	6.31E-39	1.95E-03	1.28E-02	-6.40E-02	9.53E-09
190	1.29E-02	7.06E-01	-1.60E-01	6.30E-04	6.47E-02	8.15E-03	4.91E-03	2.69E-01	-2.12E-01	5.41E-04
240	2.50E-02	4.90E-06	-2.56E-03	6.06E-01	3.78E-02	1.09E-20	6.01E-03	4.39E-14	-6.24E-03	5.35E-01
250	3.46E-02	2.19E-06	-1.54E-02	2.30E-02	4.90E-02	2.92E-22	8.30E-03	8.60E-16	-5.95E-02	1.58E-05
260	2.55E-02	5.88E-02	-4.17E-03	3.79E-04	5.75E-02	2.61E-11	6.91E-03	2.51E-04	-9.40E-02	2.98E-04
270	4.68E-02	2.75E-10	2.21E-12	3.28E-58	7.12E-02	4.42E-45	6.77E-03	5.76E-11	-8.22E-02	7.13E-09
280	5.41E-02	9.33E-16	-8.19E-03	2.18E-01	3.84E-02	1.78E-16	6.50E-03	4.44E-12	-6.05E-02	3.78E-06
290	4.33E-02	1.40E-07	-4.78E-02	5.73E-05	6.86E-02	2.11E-31	7.49E-03	5.55E-11	-6.47E-02	5.78E-05
300	4.94E-02	2.55E-10	-3.71E-03	6.63E-01	5.44E-02	1.71E-26	2.21E-03	3.83E-02	-7.05E-02	1.84E-06
320	1.96E-02	1.92E-02	-1.90E-02	1.11E-02	6.23E-02	3.75E-29	8.29E-03	1.94E-12	-5.94E-02	1.81E-04
330	3.74E-02	7.14E-02	-7.88E-02	9.00E-14	1.17E-01	4.29E-16	1.26E-02	7.89E-06	-2.22E-01	7.65E-08
350	-2.41E-02	7.93E-02	-8.07E-03	9.44E-02	1.05E-01	2.20E-32	5.70E-03	3.37E-03	-6.22E-02	1.04E-02
360	8.31E-03	3.84E-01	-2.21E-02	2.85E-01	6.13E-02	1.94E-21	7.93E-03	1.45E-08	-4.56E-02	1.01E-02

Station ID	Stay at home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
370	1.42E-02	5.82E-02	-3.65E-04	6.88E-01	6.15E-02	3.26E-32	6.76E-03	2.68E-10	-6.66E-02	2.71E-06
380	1.39E-02	2.83E-02	-4.41E-04	6.36E-01	4.94E-02	9.59E-30	2.96E-03	9.20E-04	-6.33E-02	1.44E-07
390	3.26E-02	2.91E-08	-1.22E-11	3.63E-160	5.54E-02	3.05E-46	5.33E-03	7.92E-11	-4.47E-02	5.98E-05
400	-2.50E-04	9.83E-01	2.43E-12	2.30E-23	5.71E-02	6.44E-14	1.23E-02	2.61E-13	-5.39E-02	1.39E-02
420	8.86E-02	7.26E-26	2.44E-02	4.05E-01	4.26E-02	3.24E-14	1.19E-02	3.08E-23	-8.47E-02	3.20E-08
430	-8.62E-03	1.34E-01	7.57E-04	6.00E-01	5.21E-02	9.47E-41	4.00E-03	9.32E-07	-4.14E-02	1.29E-04
440	7.17E-02	9.53E-03	-1.59E-01	5.57E-12	6.68E-02	7.28E-05	1.81E-02	4.31E-06	-1.07E-01	2.60E-02
450	2.34E-02	1.82E-05	-8.38E-03	2.03E-01	2.62E-02	4.29E-12	3.33E-03	2.66E-05	-9.43E-04	9.25E-01
460	-7.38E-03	2.18E-01	-7.98E-03	3.05E-05	4.84E-02	3.87E-35	3.39E-03	5.04E-05	-3.22E-02	4.11E-03
470	-1.93E-02	7.91E-02	-1.13E-02	1.28E-01	5.38E-02	7.25E-14	4.58E-03	2.12E-03	-4.60E-02	4.16E-02
480	4.22E-02	1.14E-09	-2.29E-02	3.84E-06	4.61E-02	6.89E-23	7.11E-03	4.33E-13	-4.12E-02	1.65E-03
490	3.92E-02	2.56E-04	-1.49E-02	8.65E-04	6.32E-02	2.26E-19	9.02E-03	2.41E-09	-1.00E-01	8.98E-07
520	-8.71E-03	5.13E-01	1.31E-16	1.39E-41	6.39E-02	4.54E-13	9.68E-03	2.92E-07	-4.34E-02	8.51E-02
530	1.54E-03	8.12E-01	-1.46E-02	1.82E-01	4.48E-02	3.83E-24	6.54E-03	6.74E-12	-3.19E-02	8.80E-03
540	3.47E-02	5.84E-05	-1.51E-02	8.12E-03	6.97E-02	2.49E-31	8.78E-03	7.06E-13	-1.16E-01	1.26E-11
550	5.21E-02	7.49E-15	-3.16E-02	1.18E-02	6.49E-02	9.46E-45	1.01E-02	4.63E-26	-8.88E-02	2.81E-12
560	-1.47E-02	8.82E-02	-8.41E-03	2.11E-04	8.70E-02	4.36E-50	5.22E-03	1.91E-05	-3.62E-02	3.02E-02
570	1.82E-02	1.46E-02	-1.48E-02	1.80E-01	6.68E-02	4.24E-37	6.90E-03	1.26E-10	-6.22E-02	1.00E-05
580	4.74E-02	5.49E-10	9.06E-12	2.02E-92	2.34E-02	1.57E-06	1.25E-02	1.80E-29	-7.33E-02	2.06E-07
590	2.90E-02	2.69E-03	-5.41E-02	4.12E-05	8.12E-02	2.88E-34	8.63E-03	3.08E-10	-7.03E-02	1.55E-04
600	2.44E-02	9.21E-04	4.04E-03	4.46E-01	3.12E-02	1.18E-10	9.88E-03	3.19E-20	-1.84E-02	1.70E-01
610	1.00E-02	1.04E-01	1.53E-02	1.91E-01	4.59E-02	1.28E-29	2.95E-03	6.42E-04	-6.78E-02	1.04E-08
630	2.35E-02	4.05E-02	-8.52E-02	4.29E-10	1.01E-01	2.37E-35	1.15E-02	5.82E-13	-1.14E-01	5.78E-07
650	2.29E-02	3.46E-03	-1.15E-02	1.32E-05	5.93E-02	5.00E-27	1.18E-02	2.28E-25	-5.10E-02	5.62E-04
660	5.27E-04	9.53E-01	-2.35E-02	1.58E-02	4.73E-02	2.59E-16	7.33E-03	4.32E-09	-7.12E-02	2.99E-05
670	1.55E-02	2.64E-02	-5.09E-03	6.50E-01	5.97E-02	3.74E-37	6.36E-03	1.00E-10	-5.52E-02	2.71E-05
680	-1.65E-02	2.41E-01	-2.76E-02	6.25E-15	4.07E-03	6.50E-01	4.86E-03	1.34E-02	-9.70E-02	7.95E-04
690	2.49E-02	2.84E-03	-2.03E-12	6.27E-52	6.28E-02	2.26E-26	8.20E-03	3.37E-12	-1.13E-01	4.11E-12
700	4.52E-02	1.22E-08	-1.57E-02	2.74E-02	3.48E-02	8.74E-11	5.61E-03	4.09E-07	-8.90E-02	5.29E-09
710	2.80E-02	6.16E-05	-2.26E-02	4.42E-11	5.68E-02	1.19E-36	6.28E-03	1.09E-10	-5.66E-02	1.58E-05
720	6.53E-02	4.92E-11	-2.49E-02	5.17E-02	6.24E-02	7.22E-19	5.75E-03	2.55E-05	-8.31E-02	1.57E-05

Station ID	Stay at home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
740	3.95E-02	1.78E-07	-1.69E-02	4.77E-04	3.11E-02	4.92E-10	1.50E-02	1.10E-39	-9.93E-03	4.77E-01
750	2.62E-02	1.40E-04	-7.66E-02	2.60E-04	4.67E-02	3.69E-25	7.66E-03	2.55E-15	-8.32E-02	1.86E-10
760	1.08E-02	2.52E-01	2.44E-03	8.00E-01	1.09E-01	2.74E-60	1.25E-02	1.62E-20	6.06E-03	7.33E-01
780	3.56E-02	1.29E-06	-1.85E-02	1.29E-02	4.02E-02	4.89E-16	8.90E-03	1.26E-16	-3.08E-02	2.20E-02
800	1.61E-03	8.92E-01	-3.38E-02	9.74E-04	5.92E-02	1.78E-14	6.64E-03	4.66E-05	-1.19E-01	3.29E-07
810	3.21E-02	7.86E-05	-1.38E-02	3.48E-03	4.58E-02	2.49E-18	8.03E-03	2.30E-12	-2.23E-02	1.43E-01
820	3.81E-02	4.00E-05	-1.42E-01	1.28E-01	5.18E-02	4.86E-18	8.99E-03	8.79E-12	-9.78E-02	1.59E-08
830	5.08E-02	1.27E-06	-2.25E-02	1.40E-05	4.22E-02	9.34E-10	1.40E-02	1.93E-20	-6.48E-02	7.22E-04
840	2.57E-02	6.37E-05	-2.58E-02	1.68E-01	4.88E-02	2.93E-30	5.03E-03	2.30E-08	-8.28E-02	2.68E-11
850	-2.03E-03	8.27E-01	-3.59E-03	4.52E-02	6.68E-02	3.46E-26	6.32E-03	2.00E-06	-5.59E-02	1.60E-03
870	1.74E-02	4.29E-03	-1.31E-02	9.00E-02	5.52E-02	3.78E-42	7.08E-03	2.83E-15	-3.01E-02	5.96E-03
880	1.34E-02	8.72E-02	4.15E-03	5.75E-01	8.58E-02	6.79E-58	1.02E-02	3.04E-20	-1.51E-02	3.07E-01
890	4.47E-02	6.79E-04	-1.84E-02	3.64E-01	3.31E-02	1.07E-03	1.05E-02	1.19E-08	-2.26E-01	2.11E-18
900	3.29E-02	6.31E-08	-7.39E-03	4.08E-01	4.72E-02	1.02E-28	7.94E-03	2.36E-20	-5.75E-02	7.80E-07
910	2.03E-02	2.42E-04	-6.66E-03	8.52E-03	4.82E-02	8.29E-32	2.36E-03	3.16E-03	6.89E-04	9.48E-01
920	1.16E-02	7.04E-02	-8.22E-03	5.28E-02	3.65E-02	2.93E-14	1.24E-02	1.71E-38	-7.75E-02	4.67E-10
930	3.40E-02	2.36E-04	-6.13E-02	2.19E-01	3.36E-02	2.80E-08	8.03E-03	5.09E-10	-1.23E-01	3.14E-12
940	5.76E-02	6.43E-09	-1.50E-02	2.73E-02	6.49E-02	2.41E-24	7.61E-03	2.59E-08	-1.09E-01	2.46E-09
960	4.07E-02	6.93E-07	-3.74E-02	2.00E-02	2.18E-02	3.14E-05	6.69E-03	7.11E-09	-9.68E-02	9.33E-10
970	6.87E-02	9.56E-21	-1.60E-02	1.10E-04	4.09E-02	4.37E-17	6.43E-03	3.36E-10	-6.70E-02	1.16E-06
980	4.34E-02	8.74E-09	1.87E-17	5.04E-15	4.96E-02	1.70E-24	7.74E-03	3.51E-13	-6.27E-02	9.75E-06
990	3.52E-02	2.81E-10	-1.28E-02	2.55E-03	3.35E-02	2.82E-17	4.69E-03	5.85E-09	-3.22E-02	2.05E-03
1000	6.64E-02	6.89E-05	2.81E-03	7.57E-01	1.99E-02	1.67E-01	9.67E-03	4.57E-05	-2.49E-01	3.69E-13
1010	-2.44E-03	6.71E-01	-3.72E-04	9.51E-01	4.80E-02	8.32E-35	5.44E-03	7.58E-11	-2.08E-02	4.87E-02
1020	2.34E-02	5.11E-04	-3.80E-02	1.08E-02	5.72E-02	1.36E-34	7.49E-03	7.26E-15	-5.48E-02	1.43E-05
1030	3.56E-02	1.14E-07	-1.19E-02	5.05E-04	2.56E-02	2.01E-09	1.35E-02	2.78E-41	-3.14E-02	9.40E-03
1040	6.00E-02	1.11E-01	-1.50E-01	4.28E-05	8.65E-02	5.65E-04	1.96E-02	2.15E-04	-1.07E-01	1.32E-01
1060	5.22E-02	8.11E-11	-1.73E-02	3.39E-02	1.55E-02	2.51E-03	9.38E-03	1.29E-16	-7.88E-02	2.07E-07
1070	2.49E-02	1.54E-03	-1.18E-02	3.69E-02	3.80E-02	9.95E-14	-1.45E-03	1.85E-01	-5.26E-02	4.30E-04
1080	6.38E-02	1.03E-14	-8.22E-03	4.80E-01	5.16E-02	1.82E-21	5.61E-03	6.31E-07	-5.56E-02	4.38E-04
1090	4.39E-04	9.52E-01	-5.47E-03	1.43E-03	7.24E-02	6.22E-46	5.69E-03	4.65E-08	-4.60E-02	7.98E-04

Station ID	Stay at home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
1120	2.64E-02	5.28E-02	2.77E-03	8.17E-01	8.33E-02	1.07E-21	1.09E-02	7.18E-09	-1.09E-01	1.62E-05
1130	1.70E-02	2.18E-02	-1.91E-02	5.21E-02	4.00E-02	3.58E-16	5.86E-03	2.53E-08	-5.38E-02	1.73E-04
1140	8.62E-02	3.74E-14	-1.63E-02	3.03E-02	6.63E-02	2.96E-18	5.32E-03	5.92E-04	-1.11E-01	4.54E-07
1150	4.47E-02	9.37E-09	-4.07E-02	8.18E-05	2.51E-02	9.39E-07	9.53E-03	1.77E-17	-8.03E-02	4.68E-08
1160	1.01E-02	9.77E-02	3.86E-03	6.92E-02	5.53E-02	4.42E-42	5.38E-03	4.95E-10	-4.29E-02	1.74E-04
1170	2.35E-02	5.82E-05	-8.93E-03	6.49E-02	2.05E-02	9.58E-07	4.91E-03	6.85E-09	-3.20E-02	3.70E-03
1180	5.12E-02	3.37E-12	-3.85E-03	6.47E-01	4.56E-02	1.93E-20	9.44E-03	9.94E-19	-4.70E-02	4.82E-04
1190	3.52E-02	5.34E-07	-1.81E-03	6.74E-01	4.65E-02	5.67E-20	8.60E-03	7.14E-18	-6.37E-02	1.87E-06
1200	7.75E-03	4.65E-01	-1.30E-02	9.20E-02	5.88E-02	1.83E-15	1.18E-02	6.84E-15	-2.01E-01	1.34E-22
1210	2.72E-03	6.70E-01	-8.63E-03	2.85E-01	4.38E-02	7.96E-25	6.62E-03	1.75E-12	-3.58E-02	2.75E-03
1220	-1.18E-02	2.79E-01	-2.88E-02	1.00E-01	6.34E-02	2.24E-19	6.15E-03	6.26E-05	-4.78E-02	1.82E-02
1230	4.15E-02	6.03E-13	-8.97E-03	9.29E-03	3.78E-02	1.04E-20	4.29E-03	2.28E-07	-3.50E-02	1.15E-03
1240	1.90E-02	8.14E-03	-1.18E-03	8.50E-01	4.93E-02	8.91E-26	1.85E-03	6.46E-02	-7.51E-02	5.43E-08
1260	3.11E-02	3.40E-07	-1.43E-02	4.72E-02	3.98E-02	3.03E-22	7.01E-03	2.50E-16	-5.75E-02	6.33E-07
1270	5.16E-02	6.30E-12	-5.44E-03	4.62E-01	4.51E-02	2.56E-20	3.71E-03	3.07E-04	-7.95E-02	3.01E-08
1280	3.95E-02	4.26E-12	-3.84E-02	3.86E-03	4.27E-02	2.03E-28	8.73E-03	1.38E-26	-6.89E-02	2.06E-10
1290	4.02E-02	1.24E-09	1.81E-03	8.26E-01	3.84E-02	3.71E-17	9.49E-03	1.22E-22	-2.69E-02	2.62E-02
1300	2.72E-02	2.44E-02	-3.62E-02	9.05E-03	8.51E-02	5.47E-21	1.13E-02	4.20E-11	-1.01E-01	1.22E-05
1310	9.47E-03	1.77E-01	-1.35E-02	2.57E-01	5.19E-02	1.38E-26	7.56E-03	1.88E-13	-5.54E-02	2.80E-05
1320	1.42E-02	2.04E-01	-8.68E-02	7.72E-11	7.79E-02	3.12E-22	1.17E-02	1.82E-13	-7.04E-02	1.36E-03
1330	-1.41E-02	5.76E-02	-6.83E-03	5.94E-01	3.80E-02	1.71E-14	2.87E-03	5.16E-03	-4.63E-02	1.34E-03
1340	-1.44E-03	9.01E-01	-5.30E-03	9.16E-02	6.33E-02	2.75E-15	6.60E-03	3.18E-05	-9.98E-02	7.28E-06
1350	1.63E-02	1.82E-02	1.25E-03	8.95E-01	4.27E-02	3.79E-21	5.28E-03	3.83E-08	-5.75E-02	2.33E-05
1360	4.23E-02	3.18E-07	-2.85E-02	2.34E-04	1.59E-02	2.68E-03	1.03E-02	9.95E-20	-7.67E-02	1.10E-06
1380	7.89E-03	3.51E-01	2.53E-03	8.06E-01	8.71E-02	2.65E-50	1.07E-02	2.75E-19	-3.01E-02	6.68E-02
1400	3.77E-02	3.21E-04	-6.15E-03	1.61E-01	6.28E-02	7.41E-16	9.29E-03	3.56E-10	-1.03E-01	3.90E-07
1410	9.61E-03	1.86E-01	-1.05E-02	6.47E-03	5.67E-02	1.39E-31	7.13E-03	1.13E-12	-6.98E-02	5.48E-07
1430	2.84E-02	3.53E-06	-1.42E-02	1.29E-01	3.65E-02	4.09E-16	6.04E-03	7.58E-12	-2.14E-02	6.26E-02
1440	-1.06E-02	8.56E-02	-2.40E-02	1.52E-03	4.26E-02	1.38E-24	4.69E-03	1.57E-07	-1.04E-02	3.74E-01
1450	2.03E-02	2.36E-02	-3.10E-02	7.43E-06	8.03E-02	4.81E-33	1.23E-02	1.16E-21	-8.95E-02	1.13E-06
1460	9.60E-03	1.62E-01	-1.02E-02	3.70E-01	4.98E-02	2.16E-27	4.72E-03	1.61E-06	-4.17E-02	1.31E-03

Station ID	Stay at home		Crime		Gas Price		Unemployment		Discount	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
1480	3.22E-02	4.34E-05	-9.69E-03	3.41E-01	3.41E-02	1.80E-10	8.05E-03	2.76E-13	-8.82E-02	9.68E-09
1490	4.35E-03	8.13E-01	-5.67E-02	2.10E-13	1.22E-01	1.32E-20	1.29E-02	2.52E-07	-1.48E-01	5.77E-05
1500	1.03E-02	8.99E-02	-1.82E-02	7.80E-02	5.40E-02	3.32E-38	6.76E-03	2.49E-14	-4.95E-02	1.28E-05
1510	3.10E-02	9.71E-03	-6.15E-03	2.66E-02	6.68E-02	5.55E-18	9.49E-03	6.31E-08	-7.86E-02	2.92E-04
1660	1.55E-02	9.80E-02	-4.05E-03	1.89E-05	7.99E-02	4.82E-36	8.62E-03	6.31E-11	-7.38E-02	5.63E-05
1670	2.99E-02	8.17E-03	-1.41E-02	3.41E-02	4.10E-02	6.78E-08	1.21E-02	2.00E-14	-8.91E-02	2.80E-05
1680	1.16E-02	8.98E-02	7.03E-02	4.15E-01	5.80E-02	6.73E-40	5.46E-03	3.49E-08	-4.51E-02	2.20E-04
1690	1.53E-02	1.26E-01	-7.49E-03	1.98E-02	9.55E-02	1.37E-38	4.68E-03	2.40E-03	-3.49E-02	5.71E-02

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