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Literature Review and Data Analysis on the Impacts of Prolonged Events on Transit System Ridership

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16. Abstract

The COVID-19 pandemic has drastically disrupted transit operations and induced significant transit ridership losses worldwide. Given its unprecedented duration, magnitude, and scale, the long-term effects are still unclear. Despite the differences, we can learn from previous disruptive events, such as terrorist attacks and epidemics, in the past 30 years and draw qualitative and quantitative insights about public reactions, ridership recovery periods, and transit agency responses during and after those events. This study sought to understand ridership variations during the current COVID-19 pandemic and inform transit agencies' future decisions. This project's research team therefore reviewed the impacts of selected historical events. They observed the following: (i) that most of the reviewed incidents (except for the 9/11 attacks) did not impose prolonged post-event effects on transit ridership for more than one year; (ii) that executive orders (e.g., school closures), transportation services (e.g., intensified airport safety screening and rail station closures), public fear, media reports, and reduced tourism were frequently mentioned as key factors that impacted transit ridership; and (iii) that measures, such as sanitizing vehicles and facilities, improving communications with the public, and promotions and advertisements, can potentially help restore transit ridership. The research team also developed a modeling framework that integrated a Bayesian structural time-series model, a dynamics model for daily transit ridership loss, a prediction module, and ordinary least squares regression to study COVID-19's effects on the Chicago Transit Authority's rail ridership. The researchers undertook a model of ridership on the CTA rail system as a potential first step to modeling COVID-19's effects on transit ridership in northeastern Illinois. The researchers have not modeled ridership on any other transportation mode in northeastern Illinois at this time. The statistical analysis showed that remote learning/work policies and executive orders had answered for most of the ridership loss. Socioeconomic and land-use characteristics could effectively capture their effects. However, these characteristics could not explain people's different reactions to reported deaths and media attention. Different population groups may have reacted differently to policy decisions, but their responses to reported deaths and media coverage seem random and independent of sociodemographic factors.

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EXECUTIVE SUMMARY

This study mainly sought to facilitate a better understanding of the factors that have driven transit ridership's spatio-temporal variations during the COVID-19 pandemic and to predict transit ridership on the Chicago Transit Authority's (CTA's) rail system in order to help inform the Regional Transportation Authority (RTA) and CTA's decision-making. Given the limited scope of work and time constraints, the research team did not have the resources to analyze ridership on the other transit modes in northeastern Illinois. However, the research team sought to develop a larger ridership prediction model to better understand COVID-19's impacts on transit ridership in northeastern Illinois. In a future analysis, they may examine ridership on other public transit modes, consisting of CTA bus, Metra rail, and Pace bus services.

The research team conducted a historic review of the qualitative and quantitative research findings from disruptive events of transit systems in the past 30 years, focusing on public reactions, ridership recovery periods, and transit agency responses during and after those events. These events were limited to those that potentially caused travel avoidance due to fear-based responses from the public. They consisted of the London and Madrid bombings, the Tokyo sarin gas attacks, and the 9/11 attacks as well as past epidemics such as Severe Acute Respiratory Syndrome (SARS), H1N1 swine flu, Middle East Respiratory Syndrome (MERS), and Ebola. This literature review provided insights into COVID-19's impacts on transit in northeastern Illinois.

The research team also developed a modeling framework that integrated a Bayesian structural time-series model, a dynamics model for daily transit ridership loss, a prediction module, and an ordinary least squares regression to gain further insights specifically into COVID-19's impacts on CTA's rail ridership.

Most of the terrorist attacks in the past produced an immediate response from the public. For smaller scale attacks such as those in Madrid and London, the effects lasted less than four months, while the 9/11 attacks had prolonged effects lasting for one to two years. However, the Tokyo case, given its magnitude and cultural context, did not produce any fear-based response from the public.

The epidemics considered in this study varied in magnitude from localized outbreaks (e.g., Ebola) to a worldwide pandemic (e.g., H1N1). All epidemics resulted in noticeable ridership reductions on public transit systems during the outbreak. This is possibly due to passengers' travel avoidance behavior, reduced commercial activities, and executive orders. Nonetheless, the ridership reductions from all epidemics were short term once the outbreaks ended. However, it should be noted that none of the recent epidemics or pandemics and their accompanying executive orders have lasted as long as the current COVID-19 pandemic and its accompanying executive orders. The Taipei Metro and South Korea Metro showed a fast recovery within weeks of their respective outbreaks ending. Sierra Leone had an immediate recovery in ridership after their three-day national lockdown orders, and the Toronto Transit Commission (TTC) experienced a ridership reduction only during the year of the SARS outbreak. Furthermore, the Hong Kong Metro Transit Railway, Taipei Metro, TTC, and Singapore Mass Rapid Transit showed steady, annual ridership increases (particularly on the rail lines) in the years following the end of their epidemics. Annual ridership may have even exceeded pre-epidemic levels.

Based on the findings from the collected literature and datasets, the research team found that (i) the critical factors behind ridership reductions included executive orders (school closures), service decisions, travel fears, risk perceptions stemming from media reports, and depression of tourist demand, as well as differences in responses to the epidemic or pandemic from different sociodemographic groups; (ii) most past events did not induce long-term fear and prolonged ridership losses, except for the 9/11 attacks; and (iii) transit agencies usually had successfully mitigated the impacts of epidemics or pandemics by escalating safety measures, adjusting services for different routes, and launching advertisements and promotions campaigns.

The research team used the knowledge gained from the literature review to inform their statistical analysis on ridership of the CTA's rail system. They predicted counterfactual ridership on the CTA's rail system using the Bayesian structural time series to quantify ridership reductions from the COVID-19 pandemic, having considered historical ridership trends, seasonality, and holidays for each of the CTA's rail stations. They then developed a dynamics model for ridership losses which captured the impacts of people's subjective risk perceptions to daily confirmed COVID-19 deaths as well as media attention that they quantified using Google Trends scores. The dynamics model also captured transit users' reactions to executive orders, school closures, and remote working policies. This model's prediction module served to forecast future media attention as well as the pandemic's evolution. It forecasted the Google Trends scores and daily reported deaths into the upcoming months to predict transit ridership. Once the dynamics model was fitted to each CTA rail station, the research team performed an ordinary least squares regression in the model parameters to try to explain the heterogeneity of parameters as a function of the socioeconomic and land-use characteristics of city neighborhoods near each CTA rail station.

Overall, the regression results show that socioeconomic and land-use characteristics were good predictors, with an R^2 of 0.743, of the percentage reduction of ridership given the remote learning/working executive orders in the beginning of the pandemic. However, they also showed that socioeconomic characteristics were not good predictors of peoples' travel behavior during the pandemic, having R^2 values for the regression of all other parameters under 0.281. These model parameters were intended to capture the public's response given the news coverage and daily reported deaths. They may indicate that the primary drivers of transit ridership reduction and possibly recovery are policy and executive orders.

Acknowledging the fact that the statistical analysis did not consider the ridership reduction given the "new normal" and increased work-at-home opportunities, the evidence from previous epidemics have shown that fear-based ridership reduction recovers within months. Therefore, once all executive orders and restrictions are lifted and schools fully reopen, CTA rail ridership in Chicago could follow the same recovery trends as those epidemics presented in this project.

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CHAPTER 1: INTRODUCTION

The COVID-19 pandemic has had far-reaching impacts on public health, the economy, and ways of living. It adds to a long list of historic events that have thoroughly altered travel behavior and globally disrupted transportation systems (Van Cranenburgh et al., 2012; Muley et al., 2020). COVID-19 has drastically changed the demand for almost all urban transportation modes, including not only public transit, but also personal vehicles and bike-sharing systems (Teixeira & Lopes, 2020; Parr et al., 2020; Lee et al., 2020; Padmanabhan et al., 2021). Many factors such as mandatory quarantine orders, social distancing requirements, and people's fear and anxiety of being in enclosed spaces may have contributed to this phenomenon.

Transit ridership in major US cities sharply decreased after the World Health Organization (WHO) declared the COVID-19 outbreak a pandemic in March 2020. New York City, Seattle, Nashville, and Chattanooga, for example, experienced a ridership reduction of 90%, 79%, 66.9%, and 65.1%, respectively, within the pandemic's first few months (Gao et al., 2020; Wilbur et al., 2020). Besides ridership decreases, studies have consistently shown that there are socioeconomic disparities in how the pandemic has affected different social groups. Results show that lower-income people, less-educated people, and minority groups experienced the least behavioral changes (Bliss et al., 2020; Brough et al., 2020; De Vos, 2020; Garza, 2020; Sy et al., 2020; Transit, 2020; Wilbur et al., 2020; Hu & Chen, 2021; Tirachini & Cats, 2020; Liu et al., 2020; McLaren, 2020; Fissinger, 2020). These population groups usually have had jobs that are involved in society's "essential" functions, and therefore had to continue working in person through the pandemic (Kantamneni, 2020). People who earned less money were also less likely to own a car and therefore depended on public transit (Klein & Smart, 2017).

The trends and patterns of the Chicago Transit Authority (CTA) are similar to the general trend in the United States when examining its daily rail ridership. Figure 1 presents CTA daily rail ridership from 1 March 2020 to 1 March 2021, along with daily reported deaths within the same period. The same trend can be observed on other modes such as on CTA buses and ridesharing services in Chicago, using data from their respective agencies (Hu & Chen, 2021; Fissinger, 2020; Tyler, 2021).

Figure 1 shows that CTA rail ridership suffered a sharp drop on 16 March 2020 (i.e., the start of quarantine orders), falling to approximately 20% of pre-COVID-19 ridership levels. After that, it had seemed to slowly bounce back until July, when it stabilized until the end of October at approximately 30% of the CTA rail system's pre-COVID-19 ridership numbers. In November, CTA rail ridership started declining again when it aligned with the rise on reported deaths, and finally appears to be slowly building back up.

Many other major cities, such as Seattle, New York City, Los Angeles, San Francisco, and Dallas, have also observed a very similar pattern on their transit systems as the one presented in Figure 1 (Apple, 2020). This pattern seems to be consistent even in cities and states that had "reopened" (*New York Times*, 2020), suggesting that quarantine orders may not be the only factor that has influenced transit ridership. Instead, as evidenced in past epidemics, the level of public fear has been shown to discourage passengers who use public transportation (Wang, 2014; Sung, 2016).

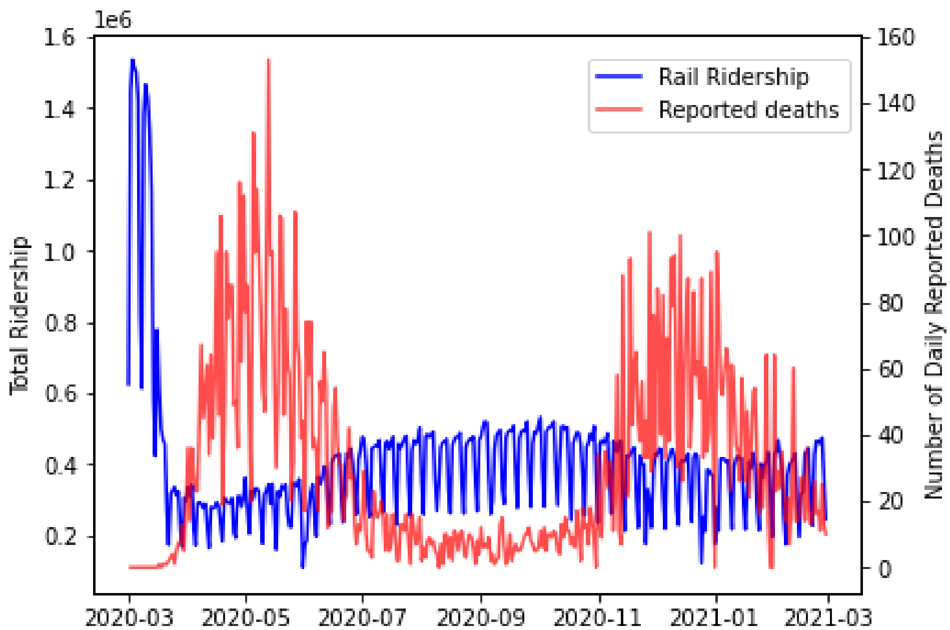


Figure 1. Graph. Total CTA rail ridership compared to daily reported deaths in Chicago from 1 March 2020 to 1 March 2021.

Amid the COVID-19 pandemic whose long-term impacts are yet to be observed, much can be learned from the effects of previous prolonged events on transit systems. The study team therefore collected quantitative and qualitative research findings from previous prolonged events to observe the time span and magnitude of their impacts on transit ridership as well as patterns of travel demand recovery. Among the numerous instances of prolonged events (e.g., epidemics, terrorist attacks, and natural disasters) in recent history that substantially altered human mobility behavior (Van Cranenburgh et al., 2012), this study focused on prolonged events that may have caused fear-based responses from the population and discouraged potential riders from using a particular transportation mode. The study team therefore focused on terrorist attacks and past epidemics. In light of the noteworthy differences of the historical context around these prolonged events (e.g., regulations, culture, and technological options), the review section focuses on events in the last three decades to help ensure the findings' compatibility with those of the COVID-19 pandemic. The research team also collected and summarized the responses of those transit agencies that the previous pandemics impacted. This information provides a reference for the Illinois Department of Transportation, the Regional Transportation Authority (RTA) and its service boards, and other transit agencies within Illinois. It can help them better react to and recover from the current pandemic. The knowledge obtained through this literature review has also served as a cornerstone for supporting the first step of a potential comprehensive statistical analysis that can further provide a deeper understanding of the COVID-19 pandemic's potential long-term effects.

The research team used information from the literature review to design a statistical model to predict transit ridership on CTA's rail system in order to help inform the RTA and CTA's decision-making. Given the limited scope of work and time constraints, the research team did not have the resources to analyze ridership on the other transit modes in northeastern Illinois. However, the research team seeks to develop a larger ridership prediction model to better understand COVID-19's impacts on transit ridership in northeastern Illinois. In a future analysis, they may examine ridership on other public transit modes, consisting of CTA bus, Metra rail, and Pace bus services.

This study's transit ridership model on the CTA's rail system integrated a Bayesian structural time series (BSTS) to estimate counterfactual ridership and to quantify ridership reductions (Hu & Chen, 2020; Scott & Varian, 2015), a dynamics model for daily transit ridership reductions that Wang (2014) inspired, a forecast model for the pandemic evolution used for forecasting (Altieri et al., 2020), and an ordinary least squares (OLS) regression analysis to draw insights between socioeconomic characteristics and ridership reductions observed during the pandemic.

This report is organized as follows. Chapter 2 focuses on the literature review, including effects of past terrorist attacks on travel ridership across all transportation modes, past epidemics and pandemics, recent COVID-19 studies with a focus on any of the Chicago transit or bike-sharing systems, and transit agency responses to previous and current epidemic events. Chapter 3 presents the statistical modeling framework that the research team developed for this study and presents results of the CTA rail ridership analysis. Detailed results are summarized in the appendix. Chapter 4 provides concluding remarks.

CHAPTER 2: LITERATURE REVIEW

TERRORIST ATTACKS

Like epidemics, terrorist attacks on transportation systems induce fear on transportation users and may change their travel behavior. Epidemics and terrorist attacks on transportation systems can cause “abrupt substantial changes” in the transportation system (Van Cranenburgh et al., 2012). The literature has documented and quantified the severity and duration of these changes, as manifested in aggregated travel pattern variations (Gigerenzer, 2004, 2006; Gaissmaier & Gigerenzer, 2012; López-Rousseau, 2005; Prager et al., 2011; Von Winterfelt & Prager, 2010). These attacks include the 9/11 terrorist attacks in New York City in 2001, the London bombings in 2005, the Madrid bombings in 2003, and the Tokyo sarin gas attack in 1995.

The 9/11 terrorist attacks in New York City caused almost 3,000 deaths and direct financial losses of approximately 36 billion dollars in property damage, earning losses, and restoration costs (Bram et al., 2002). This event caused a well-recorded immediate reduction of air travel in the United States of over 30% in September 2001 as compared to the same period of the previous year (Ito & Lee, 2005; Blunk et al., 2006). Nonetheless, researchers have found mixed evidence on whether this attack caused a prolonged mode shift away from flying in the United States or a general travel reduction (Gigerenzer, 2004, 2006; Sivak & Flannagan, 2004; Gaissmaier & Gigerenzer, 2012; Lai & Lu, 2005). Blunk et al. (2006) studied the change in revenue passenger miles from 1989 to 2002 and concluded that travel demand by December 2002 had not gone back to the predicted counterfactual levels (i.e., if no attack had occurred). Revenue passenger miles in December 2002 were 11.6% less than the predicted counterfactual values. They attributed this prolonged impact to passengers’ reluctance to travel because increased screening time and mandatory earlier arrivals at airports after 9/11 increased air travel’s opportunity cost (Blunk et al., 2006). Ito and Lee (2005) also studied domestic revenue passenger miles from 1986 to 2003. They concluded that, by the end of 2003, there was an ongoing demand reduction of 7.4% that their cyclical, seasonal, or other explanatory variables could not explain. This shows that the 9/11 attack had a prolonged impact.

Gordon et al. (2007) studied 9/11’s impacts on the economy and air traffic, by analyzing passenger numbers in international and domestic flights from 1999 to 2003. This study found an approximately 8% reduction in the first year of the 9/11 attacks and a 4% reduction in the second year. Figure 2 presents the forecasts of domestic and international flight travelers by the Holt-Winters forecasting approach along with actual observed numbers. This plot shows a long-term decrease in demand. Although some other studies, e.g., Lai and Lu (2005) and Cunado et al. (2008), claimed no evidence of long-term consequences from the 9/11 attacks, these conclusions were based on univariate time-series techniques that had limitations according to King (2010).

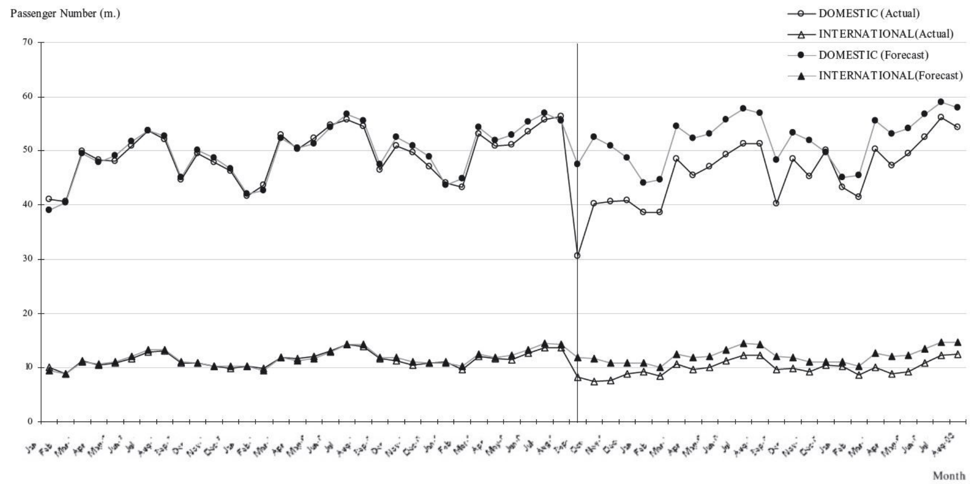


Figure 2. Graph. Forecasts of monthly domestic and international air passengers.

Source: Gordon et al. (2007)

Gigerenzer (2004, 2006) proposed the "dread hypothesis" in his studies about the impacts of the 9/11 terrorist attacks. This hypothesis stated that American residents avoided air travel after the attacks, then switched to a riskier alternative transportation mode, which resulted in more transportation-related fatalities. Gigerenzer (2006) found evidence for this hypothesis based on the observation of a decrease in air travel followed by an increase in vehicle miles traveled in 2001, and then a corresponding increase in fatal crashes in 2002. The trend of fatality crashes is depicted in Figure 3, suggesting that people's prolonged fear had lasted one year after the attacks. Although this literature review does not seek to evaluate traffic fatalities, evidence of the switch in modes and duration of the change in travel behavior can provide insights on travelers' fear associated with a particular mode.

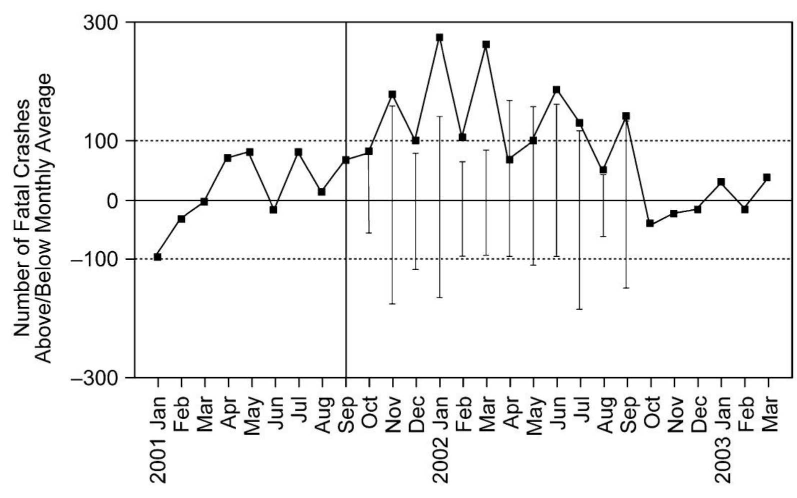


Figure 3. Graph. The number of fatal traffic accidents in the United States increased after the terrorist attacks on 11 September 2001 for a period of 12 months. Numbers are expressed as deviations from the five-year baseline 1996–2000 (the zero line).

Source: Gigerenzer (2006)

Although researchers disagreed on exactly which type of road trips replaced air travel (Sivak & Flannagan, 2004), consistent evidence shows that roadway travel increased across the United States (Blalock et al., 2005). This increase did not occur uniformly across the United States but instead correlated with driving opportunity and vehicle ownership in neighborhoods (Gaissmaier & Gigerenzer, 2012).

Researchers have also tested the dread hypothesis for other terrorist attacks such as the sarin gas attack in Tokyo (20 March 1995), the Madrid Bombings (11 March 2004), and the London bombings (7 July 2005) (Von Winterfelt & Prager, 2010). Although these events were smaller in magnitude than the 9/11 attacks, Madrid and London each showed evidence of short-term travel behavior changes (López-Rousseau, 2005; Prager et al., 2011). The Madrid attacks targeted interurban short-distance trains, so other modes such as buses and urban metro lines were not directly affected. López-Rousseau (2005) showed that ridership declined 4% to 6% for two months following the Madrid attacks. However, this study did not find evidence of a mode shift to driving or an increase in vehicle fatalities; see Figure 4, which compares the percentage variations of train travelers, highway vehicles, and highway fatal accidents before and after the Madrid attacks.

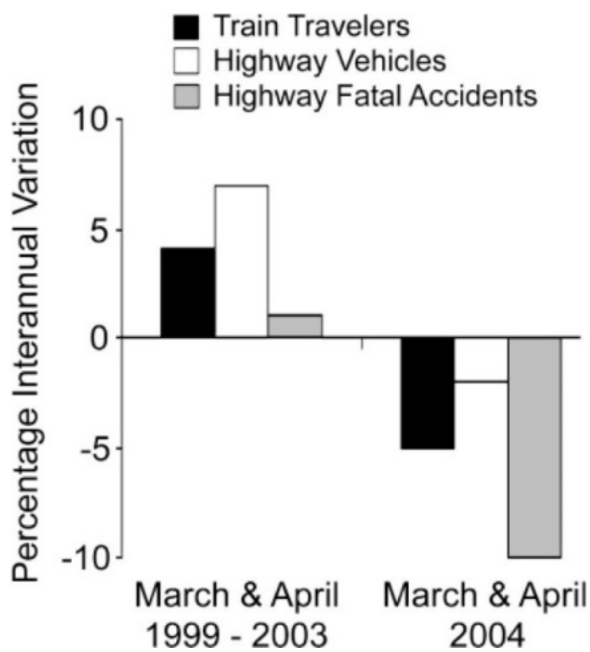


Figure 4. Graph. Average interannual variation in the number of train travelers, highway vehicles, and fatal highway accidents in March and April from 1999 to 2003 versus March and April 2004 in Spain.

Source: López-Rousseau (2005)

Baumert (2010) expanded upon López-Rousseau (2005) by considering the change in travel behavior in buses and metro trains based on daily ridership data. Surprisingly, the number of passengers riding buses only fluctuated for a couple of days. Figure 5 shows the time-series plot of bus ridership. It shows an 8% drop on the day of the attack followed by an increase of approximately 20% the next day mainly due to a massive demonstration of Madrid's citizens responding to the attack. The ridership fluctuations of metro lines were similar to that of the bus lines, as shown in Figure 6.

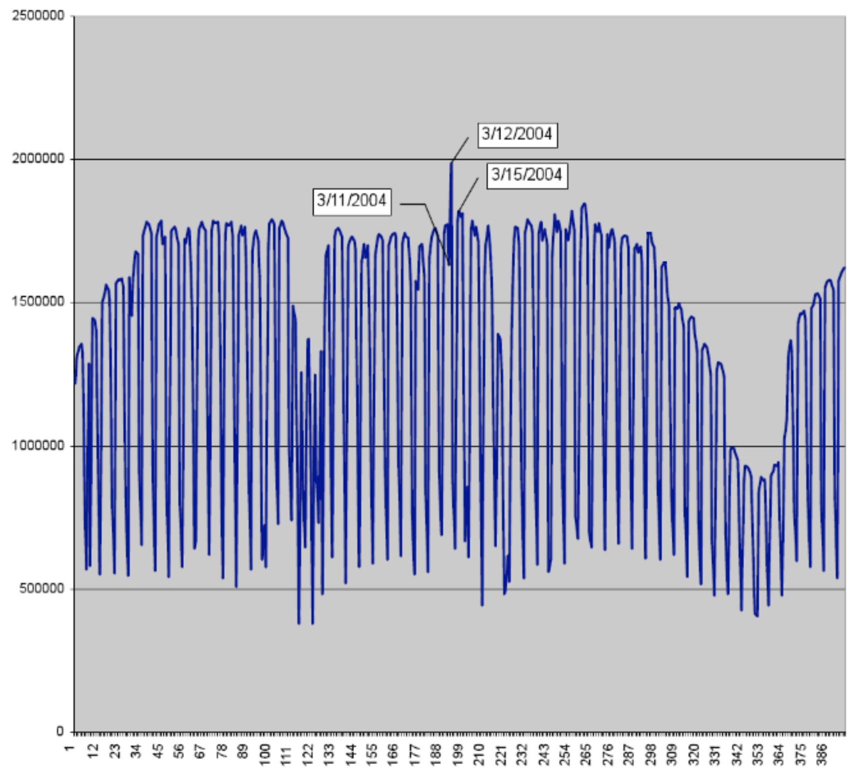


Figure 5. Graph. Daily number of passengers using the Madrid bus from 1 September 2002 to 30 September 2004.

Source: Baumert (2010)

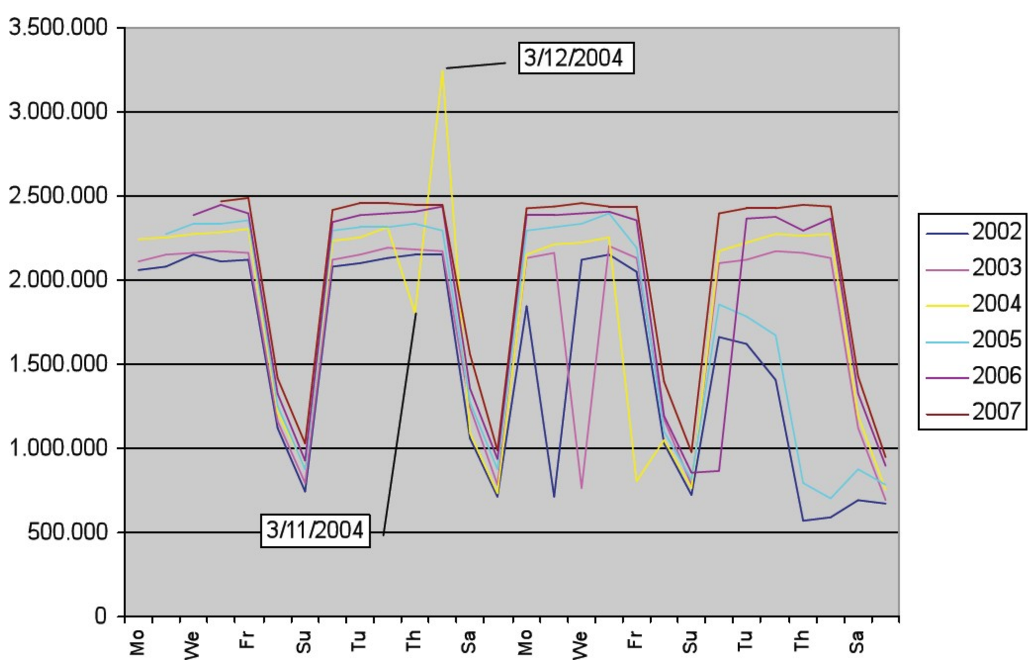


Figure 6. Graph. Number of daily passengers in the Madrid Metro from 2002 to 2007.

Source: Baumert (2010)

Fasolo et al. (2008) studied the London bombing attacks under the dread hypothesis and found that London transit users reduced their train travel in response to the attacks. The use of bikes, motorcycles, and mopeds had increased, indicating modal shift. However, no evidence showed any corresponding increase in fatalities across these modes. This evidence agrees with Prager et al. (2011), who used several multivariate time-series models to study the London bombing attacks. This study showed an approximately 8% decline in train travel over the four months following the attacks. Figure 7 presents the results of this study's time-series forecasting.

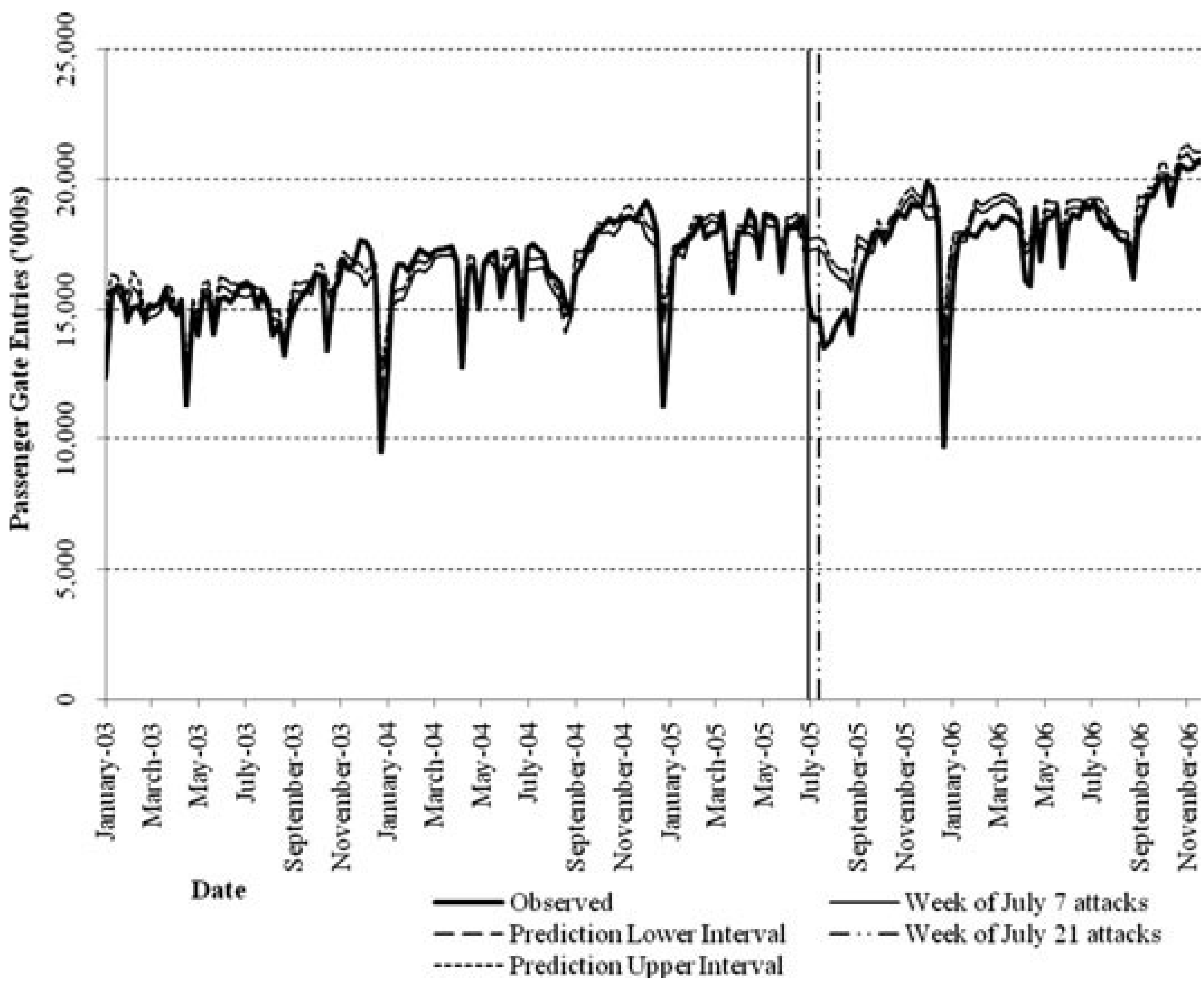


Figure 7. Graph. London Underground passenger journeys, all lines, observed and prediction 95% confidence intervals from 2003 to 2006.

Source: Prager et al. (2011)

Finally, researchers found no evidence of travel behavioral change after the Tokyo sarin gas attack (Fynnwin & Barbara, 2010). Figure 8 shows the time-series data of the Tokyo subway system's daily boardings for passengers with and without season tickets. The lack of change might be due to Japanese culture and lack of high-capacity transportation alternatives in Tokyo, as most residents rely on public transit for travel.

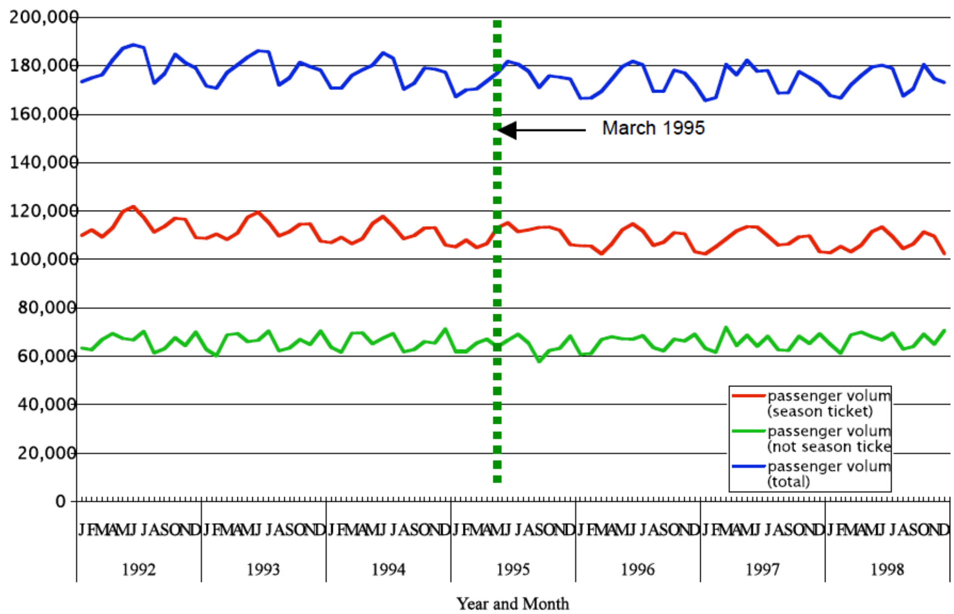


Figure 8. Graph. Time series of monthly passenger volumes from 1992 to 1998.

Source: Fynnwin & Barbara (2010)

In an attempt to understand factors that may influence the dread hypothesis's validity, Von Winterfelt and Prager (2010) summarized results across all the aforementioned terrorist attacks. This study attributed their differences to variations in the primary attack's characteristics, the attacked transportation system's characteristics, and social amplification. They found that changing risk-perception after the attacks can significantly influence transit user choices, so policy decisions after an attack should be carefully designed to avoid inducing unnecessary alarms or false comfort. They also found that any supply side service reductions can significantly influence ridership, as evidenced in Prager et al. (2011). This study shows, for example, that decisions such as station closures and cancelled dispatches accounted for approximately 18% of the ridership loss after the London bombing attacks.

Recognizing the importance of risk perception as a predictor for drops in transit ridership, researchers have studied prolonged risk perception after terrorist attacks (Von Winterfelt & Prager, 2010). These studies concluded that fear is not uniform across transit riders. Rubin et al. (2007) surveyed Londoners 11 to 13 days after the bombing attacks and followed up with another survey 7 to 8 months after the bombing attacks. They found that 11% of the respondents still experienced "substantial stress" after eight months and that 19% of all participants reported having traveled less during that time because of the attacks (Rubin et al., 2007). They also found that participants from poorer households were most likely to experience persistent substantial stress.

Milioti et al. (2019) surveyed transit users and focused on their reaction to a hypothetical terrorist attack in Athens, Greece. This study found that approximately 16% of respondents would refrain from using the metro system for more than six months if an attack were to occur in the Athens metro system. Out of this group, most were women and people who had access to a personal vehicle as a replacement travel mode.

In summary, policymakers and planners can learn from substantial changes in travel behavior, recovery periods, and transit user risk perception after terrorist attacks. The aforementioned evidence from London, Madrid, and Tokyo shows that people may change their travel behavior for only a short period (i.e., 1 to 4 months). Evidence from 9/11, however, shows that people may shift travel modes for up to 12 months after the attack.

Service supply factors can also significantly affect recovery after the attacks (e.g., the 9/11 and London attacks). Although this information cannot directly provide any prediction on how transit systems may recover from COVID-19, one may conclude that reduced service during a pandemic may further contribute to ridership drops. Permanent changes such as an increase of working at home opportunities (Barrero et al., 2020) may also produce prolonged ridership decreases just as changes in air travel did after 2001.

To draw more direct insights from past events that could inform future decisions, the next section will explore previous epidemics that may have caused considerable changes in transit ridership. These events share more similar characteristics with the current COVID-19 pandemic, which can give us a better idea about people's prolonged risk perception and travel behavioral changes.

PAST EPIDEMICS

Many epidemics throughout history severely affected people's lives and placed a huge societal burden at the regional, national, or even global level. These epidemics, in turn, have greatly challenged public transit systems. Numerous studies in the literature look into how epidemics quantitatively and/or qualitatively impacted public transit. In this section, the research team will summarize some of the literature on epidemics/pandemics that occurred in recent decades, including severe acute respiratory syndrome (SARS), H1N1 swine flu, Middle East respiratory syndrome (MERS), and Ebola (Pitlik, 2020; Muley et al., 2020). They will also show how these epidemics/pandemics quantitatively and qualitatively impacted public transit.

The research team will emphasize the reported information for each epidemic/pandemic event, including confirmed cases and deaths, event duration, executive orders, ridership reductions, ridership recovery, and transit agency revenue (subject to data availability), to provide valuable insights into the scale and duration of ridership reductions for different public transit modes. They will also emphasize the relevant literature on passenger behavioral changes and risk perceptions during epidemics to explore the mechanisms behind ridership fluctuations.

SARS

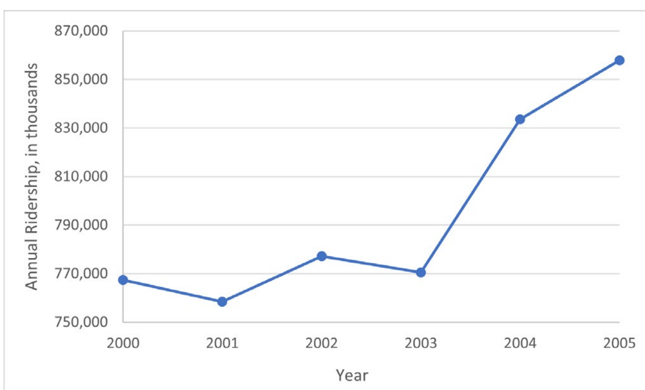
SARS was first reported in Asia in November 2002, and the World Health Organization (WHO) declared its containment on 5 July 2003. The SARS outbreak affected 29 countries and territories, with 8,096 confirmed cases and 774 deaths worldwide (World Health Organization, 2015b). Canada, Mainland China, Hong Kong, Singapore, and Taiwan were among the most severely impacted countries/regions.

In February 2003, Hong Kong reported the index patient of the SARS outbreak. On 23 June 2003, the WHO removed Hong Kong from the list of infected areas. During the SARS outbreak, there were a total of 1,755 confirmed cases and 299 deaths in Hong Kong.

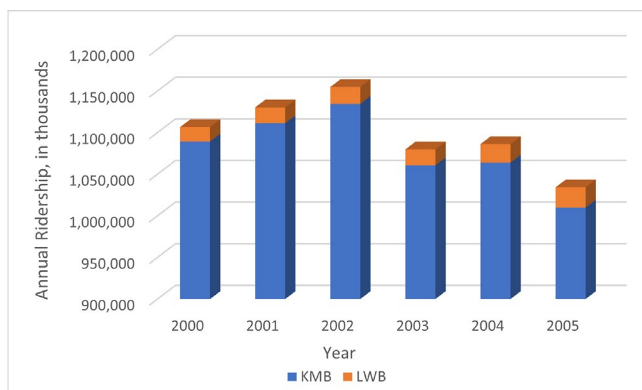
At the peak of the SARS pandemic, the Hong Kong Mass Transit Railway observed a 25% ridership decline (Hong Kong Mass Transit Railway, 2004). After the SARS outbreak was contained, however, its ridership bounced back quickly in the year's second half. The Tseung Kwan O line that opened in August 2002 played a critical role in the recovery process. Overall, its 2003 annual ridership was 1% lower than that of 2002. Ridership on the express line to the Hong Kong Airport plummeted 19% given significantly lower passenger volume at the airport.

Likewise, Kowloon Motor Bus Company Limited, Long Win Bus Company Limited, and Sun Bus Holdings Limited witnessed sharp drops in annual ridership (The Kowloon Motor Bus Holdings Limited, 2004). The Kowloon Motor Bus Company's ridership for each of the four quarters of 2003 dropped 3.9%, 15.5%, 4.6%, and 2.0% compared to its respective quarterly ridership in 2002, showing a quick recovery process. The Long Win Bus Company's annual ridership dropped approximately 5.1%, mainly due to reduced tourism. Sun Bus Holdings Limited observed a particular drop in student patronage during the SARS outbreak.

After the SARS pandemic, the Hong Kong Mass Transit Railway's ridership consistently rebounded, while bus ridership fluctuated at the same time. Figure 9-A shows that Hong Kong Mass Transit Railway's annual ridership increased 8.3% in 2004 and 5.8% in 2005, which exceeded pre-SARS ridership (Hong Kong Mass Transit Railway, 2005, 2006). However, as shown in Figure 9-B, bus ridership recovered only 0.3% from 2003 to 2004 and then decreased 5.1% in 2005 (The Kowloon Motor Bus Holdings Limited, 2005, 2006). Intensified competition with the expanding metro rail network likely slowed, or even impeded, its bus ridership's post-pandemic recovery.



Metro ridership (Hong Kong Mass Transit Railway, 2005, 2006).



Bus ridership (Kowloon Motor Bus Holdings Limited, 2006).

Figure 9. Graphs. Hong Kong metro and bus ridership from 2001 to 2005.

Taiwan identified its first SARS case on 5 February 2003 and had 346 confirmed cases and 3,032 suspected cases reported by the end of 5 July 2003. The Taiwanese authorities did not issue any stay-at-home orders for the general population but did require home quarantine for those who had close contact with suspected patients or who traveled from affected countries/territories (Hsieh et al., 2005). By focusing on the fluctuation of Taipei Metro's ridership during this time, Wang (2014) observed that the peak of ridership loss was approximately 50% of the pre-pandemic level. It took approximately four months after the end of the outbreak for Taipei Metro's ridership to recover to its normal level.

More specifically, Wang (2014) modeled ridership reduction from the perspective of "public fear." Wang distinguished the reasons behind the ridership reduction into (i) "fresh fear," which accounts for immediate ridership loss after each reported SARS case; and (ii) "residual fear," which represents the lasting but decaying impacts of each confirmed case on ridership after the reporting date. This study found that "fresh fear" diverted approximately 1,200 passengers away from transit. This fear would remain in people's minds for approximately 28 days as "residual fear."

Researchers also collected the yearly ridership of Taipei Metro from 2001 to 2005 (Metro Taipei, 2021), as plotted in Figure 10. It shows that despite the significant drop in 2003, ridership steadily increased from 2004 to 2005, showing no long-term effects (i.e., more than a month) from the SARS outbreak.

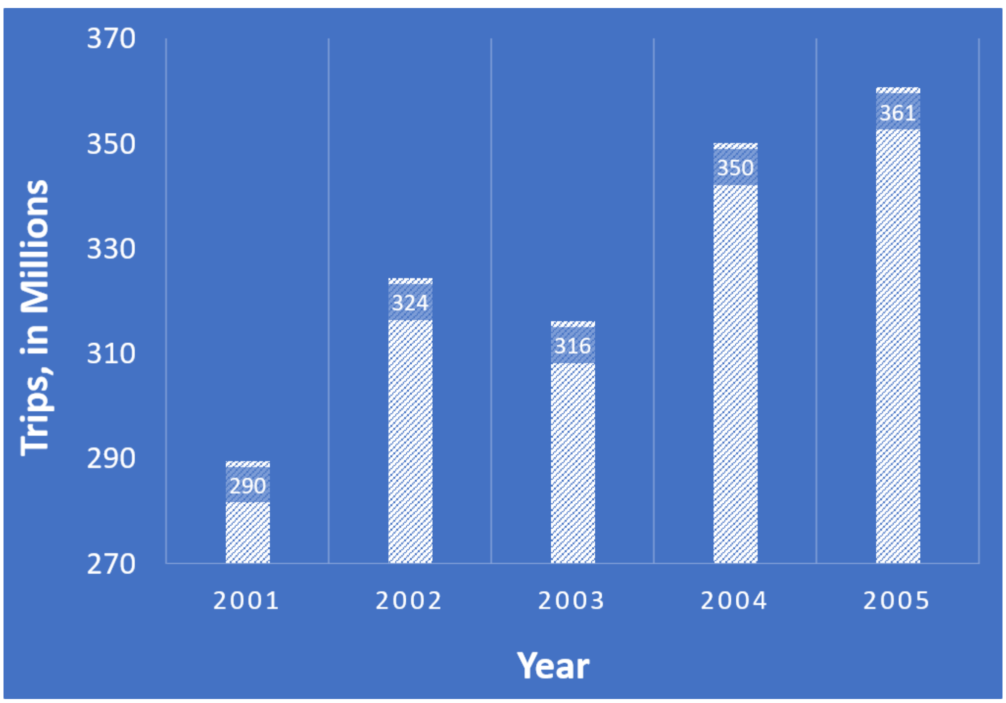


Figure 10. Graph. Yearly ridership of Taipei metro from 2001 to 2005.

Source: Metro Taipei (2021)

SARS also severely affected Toronto, Canada, with 361 reported cases from 23 February 2003 to 7 June 2003. Systemwide transit passenger trip data from the Toronto Transit Commission's annual reports show that Toronto's public transit system lost approximately 10 million riders in 2003. This can be partially attributed to the following compounding factors: the SARS outbreak, which accounted for approximately 3.5 million missing riders; North America's Northeastern Seaboard power outage, which led to a loss of 2.5 million trips; and increased fares for all modes (Toronto Transit Commission, 2005b). Ridership recovered in 2004 and continued to increase in 2005, as shown in Figure 11.

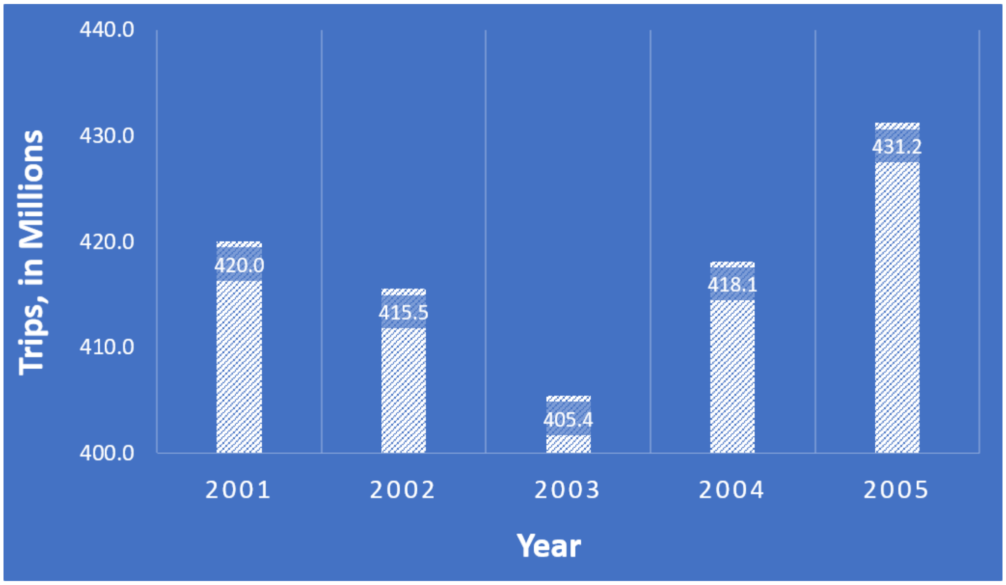


Figure 11. Graph. Yearly ridership of Toronto Transit Commission from 2001 to 2005.

Source: Toronto Transit Commission (2005b)

Singapore identified the first confirmed SARS case on 1 March 2003. To contain the spread of the virus, Singapore shut down schools on 27 March 2003, and then successively reopened its junior colleges, secondary schools, and primary schools before mid-April (Singapore Government Press Release, 2003). The WHO removed Singapore from the infected area list on 31 May 2003. Singapore had 238 total confirmed cases and 33 deaths (World Health Organization, 2015b).

During April and May of 2003, Singapore Mass Rapid Transit (SMRT) observed drastic ridership drops. Its bus service lost 4.6% of its ridership and its peak rail ridership dropped almost 9.5% when compared to pre-SARS values (SMRT Corporation Ltd., 2004). When the pandemic was contained by the end of May 2003, rail ridership started to gradually recover and continued to increase in the following years. Bus ridership kept declining until mid-2004, however. It began to rise in 2005 but declined again in 2006. Please see Figure 12.

In 2003, SARS, an increase in goods and services taxes, and reduced average fares caused a 4.8% loss in annual rail service revenue for SMRT. Despite reduced ridership during the SARS outbreak on its bus service, however, increased bus fares and SMRT's efforts to prevent fare dodgers stabilized annual revenue on its bus system during this time. Its advertising revenue also remained roughly the same as in previous years, since better economic conditions in 2003's second half offset the first half's weak performance.

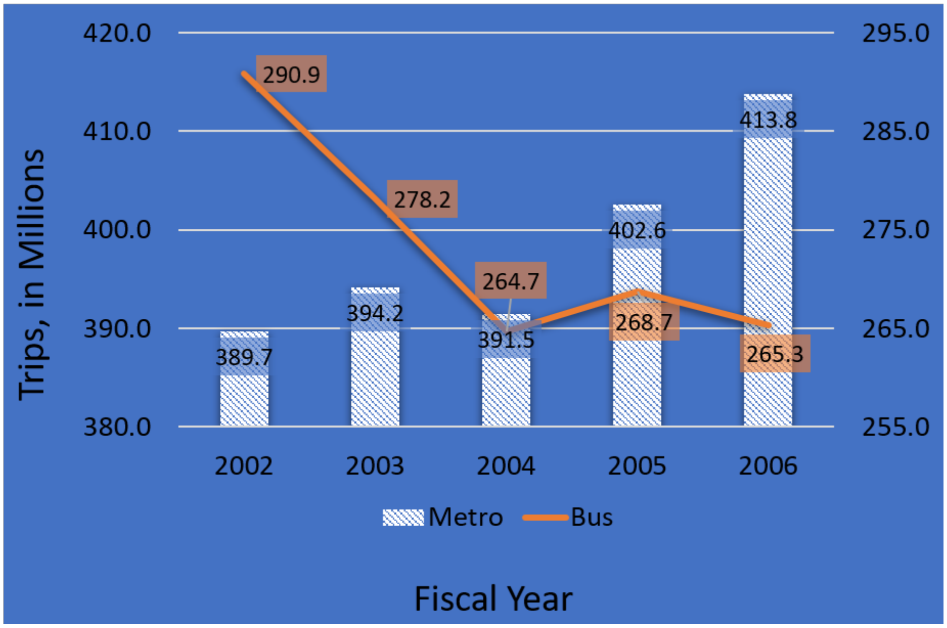


Figure 12. Graph. Yearly ridership of SMRT rail and SMRT bus from FY2002 to FY2006.

Source: SMRT Corporation Ltd. (2006)

On a global scale, Sadique et al. (2007) analyzed the population's perception of SARS-related risks. They collected and analyzed survey data from respondents from (i) Denmark, Great Britain, the Netherlands, Poland, and Spain, which SARS did not directly affect; and (ii) Guangdong Province (China), Hong Kong, and Singapore, which SARS directly affected. This study found that over 54% of the respondents considered public transportation as the riskiest place, ranging from 43% of Singaporean respondents to 63% of Spanish respondents. Most respondents also avoided taking public transit as a precautionary action, ranging from 65% of Singaporean respondents to 85% of British respondents. It suggests that fear perception regarding epidemics may be similar across cultures, which may explain why public transit systems worldwide are struggling to regain ridership even when no clear evidence exists to corroborate the connections between transit usage and the higher risk of COVID-19 exposure (Maxine, 2020; Solomonow, 2020; Schwartz, 2020).

H1N1

The H1N1 swine flu was first identified on 15 April 2009; the pandemic lasted approximately 14 months, until 11 August 2010 (Centers for Disease Control and Prevention, 2019). There were 491,382 lab-confirmed cases (World Health Organization, 2010b) and at least 18,449 deaths (World Health Organization, 2010a).

Fenichel et al. (2013) investigated air passengers' voluntary defensive behaviors during the H1N1 pandemic in the United States. They used air passenger records from US Airways to show the number of missed flight reservations during the H1N1 pandemic. They also used Google Trends data (i.e., internet search frequency) on "swine flu" and "H1N1" to show public perceptions of H1N1-related risks, and reported H1N1 cases from the WHO's FluNet database to represent the H1N1 pandemic's actual risks. These metrics are shown in Figure 13.

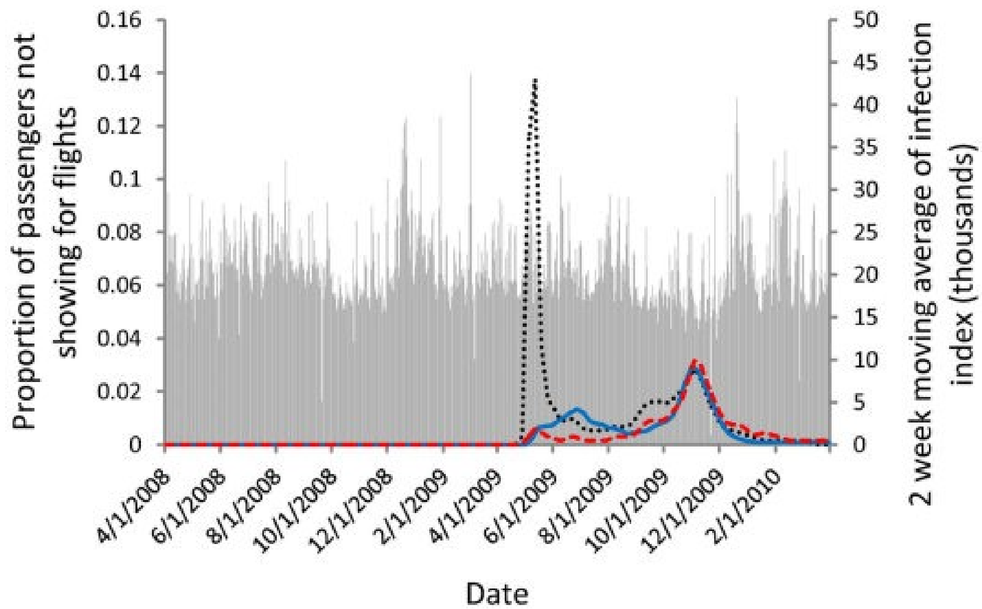


Figure 13. Graph. Percentage of flight reservations missed (grey bar), two-week moving average of reported H1N1 cases (blue line), and two-week moving average of Google Trends ("Swine Flu" in black dotted line, "H1N1" in red dashed line) during H1N1 pandemic in the United States.

Source: Fenichel et al. (2013)

The results indicated that 0.34% of missed flights can be attributed to passengers' defensive actions, and that people were more sensitive to epidemic-related media coverage than objective risk measurements, such as the number of reported cases. These results emphasize the importance for agencies or authorities to convey clear information to the public. Proper information sharing and transparency help people avoid irrational behaviors induced by their fear of catching the virus, and in turn, help societies avoid excessive costs during pandemics.

In March 2016, Hotle et al. (2020) collected surveys from 2,168 respondents in the United States to analyze people's perception of influenza risks under the following three scenarios: risk perception when not infected, risk mitigation when infected, and risk mitigation when not infected. They analyzed the data using an ordered logit model and found a clear disparity between males and females regarding behavior change during epidemics. For the risk perception, females had a stronger sense of risk for trips to school, the workplace, and hospitals, while males tended to keep their same travel habits. Moreover, this study identified the information source that informed respondents about the influenza's spread as another significant factor to affect risk perception. If people found out about the influenza outbreak by word of mouth, their risk perception about mandatory trips and medical trips increased. However, if people heard about the influenza outbreak through television, their risk perception increased more for discretionary trips than for medical and mandatory trips.

Regarding risk mitigation, males were less likely to avoid public places, including public transit, as a measure to prevent the spread of virus once infected. The study also found that respondents with higher family incomes were less likely to stay home or take social distancing actions. Similarly, they found that respondents with higher family income and higher education (i.e., at least a bachelor's degree) were less likely to stay home to reduce exposure. However, it is important to note that this study was carried out before the COVID-19 pandemic and that observed patterns may have changed with increased opportunities for working remotely.

MERS

The first MERS case occurred in Jordan in April 2012. Up to March 2020, cases have been reported in 27 countries in the Middle East, Africa, and Asia, leading to 885 known deaths due to infection and related complications (World Health Organization, 2020).

South Korea suffered the largest MERS outbreak outside of the Middle East. The first case was reported in May 2015, and over the course of the following two months, 136 cases and 38 deaths were reported (Oh et al., 2018). South Korea never issued national quarantine orders but used quarantine as a strategy to mitigate the virus spread among those who were exposed. Korea had nearly 17,000 quarantined individuals (Oh et al., 2018).

Sung (2016) studied how the MERS outbreak affected rail transit ridership in Seoul Metropolitan City. They implemented a combination of ARIMAX models to produce counterfactual series and compared them to observed ridership during the outbreak. Figure 14, which plots daily rail ridership from May 20 to the end of the year (i.e., indexed as day 0 to 250) for 2013, 2014, and 2015, respectively, shows ridership drops during the MERS outbreak. This study found that ridership did not considerably drop until the number of infections increased. The magnitude and frequency of notable ridership drops also depended on trip purpose. More consistent morning commute trips were affected much later and in lesser magnitudes, while evening hour trips (often for leisure) were immediately affected and in greater magnitudes. Nonetheless, the data showed that the reduction in trips for morning and evening rush hours was temporary. Ridership recovered to pre-epidemic levels after August, when the virus spread was mostly contained.

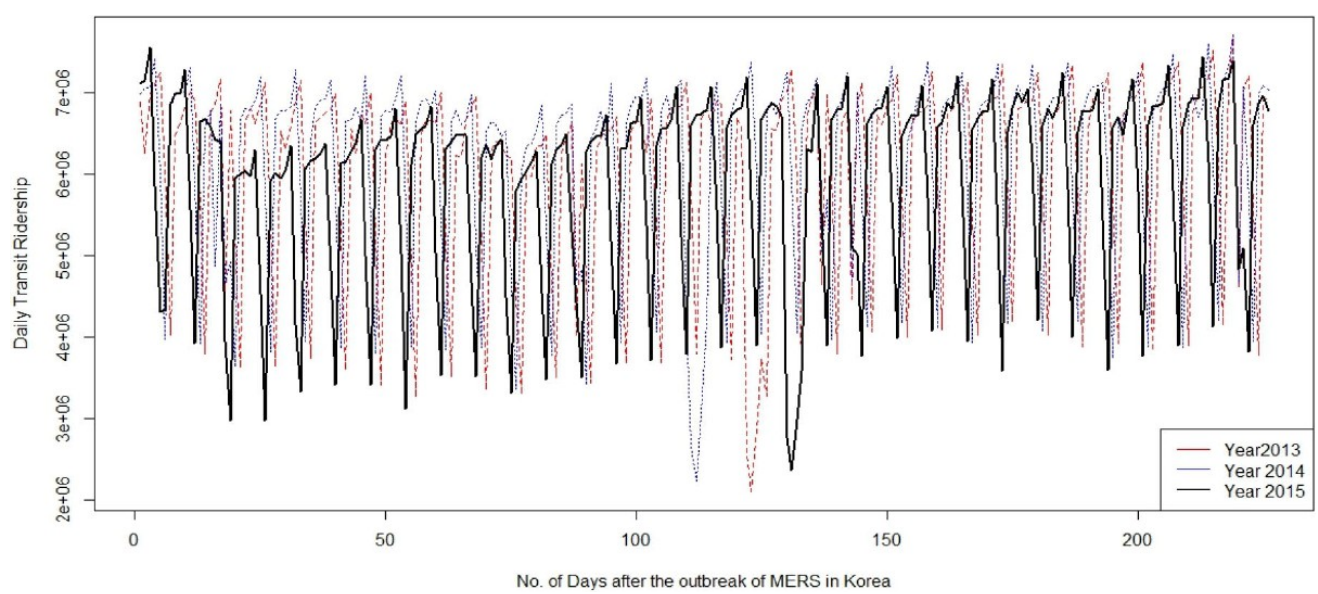


Figure 14. Graph. Daily rail transit ridership by year (day 0 = May 20).

Source: Sung (2016)

Kim et al. (2017) studied MERS' effects on transit ridership in Seoul Metropolitan City across population groups, regions, and modes. This study specifically proposed the concept of "life fixity" to understand the differences in travel behavior among demographic groups and geographical areas. Although they did not formally define the concept, they explained that life fixity is the opposite of the "degree of freedom to change the details of daily life activities." They hypothesized that this social activity–based metric should be highly correlated with social status and income level. They used land price as a proxy for life fixity and studied the change in travel behavior spatially as a function of land prices. A higher land value was found to be associated with a higher reduction in trip frequency, which can be seen in Figure 15. Nonetheless, the model for peak-hour travel alone showed that those traveling during peak hours were less sensitive to the epidemics and exhibited less behavioral change. This observation supports their hypothesis that peak hour travelers (likely lower-level workers) are more likely to have a higher life fixity (i.e., lower freedom to change their daily activities).

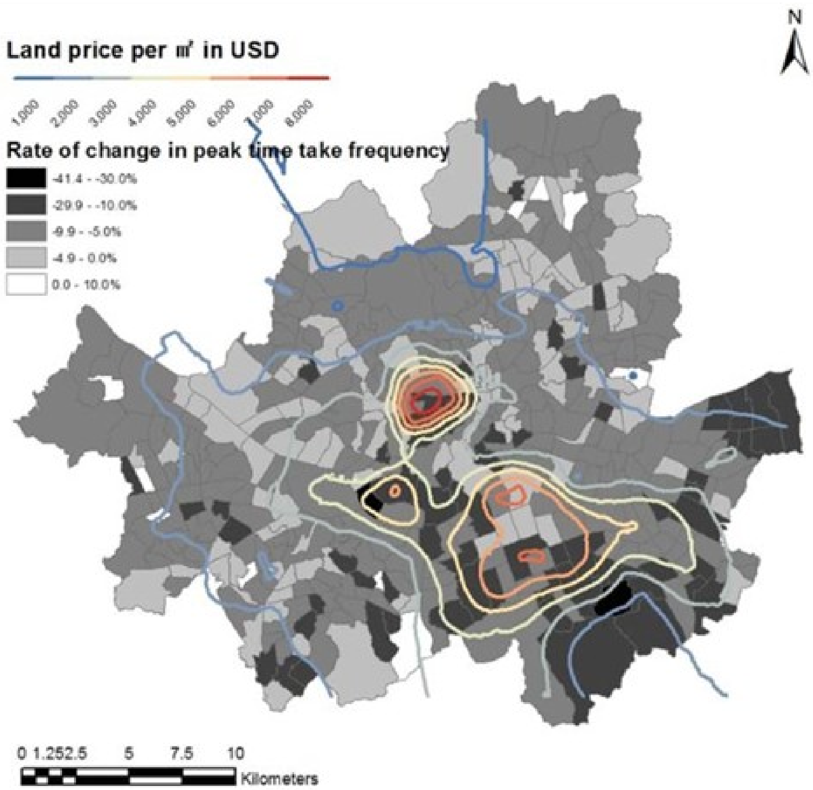


Figure 15. Map. Land price contour and rate of change in transit get-on frequency during peak hours.

Source: Kim et al. (2017)

Ebola

The Ebola virus was first discovered in 1976, but its biggest outbreak occurred from 2014 to 2016 in Sierra Leone, Liberia, and Guinea (World Health Organization, 2021). This outbreak took over 11,000 lives. In Sierra Leon, the WHO officially declared the end of that Ebola outbreak on 7 November 2015 (World Health Organization, 2015a).

The Sierra Leone government had two national lockdowns to fight the Ebola virus, one in September 2014 and one in March 2015 (Peak et al., 2018). They also launched Operation Northern Push from June to September 2015, which focused on instituting curfews, increasing surveillance, and contact tracing.

Peak et al. (2018) studied the effects of the second lockdown from 27 March 2015 to 29 March 2015. To capture the change in people's mobility, they analyzed mobile phone call detail records from a leading operator in the country between 20 March 2015 and 1 July 2015. They compiled the sequence of phone towers visited in the study period to quantify the number of trips. With this information, they applied a time-series intervention analysis to evaluate changes in the number of trips among chiefdoms. Their results showed that the change in travel was not uniform across all trip lengths; e.g., the numbers of trips with distances shorter than 15 km, in between 15–30 km, and longer than 30 km were reduced 31%, 46%, and 76%, respectively. They also found no immediate increase in trip numbers after the lockdowns ended, which shows that people did not overcompensate for their missed travels after the lockdown orders were lifted. Figure 16-A presents the daily time series of trips among all chiefdoms, while Figure 16-B shows the statistically significant anomalies in the time series. Using the generalized extreme studentized deviate many-outliers procedure (Rosner, 1983), the latter figure identified the number of outlying trips from 95% confidence intervals and showed that the lockdown did not significantly affect travel demand after March 29.

Peak et al. (2018) also found that the reduction in travel demand was up to two times larger in regions that had experienced a higher number of Ebola cases, showing that the lockdown's effect was spatially heterogeneous. Operation Northern Push lasted until September 2015, so this study only captured this Operation's beginning stage. Even so, they were able to quantify a 6.1% decrease in trips into the targeted chiefdoms, and a 4.5% decrease in trips out of the targeted chiefdoms. This general trend is captured by the downward trend during the operation, as shown in Figure 16-A.

The 2014 Ebola outbreak mainly affected African countries, but for a period, the confirmation of a few cases in the United States triggered growing concerns about a potential outbreak in the United States. Cahyanto et al. (2016) studied the public perception of Ebola in the United States, specifically focusing on the relationship between perceived risk and observed domestic air travel avoidance. Although there was only a negligible risk of contracting Ebola on commercial flights, the public was not widely aware of this scientific fact. This study developed a health belief model, which focused on quantifying sociodemographics and respondents' perceived travel risk, perceived susceptibility, perceived severity, self-efficacy, and subjective knowledge. They surveyed 1,613 representative US residents. This study showed that most respondents considered Ebola a serious health threat. However, most of them demonstrated no (or a minimal) plan to avoid travel. This study identified the strongest predictor of travel avoidance to be the perceived Ebola-related risks; the higher the perceived risk level, the greater the travel avoidance. This study also found no significant relationship between the respondents' perceived severity of a health crisis condition and travel avoidance.

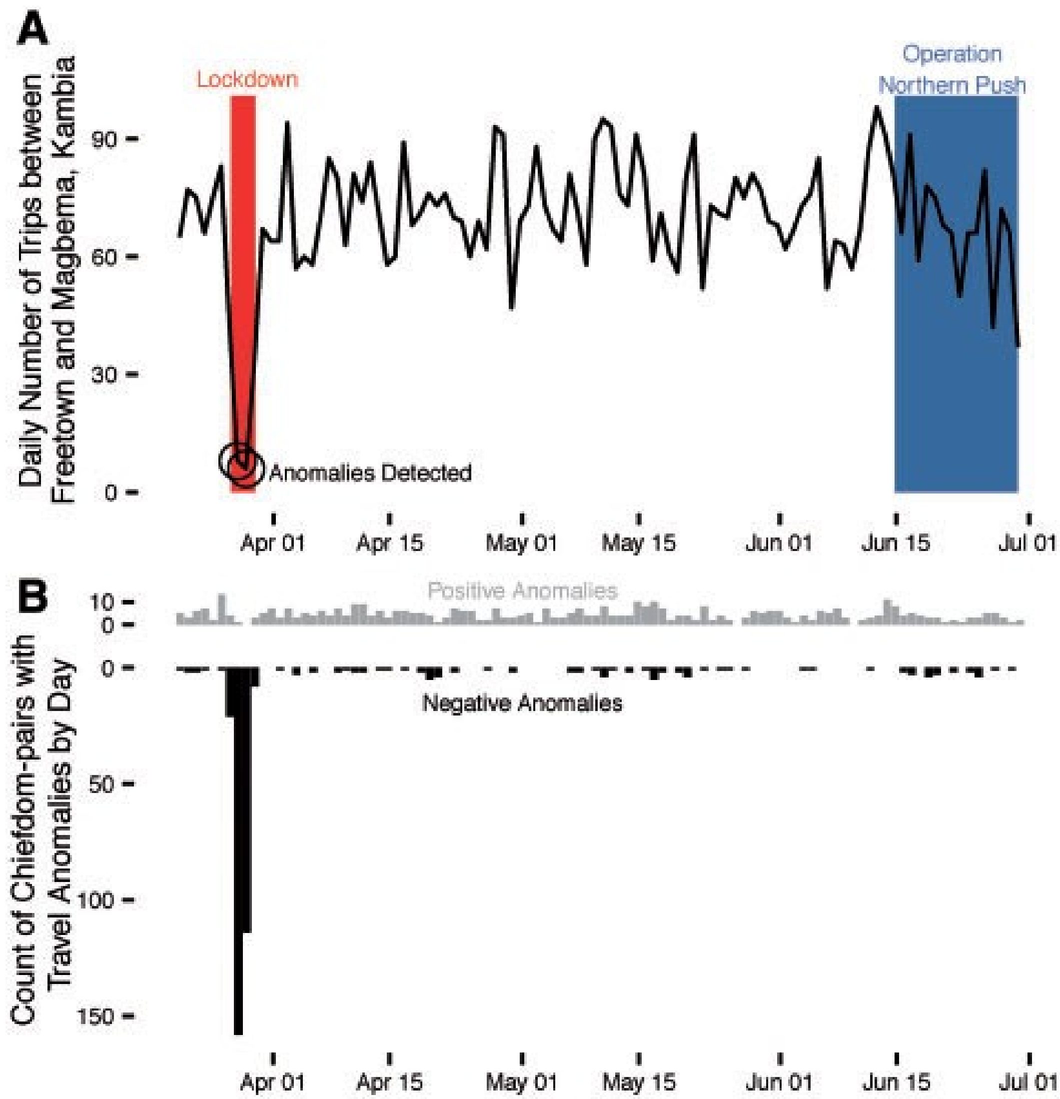


Figure 16. Graph. (A) Daily number of trips between Freetown and Magbema, the largest chiefdom in the northern district of Kambia. (B) Daily number of positive (grey) and negative (black) travel anomalies detected between all chiefdom pairs with an average of at least 10 trips per day.

Source: Peak et al. (2018)

COVID-19

Researchers have recently conducted numerous studies attempting to understand changes in travel behavior in the United States during the current COVID-19 pandemic. Some of their results have increased the knowledge about ongoing travel behavior changes in Chicago.

Hu and Chen (2021) studied ridership decline on the CTA's rail system in Chicago until 30 April 2020. They analyzed this ridership reduction through a framework that combined (i) a Bayesian structural time-series (BSTS) model to produce the counterfactual ridership numbers to quantify the ridership decline, and (ii) a partial least square regression model to evaluate the significant sociodemographic variables that may explain this decline. Figure 17 shows predicted ridership from the BSTS model and an estimation of epidemic-related ridership reduction (as a percentage). Each green line represents the number of entries at a rail station, and the black line represents the mean. In the partial least square regression, the independent variables include demographic (at the census block group level), economic, and land-use characteristics, as well as cumulative COVID-19 cases and deaths. The proportion of people with college (or higher) degrees, median household income, and proportion of white people in a neighborhood were the main characteristics found to negatively affect transit ridership during the pandemic. In contrast, the proportion of black people in a neighborhood had the largest positive effect on ridership. These results are consistent with other studies around the United States (Brough et al., 2020; Sy et al., 2020; Wilbur et al., 2020; Liu et al., 2020), which found evidence of disparities in travel behavior during the COVID-19 pandemic.

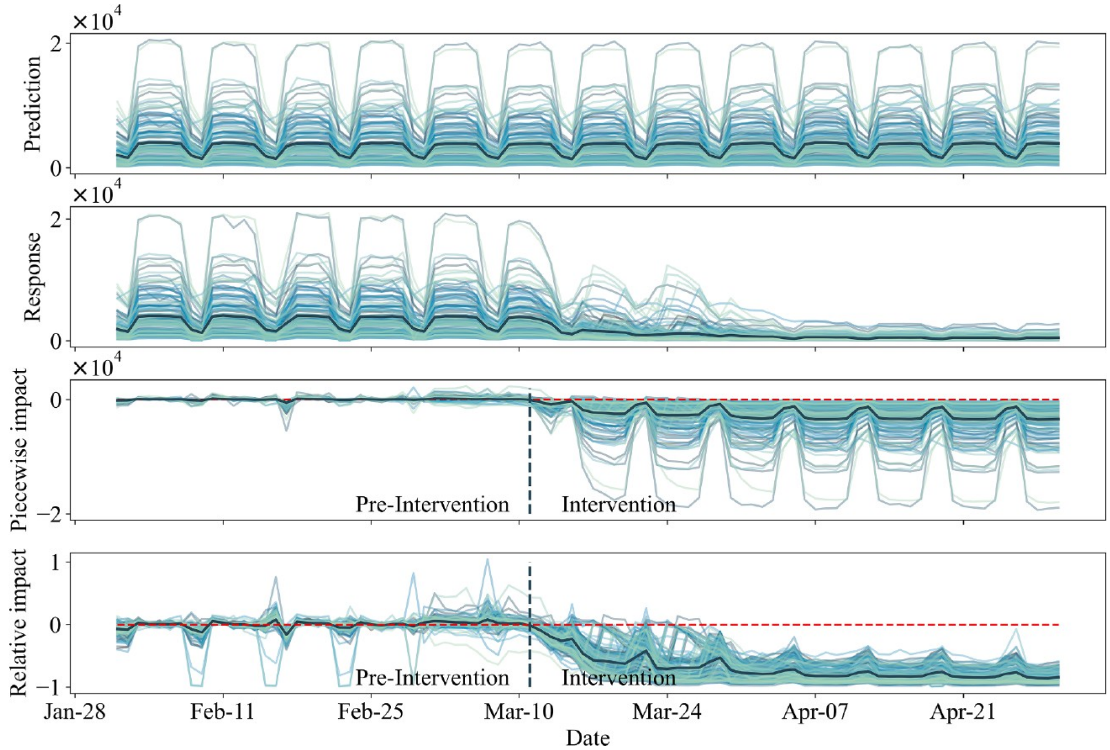


Figure 17. Graph. Station level impact during the COVID-19 pandemic until 30 April 2021.

Source: Hu & Chen (2021)

Padmanabhan et al. (2021) looked at how COVID-19 affected the bike-sharing system in New York City, Boston, and Chicago from 19 October 2019 to 1 June 2020. They used daily trip data from bike-sharing systems along with the time series of reported COVID-19 cases to draw relationships between them. They applied correlation analysis and a random-effect least square regression model that explicitly accounted for unobserved heterogeneity. For the three cities, they found that the highest number of COVID-19 cases and the lowest number of bike-sharing trips were recorded in the month of April. They also found that the number of bike-sharing trips started to rebound after the number of daily cases had peaked. However, it was still only about 54% of the recorded value in the first month of the study period. Figure 18 shows these trends in the time-series data. The average trip duration was positively correlated with the COVID-19 cases for all three cities. Per this study, this phenomenon may not be due to people riding longer distances, but instead people riding shorter trips less frequently under the impact of COVID-19.

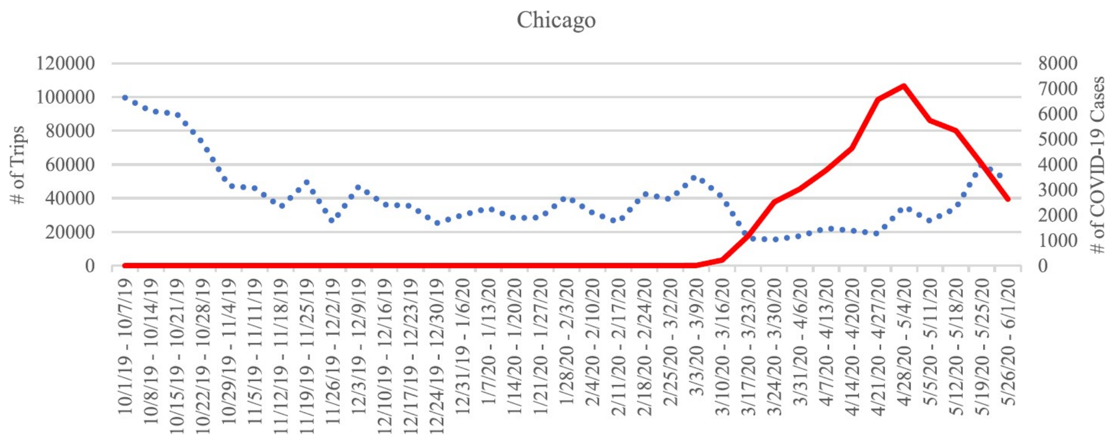


Figure 18. Graph. COVID-19 cases and bike-sharing trips by week in Chicago.

Source: Padmanabhan et al. (2021)

Fissinger (2020) studied travel behavior among Chicago travelers before and during the COVID-19 pandemic. The existing literature mainly used aggregated ridership numbers by time of day or by transit routes or stops. However, this study used daily account-based data from the Ventra fare payment system to study the trips each individual made as a basic unit of analysis. This study used a k-mean clustering algorithm in both space and time dimensions to classify riders into particular behavior groups, such as those based on trip length and time of travel. Consistent with other studies, Fissinger (2020) found ridership change to be highly heterogeneous among two identified groups of riders: "high range frequent peak rail riders" and "high range frequent off-peak bus riders." The riders in the former group, primarily located on Chicago's north side, were composed of higher income individuals and were mostly Caucasian. This group of trips declined 80%. In contrast, the latter group of trips only decreased 33%. This study also performed a spatial regression analysis to determine the predictors of ridership loss among census tracts. It showed that the proportion of users holding transit passes were associated with higher ridership during the COVID-19 pandemic, most likely due to these users' transit dependence. This study also found that the rate of transfers and percent of trips taken on buses were strong predictors of large ridership. This observation agrees with Boisjoly et al. (2018), who suggested that investing in bus services can particularly help mitigate the drop in ridership in North American cities. Much like other aforementioned studies on transit in the United States, this study found a significant racial disparity, showing that the proportions of black and Spanish-speaking residents are strong predictors of small ridership drops.

AGENCY RESPONSE

To help public transit agencies plan for and respond to epidemic events, the Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2014) issued a guidebook (referred to as the "Guidebook"), which outlined important aspects, such as pandemic preparedness, partnerships with other agencies or authorities, safety measurements, operating adjustments during pandemics, workforce management, and risk management. Agency experiences from historical events (Hong Kong Mass Transit Railway, 2004; SMRT Corporation Ltd., 2004) have supported these suggestions and guidelines, and the agencies' reactions toward the current pandemic (Schwartz, 2020; Toronto Transit Commission, 2021; SMRT Corporation Ltd., 2021) have applied and further enriched these guidelines. Guidelines from this Guidebook are highlighted below and are connected to field measures that have successfully helped agencies recover from the impacts of this epidemic's events. This information is intended to serve as reference for this pandemic's ongoing and incoming challenges and those of similar future events.

SAFETY MEASURES

The safety measures mentioned in the Guidebook include the following: coordinating with the health department to keep up with the latest health advice and medical supports for employees, educating staff about the proper way to disinfect facilities and vehicles, setting up plastic shields to isolate drivers from passengers, distributing personal protective equipment, requiring social distancing, as well as emphasizing ventilation and cleanness of vehicles and facilities. These efforts help reduce riders' perception of safety risks associated with using transit services.

During the SARS outbreak, the Hong Kong Mass Transit Railway and Singapore Mass Rapid Transit took multiple efforts that were similar to the aforementioned measures, such as distributing facial masks; offering staff vitamin C tablets; enhancing cleaning, disinfection, and ventilation of vehicles and transit facilities; and mandating routine temperature checks for their employees (Hong Kong Mass Transit Railway, 2004; SMRT Corporation Ltd., 2004). Additional practices have gradually become widely adopted among transit agencies worldwide during the COVID-19 pandemic. These practices include placing hand sanitizer dispensers in vehicles and within stations, equipping vehicles with hospital-grade filters and fresh air dampers, as well as using UV tubes to sterilize HVAC units (Schwartz, 2020).

A common social distancing strategy during the COVID-19 pandemic, as Schwartz (2020) summarized, is limiting vehicle occupancy and skipping stops after reaching reduced capacity to allow sufficient rider separation on board. New Jersey Transit, Portland TriMet, and Vancouver TransLink have adopted this strategy. They have dynamically adjusted the capacity limit based on this pandemic's evolution (e.g., infection rate) and other factors (e.g., executive orders). Transit operators can enforce a no-standing policy or set a maximum number of on-board passengers to reduce rider capacity on buses. These policies rely on the bus drivers' judgment on vehicle occupancy. However, after a vehicle reaches capacity, the "skipping stop" operation is difficult to implement, because bus drivers must balance capacity restrictions with the needs of on-board passengers to alight.

Many public transit bus operators also instituted a rear-door boarding policy (exceptions may have applied to riders with disabilities) with suspended fare collection to ensure sufficient space between riders and the driver. Once transparent plastic shields were placed around drivers (e.g., on Dallas Area Rapid Transit and Florida's Palm Tran), the rear-door boarding policy was gradually rescinded and front-door boarding operations were restored.

SERVICE ADJUSTMENT

Transit agencies may reasonably adjust service to save operating costs when facing great challenges amid epidemics. The Guidebook suggests that transit agencies categorize their services into essential and nonessential services during epidemics. Essential services should include transit agencies' critical functions, such as guaranteed service for passengers who lack access to alternative transportation modes and required or customized services for healthcare workers and patients. Transit agencies in urban areas could then reduce their nonessential services, such as commuting routes, which will likely have drastically reduced demand. Government executive orders (e.g., stay-at-home orders), fear of catching the virus on public transit, reduced commercial activities, and reduced commuting needs (e.g., due to remote work and online schooling) are major reasons behind these ridership losses. Transit operators in rural areas may extend headways on fixed routes or switch to demand-responsive services in response to new travel demand patterns.

These guidelines have been implemented and further expanded with details during the COVID-19 pandemic, as summarized in Schwartz (2020). Right after the COVID-19 outbreak, many transit agencies reduced their service levels and only maintained essential services for those passengers relying on public transit. As the situation ameliorated after June 2020, ridership slightly bounced back, and these agencies have accordingly adjusted their services. Many agencies, including New York's Metropolitan Transportation Authority, Philadelphia's Southeastern Pennsylvania Transportation Authority, and New Jersey Transit, have gradually restored their services to their pre-COVID-19 service levels. Although New York's Metropolitan Transportation Authority stopped its subway service after midnight for thorough cleaning and disinfection of its vehicles and stations, it operated supplementary bus services to continue providing overnight service coverage. Houston METRO reduced its headways, with more frequent vehicle dispatches, to ensure social distancing on board when demand had bounced back. Other strategies, including deploying standby buses around routes with downgraded services, adopting demand responsive transit, and collaborating with transportation network companies (e.g., Uber and Lyft) were common practices in the past year to serve areas with low transit demand (e.g., Utah Transit Authority, Pullman Transit, Transit Authority of Northern Kentucky, Palm Tran, Miami-Dade Transit, and the Toronto Transit Commission). SMRT has been using customized vehicles that separate drivers and passengers into two compartments to provide convenient transportation service between hospitals, communities, and dormitories (SMRT Corporation Ltd., 2021).

RIDERSHIP RECOVERY CAMPAIGN

Many transit agencies have been actively engaged in various public campaigns and advertising efforts to maintain/regain ridership during and after epidemic events. These efforts have been particularly effective in helping alleviate risk perceptions and fears among potential transit riders.

When the City of Toronto was put on the WHO's travel advisory list during the SARS outbreak, the Toronto Transportation Commission collaborated with the tourism industry and formed the Toronto Tourism Recovery Coalition (Johnson Tew et al., 2008; Goldberg, 2012) to revive the city's tourism activities and mitigate SARS's impacts on transit ridership. They were able to employ a short-term strategy of running advertising campaigns to market the City of Toronto as a safe destination. The coalition focused on alleviating travelers' fears given their belief that the epidemic was more about "psychology than epidemiology" (Johnson Tew et al., 2008).

Based on personal experience, Peter Shier—former president of the Foote, Cone & Belding Toronto agency, the advertising company in charge of helping Toronto bounce back from reduced tourist demand—stated that in moments like SARS, industry partnerships, even among competitors, were crucial to the recovery (Shier, 2020). As the SARS outbreak was contained, the Toronto Transportation Commission adopted different strategies to regain ridership and counteract against the harsh reduction experienced in 2003. Implementation of the Ridership Growth Strategy initiatives was a major contributor to Toronto Transit Commission's success (2005a). These strategies included (i) improving service quality, such as planning dedicated right-of-way for streetcars, increasing fleet size, and enhancing service during peak hours; and (ii) launching promotional activities, such as the Volume Incentive Pass program, which provided monthly pass discounts.

Similarly, the Hong Kong Mass Transit Railway (2004) launched various promotional activities to facilitate its ridership recovery. The Hong Kong Airport Express Line provided "2 Trips" tickets to attract frequent travelers; "Ride 7 Get 1 Free" tickets for airport workers; free tickets for children; half-price tickets for students and the elderly; and discounted tickets for group passengers. For local trips, Hong Kong Mass Transit Railway offered a series of promotions, such as "Ride 10 Get 1 Free," "Ride 5 Get Cash Coupons," and "$2 Holiday Ride," etc. For additional publicity, it launched an Unsung Heroes TV campaign and a thematic campaign based on the Snoopy character to advertise the fifth anniversary of the Hong Kong Airport Express Line. These efforts were found to be effective in restoring Hong Kong Mass Transit Railway's safe and reliable image among the general public.

The current COVID-19 pandemic has occurred when the Internet, social media, and smart phone applications have become widely available. Schwartz (2020) pointed out the importance of taking advantage of these social network platforms to establish timely and clear communication between transit agencies and their passengers. This report suggested that transit agencies should (i) emphasize their safety and cleaning protocols to reinstate public confidence in their systems when communicating with the public, and (ii) sharing real-time station/vehicle crowding information so that riders can conveniently choose their trip times and routes, as the New York Metropolitan Transportation Authority and the Chicago Transit Authority have practiced. Finally, the Toronto Transit Commission has again launched a fare discount program during the COVID-19 pandemic, which is similar to the one they used during the SARS outbreak to attract demand from the area's low-income population.

CHAPTER 3: MODELING

The COVID-19 pandemic's duration and scale are unprecedented. To understand observed transit ridership variations during the current pandemic and to further predict future ridership trends on the Chicago Transit Authority's (CTA's) rail system, the research team developed a comprehensive modeling framework that combines research findings from past events and observations from this pandemic. This modeling framework integrates the following:

i. A Bayesian structural time-series (BSTS) model, which considers the historical trend of transit ridership, seasonality, and holidays, to predict counterfactual transit ridership after 1 March 2020 on the CTA's rail system. It also compares observed ridership with counterfactual ridership to estimate daily percentage loss in ridership during this pandemic.

ii. A dynamics model for daily transit ridership loss on the CTA's rail system, inspired by Wang (2014), which captures the impacts of people's subjective risk perceptions of this pandemic's evolution and external factors. The former includes objective risk measurements, e.g., daily confirmed cases and daily deaths (Wang, 2014), as well as media attention, e.g., Google Trends (Fenichel et al., 2013; Winterfelt & Prager, 2010). The latter includes executive orders, school closures, and remote working policies.

iii. A prediction module, which forecasts future media attention on this pandemic using the auto regressive integrated moving average (ARIMA) model along with linear regression analysis and future daily COVID-19 deaths with the tool that Altieri et al. (2020) developed. It also predicts future ridership trends.

iv. An ordinary least squares (OLS) regression analysis module, which builds the connections between socioeconomic characteristics of city neighborhoods and people's reactions toward the pandemic (i.e., obtained from the second component—the dynamics model for daily ridership loss).

BAYESIAN STRUCTURAL TIME SERIES

The Bayesian structural time series (BSTS) is an analysis technique that combines feature selection and time-series forecasting (Scott & Varian, 2014). In general, a structural time-series model contains three components: Kalman filtering for long-term trends and seasonal components, spike-and-slab regression for contemporaneous covariates, and Bayesian model averaging for the final model selection (Scott & Varian, 2015).

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 the 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 Bayesian structural time series model to connect the daily ridership, r_t , with a vector of latent variables, including: (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 $\boldsymbol{x_t}$ with static coefficients $\boldsymbol{\beta_t}$, which captures effects of special days such as holidays. A series of error terms are defined 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:

$$r_t = \mu_t + \gamma_t^w + \gamma_t^m + \beta_t^{Tx_t} + \epsilon_t, \tag{1}$$

Figure 19. Equation. BSTS observation equation.

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t}, \tag{2}$$

Figure 20. Equation. BSTS semi-local linear trend equation.

$$\delta_{t+1} = D + \rho(\delta_t - D) + \eta_{\delta,t}, \tag{3}$$

Figure 21. Equation. BSTS semi-local linear trend transition equation.

$$\gamma_{t+1,1}^{w} = -\sum_{s=2}^{7} \gamma_{t,s}^{w} + \eta_{d,t} \tag{4}$$

Figure 22. Equation. BSTS day-of-week seasonality equation.

$$\gamma_{t+1,1}^{m} = -\sum_{s=2}^{12} \gamma_{t,s}^{m} + \eta_{m,t} \tag{5}$$

Figure 23. Equation. BSTS monthly annual seasonality equation.

Where Equations (1) defined the observation equation, Equations (2) and (3) define the semi-local linear trend, and Equations (4) and (5) define the weekly and monthly seasonality components, respectively. To evaluate the BSTS models' performance, we first use 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 forecasting errors are measured with the weighted mean absolute percentage error (WMAPE), defined as follows:

$$WMAPE = \frac{\sum_{t=1}^{T} |r_t - \overline{r_t}|}{\sum_{t=1}^{T} |r_t|} \tag{6}$$

Figure 24. Equation. Weighted mean absolute error.

The research team focused on station-level ridership at the Chicago Transit Authority's rail stations and historical data obtained through the Chicago Open Data Portal (CTA, 2021). To perform the final model fitting for each of these rail 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 the observed ridership at time t. The ridership percentage loss on each day at each Chicago Transit Authority rail station can then be calculated as follows:

$$\Delta_t = \frac{\overline{r_t} - r_t}{\overline{r_t}}, \quad \forall t. \tag{7}$$

Figure 25. Equation. Ridership percentage loss on day t.

DYNAMICS MODEL FOR RIDERSHIP LOSS

Based on the literature findings, ridership loss at each Chicago Transit Authority rail station could be attributed to people's perceptions of the epidemic's evolution, including objective risk measures (e.g., daily confirmed cases and daily deaths [Wang, 2014]), as well as subjective risk measures and media attention (e.g., Google Trends [Fenichel et al., 2013; Winterfelt & Prager, 2010]). Compared to previous epidemics, this pandemic has lasted longer and has been more widespread than any other modern pandemic and the use of new technologies has resulted in unique socioeconomic impacts. All of these characteristics require consideration in developing the dynamics model.

Many industries and schools have widely used remote access technologies during this pandemic to deter the COVID-19 virus from spreading, which has caused public transit demand to plummet. Government-mandated stay-at-home orders have also further discouraged people from leaving their homes and have further depressed transit demand from almost everyone except those people whose work has been deemed essential to ensuring society's day-to-day functioning (e.g., medical professionals, grocery store workers, and logistics workers).

Many media reports have highlighted "caution fatigue" during this pandemic (Brazell, 2020; Dozois, 2020). People have been less vigilant about the virus and about following the Centers for Disease Control and Prevention's guidelines as the pandemic drags on. Psychological studies also indicate that recurrent and continuous exposure to fear, especially when people are adjusting their expectations to outcomes, can lead to extinction of fear (Davis et al., 2006; Hofmann, 2008). The COVID-19 pandemic has lasted about 15 months in the United States (by the writing of this report) and the case fatality rate since March 2020 has continuously decreased after the end of May, as shown in Figure 26. The infection fatality rate is calculated by dividing the cumulative deaths with the cumulative cases, with data obtained from the *New York Times* (2021). Given declining expectations of the risks and the pandemic's prolonged effects, "caution fatigue" of COVID-19 is inevitable and could significantly impact people's behaviors.

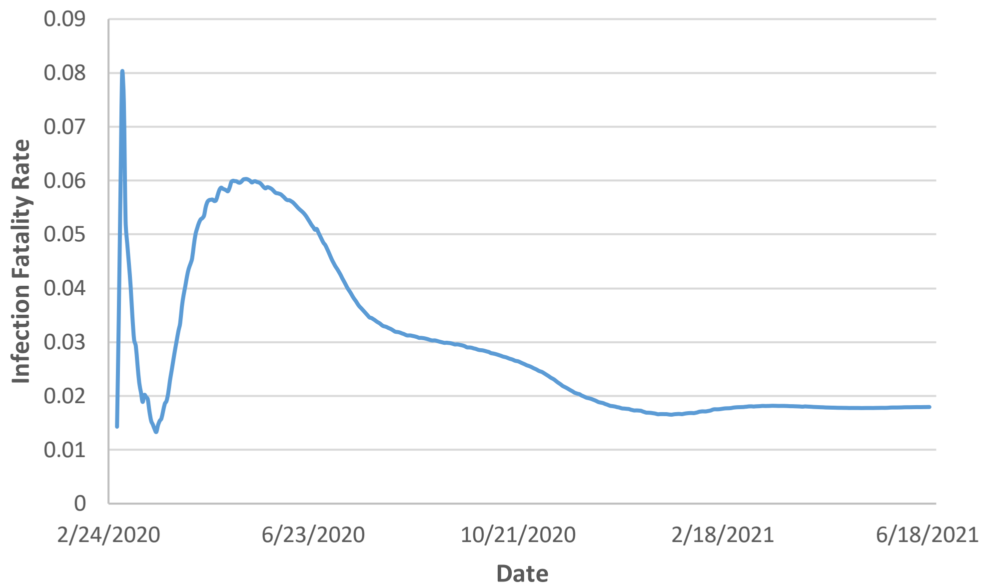


Figure 26. Graph. Infection fatality rate of COVID-19 in the United States.

In light of these aforementioned observations, this study's research team considered daily COVID-19 deaths, daily normalized Google query volumes of COVID-19–related subjects, caution fatigue, remote learning/working, and stay-at-home executive orders as factors that have led to daily ridership variations on the Chicago Transit Authority's rail stations during this pandemic.

The research team obtained daily COVID-19 deaths in Chicago from the *New York Times* (2021). The daily normalized Google Trends data provided a score per day of the proportion of searches on a particular topic over all searches in a particular place and time (Rogers, 2016). The research team used this as a proxy for people's awareness to the pandemic and access to news outlets and epidemic data. They used the keyword "covid" and the technique presented in Dyachenko (2021) to extract the Google Trends scores in Illinois from 1 March 2020 to 1 March 2021, as presented in Figure 27. They also obtained detailed information about stay-at-home orders from the City of Chicago (2021). The City of Chicago issued two stay-at-home orders during this pandemic. The first one started on 26 March 2020 and ended on 3 June 2020. The second one started on 16 November 2020 and ended on 22 January 2021. However, the research team did not have detailed data for the dates and duration of remote working in each industry and those of remote learning in different schools/universities. The research team therefore assumed that these events came into effect on 17 March 2020, when the Governor of Illinois, JB Pritzker, issued school closure executive orders. They also assumed that these events were constantly enforced throughout the study period. This model will capture caution fatigue.

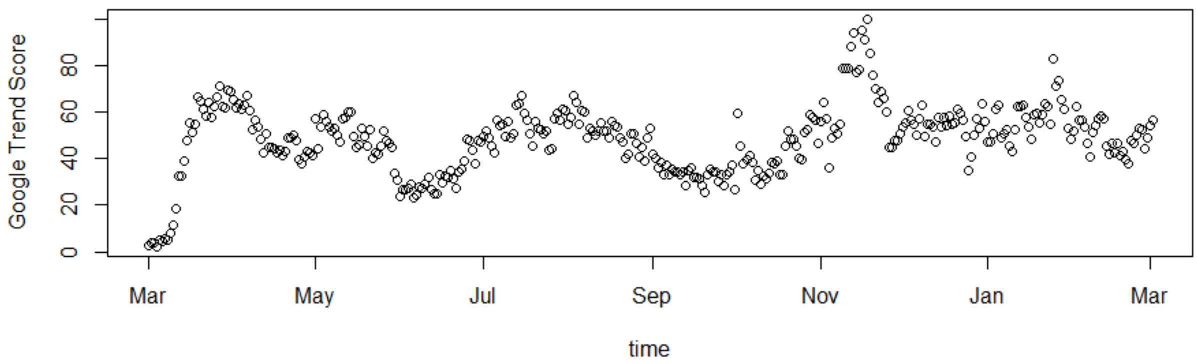


Figure 27. Graph. Google Trends score from 1 March 2020 to 1 March 2021 for the "covid" search query.

To define the modeling framework, the research team let an integer variable d_t denote the number of deaths on day t; an integer variable q_t denote the Google Trends score on day t; a binary variable c_t be equal to 1 if remote learning/working is effective on day t and 0 otherwise; a binary variable s_t be equal to 1 if the stay-at-home order is effective on day t and 0 otherwise.

Similar to Wang (2014), this study's research team modeled the impacts of daily deaths and daily Google search volumes on transit ridership on the Chicago Transit Authority's rail system based in two phases, i.e., fresh fear and residual fear. On day t, the reported daily deaths or the queries of COVID-19 topics through Google Trends represented COVID-19–related risks, which directly induced ridership loss on day t, referred to as fresh fear. The ridership loss due to fresh fear on day t was calculated as $d_t L_d$ and $q_t L_q$ for daily deaths and Google queries, respectively, where L_d (L_q) was the percentage of counterfactual ridership loss related to each reported death (each unit of Google Trends query score). Since fresh fear did not dissipate instantly, it imposed prolonged but decaying effects after day t, which are referred to as residual fear. Thus, similar to Wang (2014), transit ridership loss on day t due to the residual effects of fear that reported COVID-19 deaths induced on day $t' < t$ can be calculated by $d_{t'} L_d e^{-\tau_d (t-t')}$, and that of fear related to Google queries on day $t' < t$ can be calculated by $q_{t'} L_q e^{-\tau_q (t-t')}$, where τ_d and τ_q are the diminishing rate of the death-related fear and Google Trends–related fear, respectively. To capture the caution fatigue phenomenon, the research team hypothesized that people's risk perception decreases in a similar manner as the fear dissipation process, and that people react differently to those two types of risk measurements. We defined f_d and f_q as the decreasing rate of the risk perceptions for deaths and Google queries, respectively. Therefore, the relative risk perception of deaths and Google queries on day t are $e^{-t f_d}$ and $e^{-t f_q}$, respectively.

Because remote learning/working and stay-at-home orders are external factors, people have to comply with these events and fear no longer drives their actions. The research team thus focused on the direct ridership loss these events induced and ignored their residual effects and related perception reduction. The research team defined L_c and L_s as the fixed ridership percentage loss as a consequence of these two types of events, respectively.

Summarizing the aforementioned factors, the estimated ridership percentage loss on day t, denoted as $\widehat{\Delta}_{\mathrm{t}}$, can be calculated as follows,

$$\widehat{\Delta}_{\mathrm{t}} = e^{-tf_d} \sum_{t'=0}^{t} d_{t'} L_d e^{-\tau_d (t-t')} + e^{-tf_q} \sum_{t'=0}^{t} q_{t'} L_q e^{-\tau_q (t-t')} + c_t L_c + s_t L_s. \tag{8}$$

Figure 28. Equation. Dynamics model equation for estimating the ridership percentage loss.

The goal of Equation (8) is to find the values of all the aforementioned parameters such that $\widehat{\Delta}_{\mathrm{t}}$ is close to the actual daily reduction Δ_t as obtained from the first step. However, given the complicated mathematical form, a conventional regression tool is not viable to estimate all parameters in this model. The research team therefore uses a nonlinear optimization module implemented with the SciPy package in Python (Jones et al., 2001) to minimize the quadratic loss function. The nonlinear program is written as follows,

$$\min_{L_{\mathrm{d}}, L_q, L_c, L_s, \tau_d, \tau_q, f_d, f_q} \quad \sum_{t=0}^{End} \left(\Delta_t - \widehat{\Delta}_{\mathrm{t}}\right)^2 \tag{9}$$

Figure 29. Equation. Quadratic loss function between the observed ridership loss and estimated ridership loss.

$$s.t. \qquad 1 - \widehat{\Delta}_{\mathrm{t}} \geq 0, \qquad \forall t \tag{10}$$

Figure 30. Equation. Non-negativity constraints in the nonlinear optimization program.

where Equation (9) seeks to minimize the squared difference between observed ridership and the model's estimated ridership, and Equation (10) enforces a nonnegativity constraint. The $\boldsymbol{End}$ parameter could be defined as any number of days for the model to be trained; for this project, its value is set to 365 since the training data was from 1 March 2020 to 1 March 2021. It should be noted that using nonlinear optimization to obtain the parameter values may lead to overfitting (given noises and outliers). To avoid overfitting and to ensure its performance for prediction, the research team used cross-validation to find the suitable stopping criterion for nonlinear optimization (Arlot & Celisse, 2010).

PREDICTION MODULE

The purpose of the dynamics model is first to explain ridership reduction on the Chicago Transit Authority's rail system as a function of people's reaction to daily reported deaths, executive orders, and media exposure (i.e., Google Trends). The second main objective is to be able to apply it for forecasting ridership in the near future. As explained in the previous section, Equation (8) estimates daily ridership loss as a function of daily deaths, daily Google Trends score, stay-at-home orders, remote working/remote learning, and estimated counterfactual ridership. Hence, to predict future ridership on the Chicago Transit Authority's rail system, all these independent variables (i.e., inputs to our model) need to be forecasted as well.

For starters, the research team assumed that there would be no stay-at-home orders in the near future, because more and more people are getting vaccinated and the situation has been continuously ameliorating. Yet, they assumed that remote learning/remote working would be still in place during the forecast period.

To forecast the daily reported deaths, the research team used the tool Altieri et al. (2020) developed. This tool focuses on predicting the number of COVID-19–related deaths for each county in the United States. It uses county-level reported COVID-19 death counts from USAFacts or *New York Times* (2021) demographic data, health care data, and mobility data. This reference developed several statistical and machine learning prediction algorithms to capture different trends in the data. For this project, the research team selected the *New York Times* (2021) as the COVID-19 death data source and used the ensemble module to predict future COVID-19 deaths until July 31, 2021; please see Figure 31.

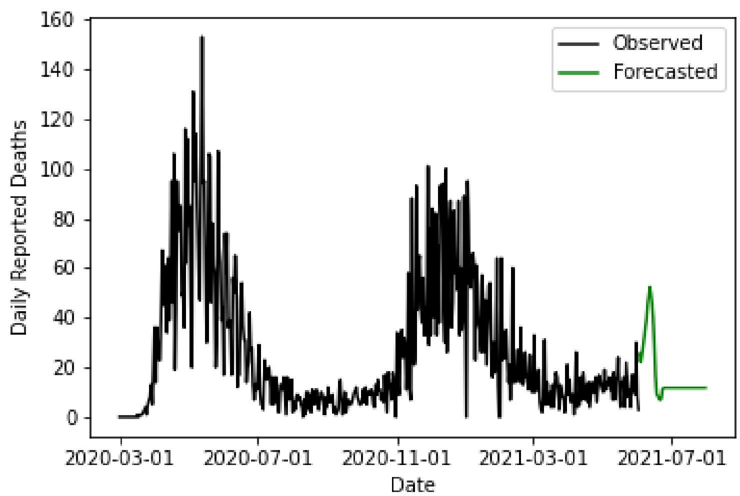


Figure 31. Graph. Observed and predicted daily reported deaths from 1 March 2020 to 31 July 2021.

Another main piece of information needed is forecasting the Google Trends index. This is not a trivial task because the Google Trends score may fluctuate according to media coverage, executive orders, a rise in COVID-19 cases, or any other event that may incite people to seek information about the virus. Here, the research team assumed that the score was going to continue its current trend, and then developed an ARIMA model to predict the Google Trends score for the near future. The research team used the R package "astsa" (Stoffer, 2020) for this task. Based on Figure 27, the Google Trends data is related to time and potentially involves the quadratic term of time. Thus, the research team considered the regression model of Google Trends data to be,

$$q_t = \phi_0 + \phi_1 t + \phi_2 t^2 + \epsilon_t'. \qquad (11)$$

Figure 32. Equation. Regression model to fit Google Trend data.

With the "astsa" package's regression analysis tool, the estimation of parameters $\hat{\phi}_0, \hat{\phi}_1$ and $\hat{\phi}_2$ were obtained, and the results indicated that the linear term t and quadratic term t^2 are significant at a 99% confidence interval. The ARIMA model analyzed and predicted the residual ϵ_t'. Based on its autocorrelation function and partial autocorrelation function of the series, the ARIMA$(0,1,1) \times (0,1,1)_7$ model is appropriate; please see the measurements in Figure 33.

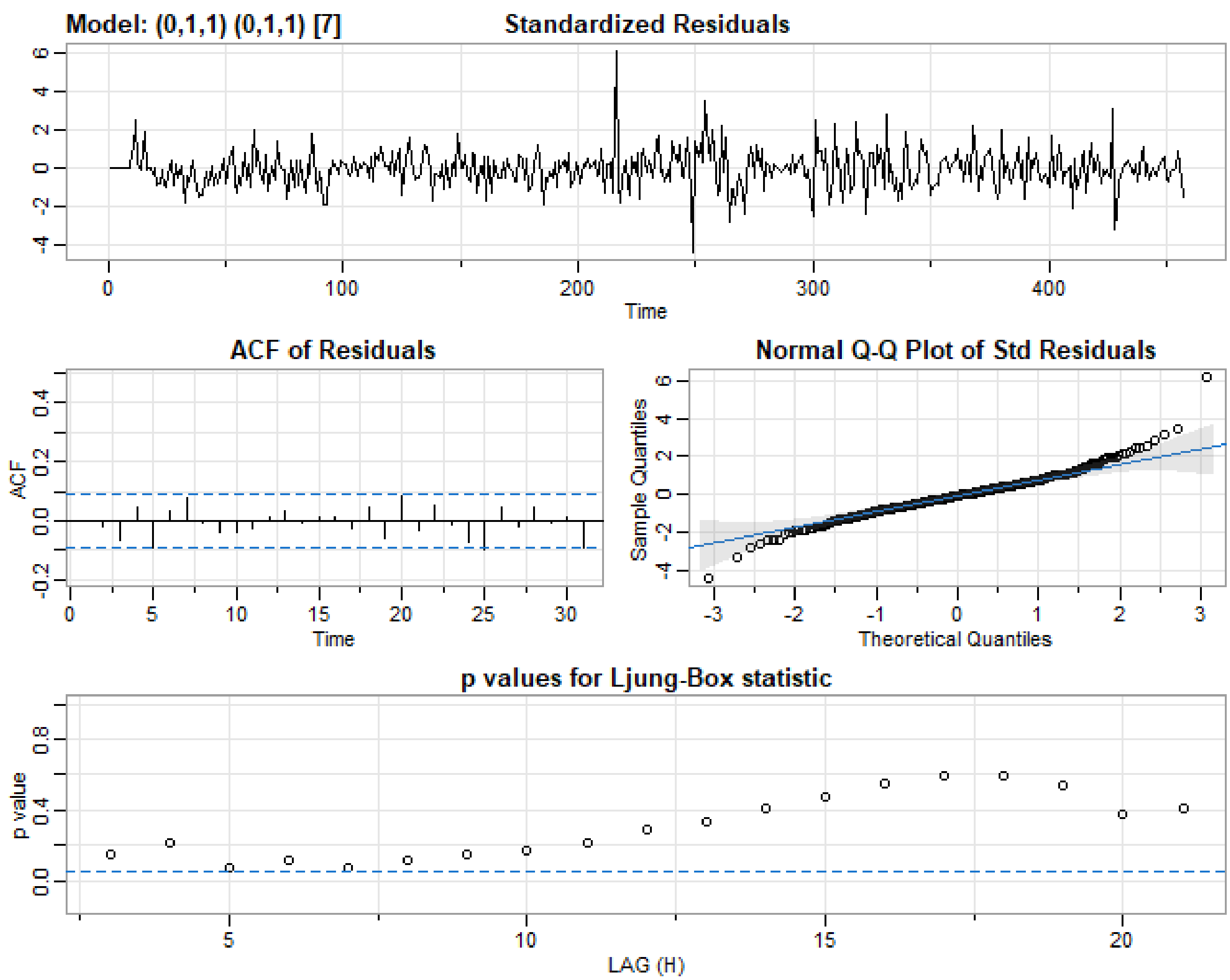


Figure 33. Graph. ARIMA model fit summary.

Finally, the research team predicted the Google Trends data with the aforementioned regression model and ARIMA model. It is plotted along with the observed trend data in Figure 34. The forecasted Google Trends values, daily reported deaths projection, assumptions of external factors, and BSTS counterfactual ridership collectively provide the necessary information for future ridership prediction at each station on the Chicago Transit Authority's rail system.

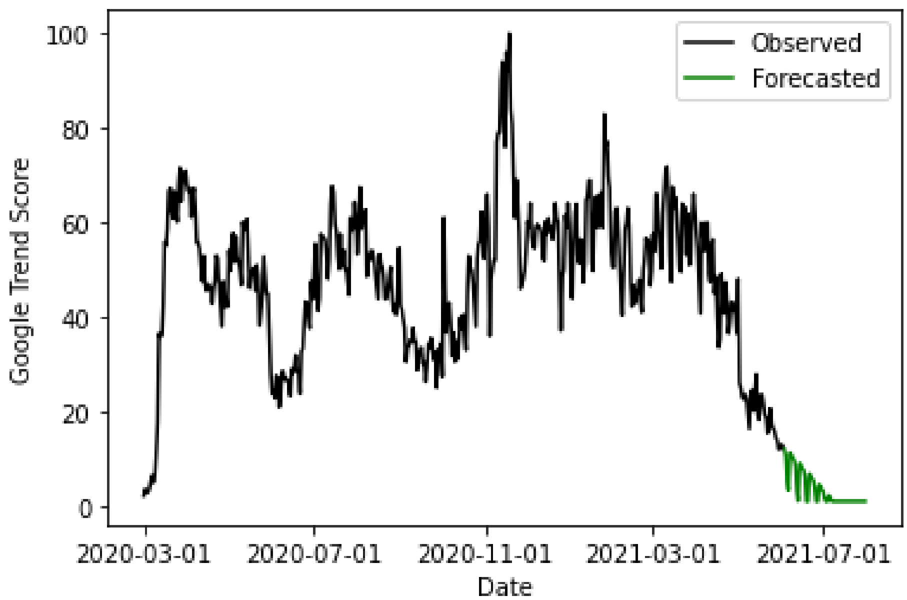


Figure 34. Graph. Observed and predicted Google Trends score from 1 March 2020 to 31 July 2021.

ORDINARY LEAST SQUARES REGRESSION

Many studies, as reviewed in Chapter 2, have observed the different magnitudes of transit ridership reduction among different urban areas and sociodemographic groups during past and current pandemics. Hu and Chen (2021) investigated the relationship between sociodemographic characteristics and static ridership losses observed by 30 April 2020. In this study, the dynamics model presented in the previous sections attributed ridership variation into eight factors. The research team thus set up an OLS model to fit these eight factors with sociodemographic characteristics to try to identify the roles of sociodemographic characteristics in ridership dynamic fluctuation.

The selected sociodemographic characteristics are summarized in Table 1. The research team considered the land-use mix index (LUM) as one of the variables which is meant to represent the degrees of mixed land use. It ranges from 0 to 1, with 0 being homogeneous, while 1 being very heterogeneous (Cervero & Kockelman, 1997). The LUM is calculated as follows:

$$LUM = \begin{cases} \frac{-1}{ln(N)} \cdot \sum_{i=1}^{N} p_i \cdot ln(p_i), & N > 1, \\ 0, & N = 1, \end{cases} \qquad (12)$$

Figure 35. Equation. Land-use mix (LUM) index.

where N is the number of land-use types in each catchment area, and p_i is the percentage of land type i within the area. The research team extracted demographic data and employment information from the US Census Bureau (2019, 2021) and land-use data from the Chicago Metropolitan Agency for Planning's land-use inventory (2015).

Table 1. Variables Considered in the OLS Regressions

Variable	Description
prop_poverty	Proportion of population under the poverty line
prop_age_0_24	Proportion of population between 0 and 24 years old
prop_age_25_39	Proportion of population between 25 and 39 years old
prop_age_40_64	Proportion of population between 40 and 64 years old
prop_edu	Proportion of population with at least a high school degree
prop_employ	Proportion of population employed
prop_R_Manuf	Proportion of residents with jobs in the manufacturing industry
prop_R_Trade	Proportion of residents with jobs in the wholesale or retail trade industry
prop_R_Edu	Proportion of residents with jobs in the educational service industry
prop_R_Health	Proportion of residents with jobs in the health industry
prop_W_Manuf	Proportion of workers with jobs in the manufacturing industry
prop_W_Trade	Proportion of workers with jobs in the wholesale or retail trade industry
prop_W_Edu	Proportion of workers with jobs in the educational service industry
prop_W_Health	Proportion of workers with jobs in the health industry
prop_white	Proportion of white population
prop_black	Proportion of black population
prop_indian.native	Proportion of Indian native population
prop_asian	Proportion of Asian population
prop_residential	Proportion of residential land
prop_commerical	Proportion of commercial land
prop_institute	proportion of institutional land
prop_industrial	proportion of industrial land
prop_transportation	proportion of land used for transportation purposes
prop_openspace	proportion of open space land
LUM	The land-use mix index

The data of the aforementioned variables are collected in different geographic units, including census tracts, census blocks, and census block groups. Based on the assumption that people generally would approach the closest Chicago Transit Authority rail station from their origin, the research team first determined the stations' catchment area using Voronoi Tessellation. The zoomed-in view of station catchment areas for the Chicago Transit Authority rail stations is shown in Figure 36. For the outer-most stations, a maximum range of five miles was set for the catchment area to avoid an unrealistic catchment area size. The research team then used the population or area of the intersected region as weights to aggregate these variables' data to each station on the Chicago Transit Authority's rail system.

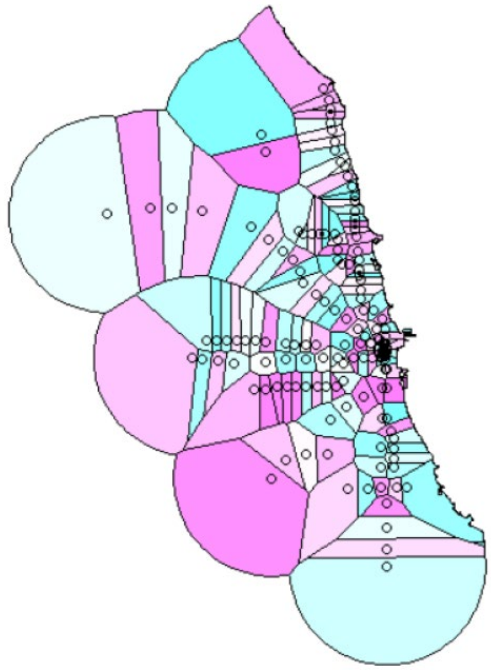


Figure 36. Map. Catchment area of each Chicago Transit Authority rail station based on proximity.

NUMERICAL ANALYSIS

The research team developed one BSTS model per Chicago Transit Authority rail station in the first step of the modeling procedure. The models were fitted to 140 valid stations, eliminating those without valid demographical data or valid ridership time-series data from this analysis. Figure 37 presents observed ridership for all stations from 1 March 2020 to 1 March 2021. Each faded red line is a station, and the black line shows the mean over all stations. Similarly, Figure 38 shows the plot of all fitted BSTS models for each station.

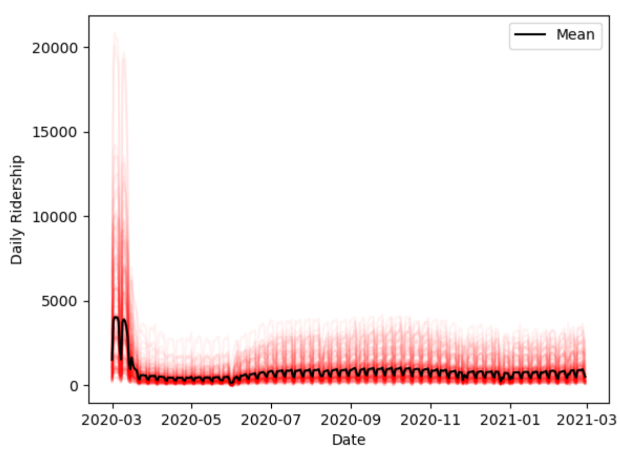


Figure 37. Graph. Daily observed ridership for all CTA rail stations (red lines) along with the daily mean value over all CTA rail stations (black line).

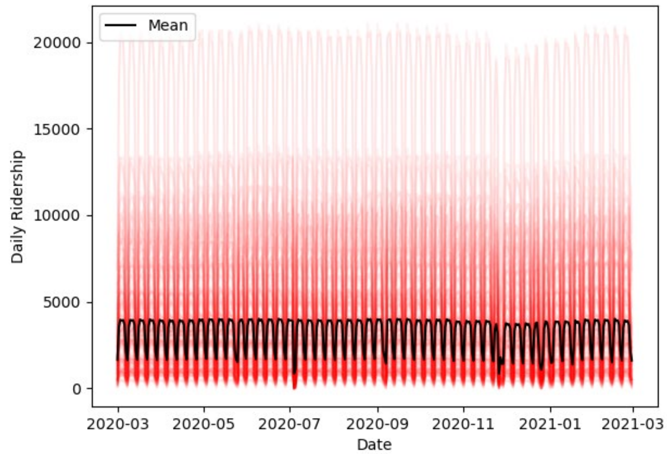


Figure 38. Graph. Daily counterfactual ridership estimated through BSTS models for all CTA rail stations (red lines) along with the daily mean value over all CTA rail stations (black line).

Regarding the BSTS models' performance, the research team used the weighted mean absolute percentage error (WMAPE), defined as follows:

$$WMAPE = \frac{\sum_{t=1}^{T} |r_t - \overline{r_t}|}{\sum_{t=1}^{T} r_t} \qquad (13)$$

Figure 39. Equation. Weighted mean absolute percentage error.

The histogram for the WMAPE statistics for all CTA rail stations included in this analysis are presented in Figure 40. The mean WMAPE among all CTA rail stations resulted in 0.211, only having nine outliers above 0.4 due to some stations having missing data or lower ridership with random fluctuations which are more unreliable to predict. Nonetheless, the WMAPE being significantly lower than 1 indicate very good fits.

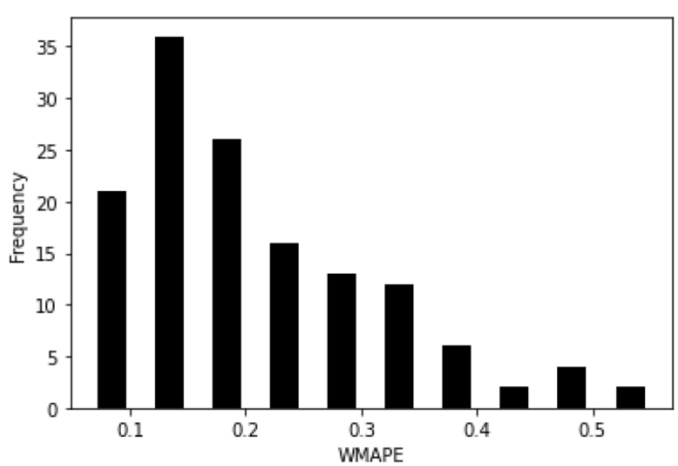


Figure 40. Graph. WMAPE statistic histogram.

Once the research team developed the BSTS models, they solved the nonlinear optimization problem presented in Equations (9) and (10) for each of the Chicago Transit Authority rail stations. To avoid overfitting with outliers and random noise, they performed a four-fold cross-validation (CV) to select the suitable stopping criterion for this nonlinear optimization problem. The four-fold CV splits the data into four data subsets. It solves the problem with three data folds and uses the remaining fold for validation. The model's validation error for a given stopping criterion is then the average of the values computed in all runs of the optimization. Please see Figure 41 for an example. Thus, by iterating over several stopping criteria, the one with the least validation error will be selected. Through preliminary tests of several stations with four-fold CV, the research team determined the stopping criterion to be the first derivative of the objective function smaller or equal to 10^{-3} and used this criterion for all Chicago Transit Authority rail stations.

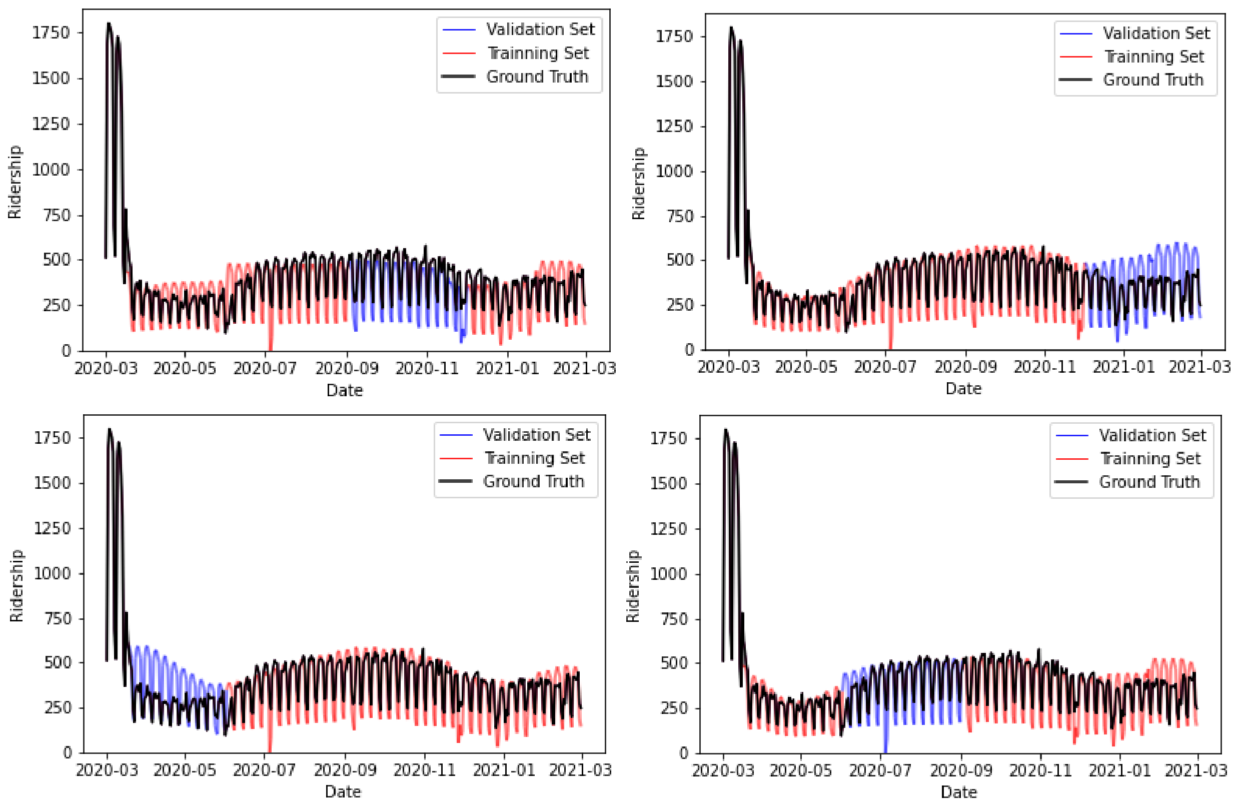


Figure 41. Graph. Example for four-fold cross-validation.

The summary statistics for the dynamics model parameters are presented in Table 2. The table also shows the percentage of Chicago Transit Authority rail stations for which the model parameter is found to be statistically significant at a 95% confidence level. It reveals that remote learning/work has induced an average daily ridership loss for the Chicago Transit Authority's rail system of approximately 70% after 17 March 2020, as represented by L_c. In contrast, the average percentage ridership losses related to stay-at-home orders for other activities, as represented by L_s, is only 2.5%. This is expected because remote work/learning policies eliminate most commuting needs that form a significant part of daily ridership and, thus, is the major reason behind ridership reductions. In contrast, the stay-at-home orders mainly limit social activities such as gatherings, parties, and close-contact group sports, which may contribute to a small portion of the daily ridership. The ridership loss due to “fresh fear” for each reported death, L_d, is 0.23% while the “fresh fear” due to each Google Trends score is 0.62% per score. Taking into account the typical number of daily reported deaths, and the typical Google Trends scores, the relatively low value of L_d generally hints to the fact that the vast majority of CTA rail ridership reductions is due to executive orders rather than people’s self-defensive behavior. It is important to note that the L_c term is found to be significant to explain ridership reductions at all Chicago Transit Authority rail stations. However, the L_s term is found to be significant only among approximately 55.2% of Chicago Transit Authority rail stations. Other terms are significant among about 85%–92% of Chicago Transit Authority’s rail stations.

Table 2. Summary Statistics of the Dynamics Model Parameters across All Stations

Parameter	Mean	Standard Dev.	Percent Significant (%)
L_c	0.70	0.11	100
L_s	0.025	0.023	55.2
L_q	0.0062	0.011	88.1
L_d	0.0023	0.0027	90.3
τ_d	0.47	0.35	85.1
τ_q	0.74	0.27	89.6
f_d	0.15	0.28	85.1
f_q	0.16	0.21	91.8

To show the fitting of the model, two representative figures are presented below based on two distinct ridership patterns that were observable among all Chicago Transit Authority rail stations. First, the pattern for approximately 50 stations looked very similar to Figure 42. This pattern is generally characterized by having a pre-COVID-19 ridership above 2,500 people on weekdays. Weekday ridership drastically decreased after the outbreak and remained relatively “flat” at approximately 10%–15% of pre-COVID-19 ridership. The second pattern is shown in Figure 43, where typical ridership is below 2,500 people on weekdays. Weekday ridership during this pandemic stayed at approximately 25%–30% of pre-COVID-19 ridership. Approximately 30 stations had this very distinct pattern. The remaining stations (approximately 90) have a “mixed” pattern, which is in between these two extremes. The dynamic model’s results, including parameters to reproduce all the fitted curves, are presented in the appendix.

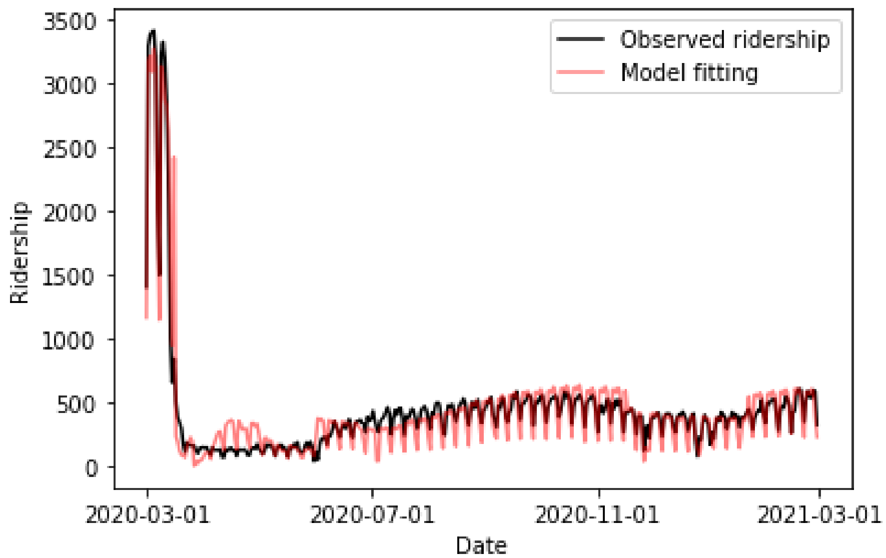


Figure 42. Graph. Dynamics model result for CTA rail station 360 as compared to the observed ridership from 1 March 2020 to 1 March 2021.

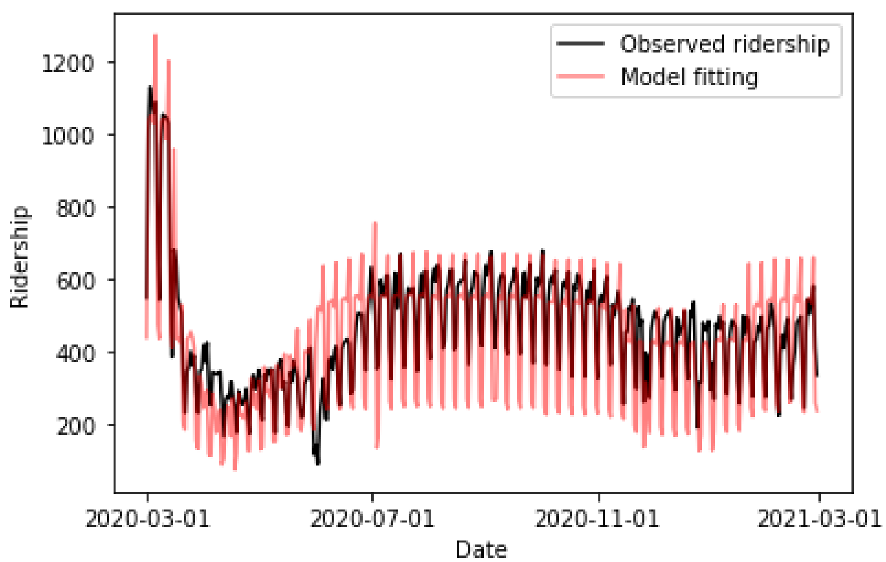


Figure 43. Graph. Dynamics model result for CTA rail station 420 as compared to the observed ridership from 1 March 2020 to 1 March 2021.

After all curves were fitted, the resulting parameters were used for forecasting purposes. The forecast was carried out up to July 31 given the limited availability of COVID-19 deaths forecast, as presented in the previous sections. For illustration purposes, Figures 44 and 45 present the forecasted ridership for Chicago Transit Authority stations 360 and 420, respectively. However, the appendix shows all the fitted curves and forecasting.

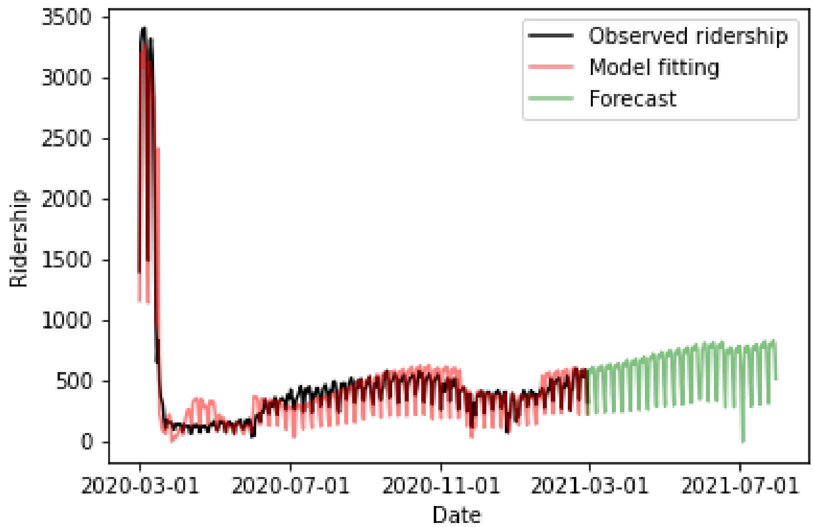


Figure 44. Graph. Dynamics model forecast for CTA rail station 360 up to 31 July 2021.

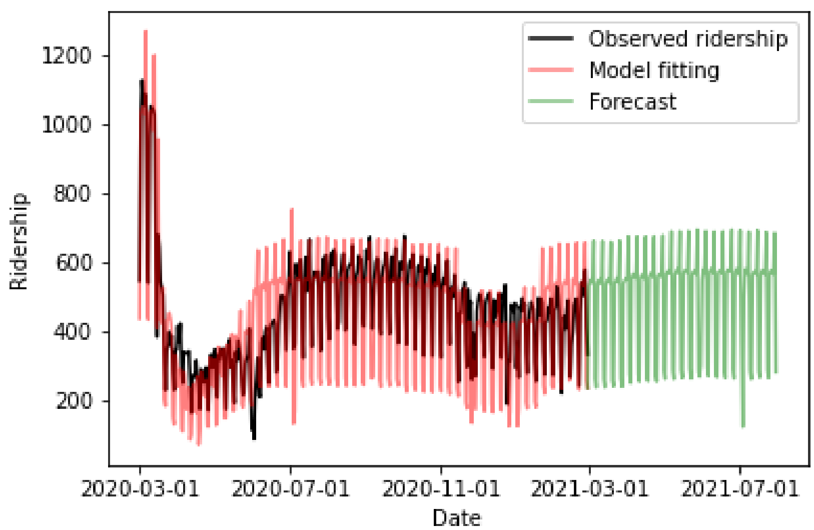


Figure 45. Graph. Dynamics model forecast for CTA rail station 420 up to 31 July 2021.

Both forecasts show a slight upward trend as fear diminishes over time and the Google Trends, i.e., media attention, dissipates. It is important to note that most Chicago Transit Authority rail stations have a flat to slight upward trend given diminishing fear, but still remain with ridership under 30%–40% of pre-COVID-19 ridership because remote learning/working, c_t, remains the major ridership reductor in the forecast and is assumed to be constant during the study period. Given this and the model's exclusion of other variables such as tourists returning to Chicago and/or vaccination rates, this model's forecast is a conservative one.

To show the effect of the $c_t L_c$ term in Equation (8), Figures 46 and 47 show the recovery process under a hypothetical reopening of Chicago, (i.e., $c_t = 0$) on 1 July 2021. It is worth noting that these hypothetical predictions do not consider the "new normal" conditions for people who may not return to daily transit use given their remote working opportunities.

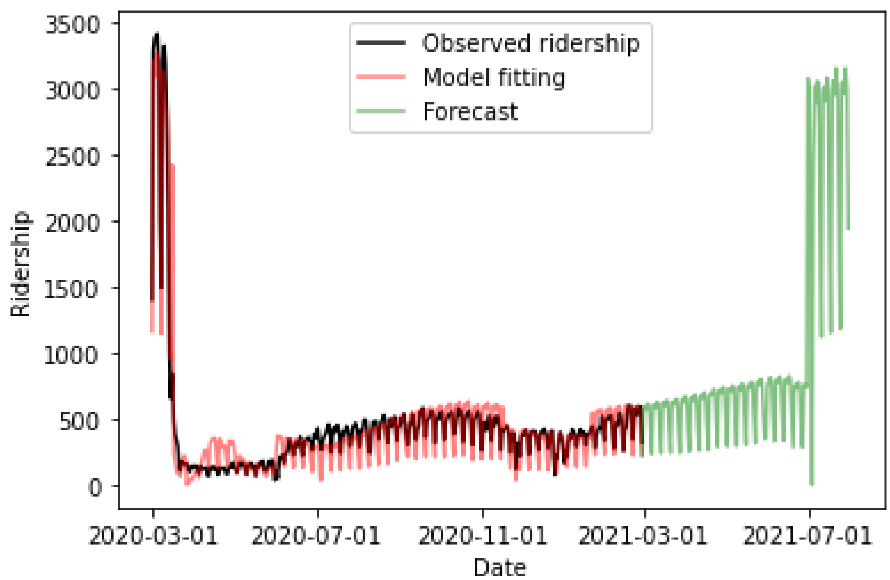


Figure 46. Graph. Hypothetical forecast for CTA station 360 up to 31 July 2021, where $c_t = 0$.

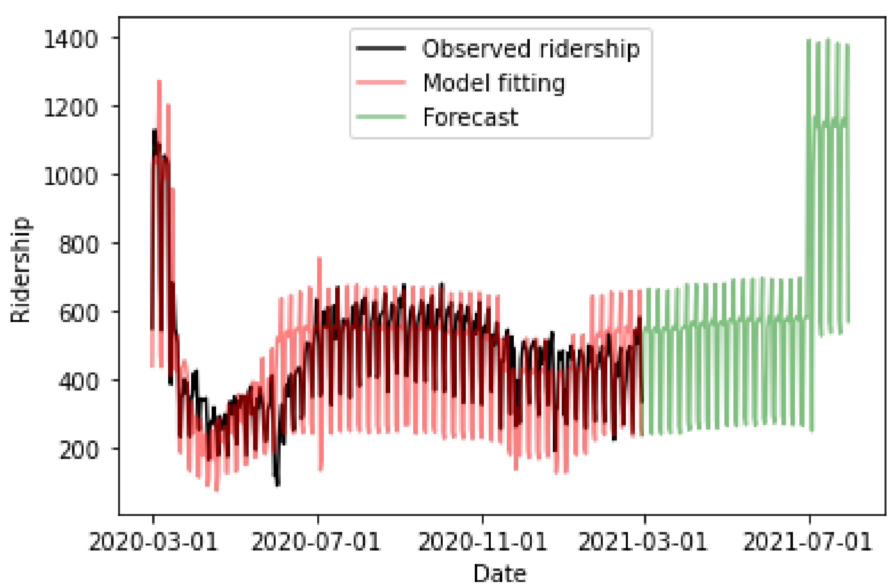


Figure 47. Graph. Hypothetical forecast for CTA station 420 up to 31 July 2021, where $c_t = 0$.

In contrast, because of the curve fitting's accuracy from 1 March 2020 until 1 March 2021, the models may provide insights on people's reaction to the executive orders, daily reported deaths, and news coverage.

As mentioned in the previous section, the research team performed an OLS regression across all Chicago Transit Authority rail stations to try to explain variability in the parameters for each station. The full regression results are presented in the appendix; however, Table 3 presents the summarized results over all parameters. Here, the research team only presents the parameter estimate and level of significance.

Table 3. Summary of the Regressions on the Dynamics Model Parameters

	L_c	L_d	τ_d	f_d	L_q	τ_q	f_q	L_s
(Intercept)	-0.0709	-0.0046	-1.4455	-1.8096	0.0276	3.0831	-0.953	**0.4347***
prop_poverty	**-0.4291****	-0.0009	0.7409	-0.3545	0.0212	0.2324	**-0.864 .**	**-0.1204***
prop_age_0_24	0.6122	0.0088	2.5930	1.110	-0.0294	-0.9698	1.267	-0.1988
prop_age_25_39	**0.5345***	0.0041	1.8132	0.9083	-0.0109	-0.1542	0.978	-0.0063
prop_age_40_64	0.4102	-0.0017	2.0395	0.0198	0.0242	-0.0242	2.013	-0.1396
prop_edu	-0.1406	-0.0453	-6.1063	-3.4346	0.0189	2.4813	-0.282	0.3706
prop_employ	0.3270	0.0114	0.1071	0.9811	-0.0524	-1.6628	0.300	**-0.2727 .**
prop_R_Manuf	0.1101	-0.0398	5.1503	2.7129	-0.1308	**-16.648 .**	-0.239	0.1580
prop_R_Trade	**-2.5427 .**	**-0.1066 .**	-12.6226	-10.404	-0.3310	**20.749***	**-9.792 .**	-0.4643
prop_R_Edu	-0.2681	**0.0701 .**	5.2539	6.620	**0.3789***	3.5318	1.743	0.3360
prop_R_Health	1.6230	0.0026	3.0859	-0.4018	0.0451	**-11.161 .**	4.394	0.0848
prop_W_Manuf	-0.0377	-0.0067	0.7578	-0.6130	-0.0038	0.0520	-0.295	-0.0426
prop_W_Trade	0.0127	**0.0013 .**	0.1163	**0.1948****	0.0003	-0.1164	0.078	0.0084
prop_W_Edu	0.0213	-0.0045	-0.3562	-0.4409	-0.0111	0.4550	-0.272	**-0.0519 .**
prop_W_Health	-0.0008	0.0001	0.0237	0.0046	0.0008	0.0097	-0.005	0.0010
prop_white	**0.1854 .**	-0.0048	0.1492	0.1080	0.0082	-0.3737	-0.233	**-0.0983****
prop_black	0.0484	-0.0055	-0.3852	0.4113	-0.0065	-0.2773	-0.099	-0.0418
prop_indian.native	1.5067	**-0.2226***	-8.2918	-8.5239	-0.4632	-11.660	-5.346	-0.0940
prop_asian	**0.3219****	-0.0001	0.5709	0.5425	0.0136	-0.1945	-0.128	-0.0379
prop_residential	-0.0358	0.0009	-0.6731	**1.1379***	0.0130	-0.0509	-0.232	0.0176
prop_commerical	-0.1306	0.0018	-0.7031	0.9217	**0.0596****	0.0897	-0.463	0.0151
prop_institute	-0.0811	0.0047	-0.5168	**0.9324 .**	0.0232	-0.0537	-0.138	**0.0854 .**
prop_industrial	**-0.3701***	0.0043	-0.7599	0.8550	0.0021	0.4628	-0.619	0.0128
prop_transportation	-0.0698	0.0066	-0.3377	**1.3317 .**	0.0335	0.0254	-0.082	0.0394
prop_openspace	-0.1491	0.0062	0.5142	**1.1605 ***	0.0088	0.0569	-0.211	0.0539
LUM	0.0884	0.0007	0.6130	-0.1421	0.0095	**-0.8564***	0.389	-0.0385
R^2	***0.743***	***0.221***	***0.224***	***0.245***	***0.281***	***0.165***	***0.1468***	***0.185***

Significance codes: "***" 0.001, "**" 0.01, "*" 0.05, " ." 0.1, " " 1.

The first thing to notice is that the R^2 values for seven of the eight regressions are below 0.3, except for the regression of the L_c parameter, which represents the percentage reduction for remote learning/working. Remote learning/working targets certain groups of the population (e.g., students), while others must go to their workplace in person (e.g., health care personnel). In contrast, the rest of the seven factors all pose impacts to the general population. Thus, it is expected that socioeconomic characteristics play a much more significant role in remote working–related ridership loss, compared to other factors.

For the term L_c, the proportion of the population under the poverty line is significant with a 99% confidence level. It is negatively correlated with the value of L_c and is consistent with literature review findings showing lower income individuals having experienced less behavioral change given a lack of flexibility in their lifestyles. The second main predictor is the proportion of Asian people within the catchment area, indicating that a higher proportion of Asian people is associated with a higher drop in ridership at Chicago Transit Authority rail stations after the first executive order. The proportion of white people was also positively associated with ridership drops at these stations.

The proportion of industrial land is a significant variable indicating that a higher proportion of industrial land is associated with lower drops in ridership at Chicago Transit Authority rail stations. Likewise, the proportion of residents working on trade jobs was significantly associated with lower drops in ridership. Industrial land and trade jobs were significantly associated with lower drops in ridership likely because many trades were considered "essential." Workers in these trades had to continue traveling during the pandemic (Illinois Department of Commerce, 2020).

For the rest of the models, one main observation is that socioeconomic characteristics are not good predictors of people's "fear" (i.e., travel behavior during the pandemic). This may hint to the fact that the major drivers of ridership decline at Chicago Transit Authority rail stations are the executive orders and the "new normal" resulting from people decreasing their need to travel daily given their remote working opportunities. The literature suggests that transit ridership loss purely due to fear recovered within months; the evidence from this regression analysis also suggests that the Chicago Transit Authority's rail ridership could follow the same trend (i.e., to "new normal" levels) once all restrictions are lifted and schools fully reopen in Illinois.

CHAPTER 4: CONCLUSIONS

In the first half of this report, the research team collected quantitative and qualitative research findings for previous prolonged events in the literature review, consisting of terrorist attacks and epidemic events around the world. These events abruptly impacted travel behaviors that historically had been attributed to transit users' risk perceptions. The research team thus paid particular attention to how these events caused fear-based responses from the population, which altered their travel behavior. They collected information about how transit agencies counteracted the impacts of these prolonged events and summarized these experiences for future reference.

Although terrorist attacks induced an immediate response from the public, their effects often lasted one to four months for smaller scale attacks (such as the ones Madrid, London, and Tokyo witnessed), or one to two years for major attacks (such as the 9/11 attacks). Studies have shown that not only did riders reduce their use of the attacked transportation modes, but they also shifted modes. Ridership losses after terrorist attacks partially resulted from changes in service supply, such as station closures immediately after the attack (as in London) or elevated security measures, which increased travel times and caused extra travel inconveniences (such as after 9/11). These observations from past events suggest that any service reduction during or after COVID-19 can significantly influence riders' travel behaviors.

Although past epidemics considered in this study have varied from more localized outbreaks (such as Ebola) to a worldwide pandemic (such as H1N1), several general conclusions can be drawn from their impacts on mobility. First, all epidemics in recent decades led to drastic ridership reductions on public transit during the outbreak, possibly due to fear-driven passengers' travel avoidance behaviors, reduced commercial activities, executive orders, and diminished commuting needs. However, these effects were only short term; ridership could rebound quickly after the outbreaks ended. Taipei Metro and South Korea Metro, for example, showed immediate ridership recoveries within weeks after the outbreak (Wang, 2014; Sung, 2016). Hong Kong Mass Transit Railway and Singapore Mass Rapid Transit bounced back to a great extent by the end of 2003, i.e., six to seven months after the outbreak (Hong Kong Mass Transit Railway, 2004; SMRT Corporation Ltd., 2004). Sierra Leone, however, did not have long-term ridership decline after the Ebola lockdown in 2015 (Peak et al., 2018). The annual ridership of Hong Kong Mass Transit Railway, Taipei Metro, Toronto Transit Commission, and Singapore Mass Rapid Transit from 2001 to 2005, as shown in Figures 8–11, indicated that their ridership (particularly rail ridership) usually steadily increased in the following years after the epidemics had ended and may have even exceeded pre-epidemic levels.

Past studies on SARS found that transit was perceived as the riskiest activity and the most likely to be avoided as a precautionary measure. This observation was similar across countries, even for those that did not experience an outbreak. Moreover, the research team observed the heterogeneity of riders' risk perceptions and mitigation strategies between sociodemographic groups from all past epidemics where research was available. Although meaningful observations can be drawn from these previous events, the situation with the COVID-19 pandemic is still largely unknown, given its unprecedented scale and duration. The observations from previous epidemics should be examined cautiously. It is necessary to keep track of the COVID-19 pandemic's evolution and related ridership fluctuations as new information becomes available.

The research team identified three studies as relevant for quantifying transit ridership changes during this current pandemic in the United States and specifically in Chicago. Two of these studies stated that the COVID-19 pandemic has depressed Chicago Transit Authority bus and rail ridership. These ridership losses exhibited significant spatial heterogeneity; areas with higher population income witnessed more severe ridership drops. The other study showed that the COVID-19 pandemic discouraged shared bike usage in Chicago. These findings support other studies conducted nationwide that had shown socioeconomic factors significantly affecting the magnitude of travel reductions across all modes in the United States.

The Transportation Research Board's Guidebook (2014) is intended to help transit agencies prepare for pandemics as well as to timely and properly adjust their operations during pandemics. The agency responses collected in this report have further enriched the measures this Guidebook recommends. Safety precautions, such as distributing personal protective equipment, providing hand sanitizer/dispensers, requiring social distancing, and intensifying cleaning and ventilation systems, all play a critical role in reducing public transit's health risks. Transit operators should also clearly communicate the safety measures that they have implemented on their transit systems to the public through proper platforms, such as social media and mobile applications, to reassure passengers about the safety of using transit. Regarding adjustment to transit operations, the first step is to identify essential services and nonessential services, where the former should be guaranteed and the latter can be reduced. For low-demand areas, it is inevitable to downgrade service, but transit agencies can seek supplementary service to avoid accessibility and mobility concerns in those areas, e.g., by exploring the benefits of using demand-responsive service and cooperation with transportation network companies, e.g., Uber and Lyft. These strategies have been widely practiced during the COVID-19 pandemic (Schwartz, 2020).

As widespread vaccine use has been ameliorating the COVID-19 pandemic, ridership recovery has become a critical and pressing issue for public transit agencies. Theoretical studies and real-world practices stress the importance of communication, advertising, and publicity when recovering from previous pandemics. Studies revealed that people tend to be more responsive to epidemic-related reports than to objective risk measures (Fenichel et al., 2013) and that people's risk perceptions were the strongest predictor of travel avoidance behavior (Cahyanto et al., 2016). To avoid people's false perceptions of transit-related risks during epidemics, the Hong Kong Mass Transit Railway and the Toronto Transit Commission relied heavily on advertising and publicity campaigns to reinstate public confidence in public transit. These campaigns successfully and promptly helped them regain ridership (Hong Kong Mass Transit Railway, 2004; Johnson Tew et al., 2008). Amid the COVID-19 pandemic, many agencies have been taking advantage of information technologies to timely deliver information, e.g., safety protocols and crowding information, to the public.

Discounts and promotions have also effectively attracted riders, such as discount and/or loyalty programs that the Hong Kong Mass Transit Railway and Singapore Mass Rapid Transit system (Hong Kong Mass Transit Railway, 2004; SMRT Corporation Ltd., 2004) have used. Moreover, the Toronto

Transit Commission collaborated with the city's tourism industry to stimulate the tourism market and attract more riders to transit service (Johnson Tew et al., 2008). This successful experience agrees with suggestions from the Guidebook about the importance for transit agencies to cooperate with other institutions during epidemics.

The review of previous epidemics and existing literature provided constructive insights on how to enrich this project's data analysis. The research team developed a series of statistical and dynamic models for ridership loss to quantify heterogeneous ridership declines among all Chicago Transit Authority rail stations. This analysis integrated time-series prediction through a Bayesian structural time-series model, a ridership loss model based on the public's reaction to daily reported deaths and news coverage, a prediction module to forecast future ridership, and a statistical regression to quantify the heterogeneous ridership declines.

The research team fitted a set of parameters to each Chicago Transit Authority rail station and consequently applied them to generate rail ridership forecasts for the following months up to 31 July 2021. A four-fold cross-validation was used to avoid overfitting of the model. The forecast curves generated had a flat to slowly upward trend, signifying a slow recovery of the pre-COVID-19 numbers as the fear from the reported deaths and trends dissipates. It is important to note that given limited data availability in the future, this model provides a conservative estimate of future ridership because other relevant factors in the recovery period were not considered such as vaccination rates and incoming air travel demand into Chicago (i.e., tourists demand returning).

The results from the ordinary least squares regression showed that socioeconomic and land-use characteristics were good predictors of people's reactions to the first remote learning/working executive order, predicting variation in the $\boldsymbol{L_c}$ with an $\boldsymbol{R^2}$ of 0.743. This result is reasonable because reaction to the first executive order may depend more on job and lifestyle flexibility (rather than a personal choice). In contrast, the socioeconomic and land-use characteristics were not clear predictors of people's reaction to the daily reported deaths and news coverage (i.e., Google Trends). The highest $\boldsymbol{R^2}$ out of all parameters describing the "residual fear" was 0.281. This outstanding result may indicate that the primary drivers of the ridership drop (and possibly recovery) are policy and executive orders. However, it is important to note that this conclusion does not consider the "new normal," and that it is possible that some riders who used to ride on a daily basis will not return given their changed work situation. Yet, just as other studies in the past have shown that fear-based ridership decline recovers within months, the evidence from the numerical analysis indicates that once all schools fully reopen and all restrictions have been lifted, the Chicago Transit Authority's rail ridership may follow the same recovery trend (similar to those observed after all other epidemics in the last three decades).

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APPENDIX

The fitter ordinary least squares (OLS) model parameters for all stations are presented in Table 4. Then, Tables 5–12 present the detailed results from the OLS regression.

Table 4. Fitted Parameters per Station

ID	L_d	τ_d	r_d	L_t	τ_t	r_t	L_c	L_s
10	0.00128	0.79894	-0.0086	0.004	0.86283	-0.09999	0.70672	0.01657
20	0.00205	0.97991	-0.00954	0.00597	0.91176	-0.09943	0.63048	0.01094
30	0.00983	0.86851	-0.05292	0	1	-0.07372	0.47725	0.06525
40	0.006146956	0.340487	-0.45535	0.014092	1	-0.15565	0.901604	0.035326
50	0.000107305	0.050604	-0.00171	0.002939	1	-0.02537	0.707619	2.86E-08
60	0.00131	0	-0.04157	0.00113	0.05217	-0.09996	0.70818	0.01616
70	0.00672176	0.0972	-0.31738	0.01515	0.391613	-0.17993	0.852672	0.039303
80	0.00117	0.9977	-0.00732	0.00233	0.99611	-0.03126	0.77162	0.02186
90	0.00078	0.43147	-0.00565	0.0098	0.85569	-0.09999	0.81739	0.00638
100	0.00136	0.9401	-0.00498	0.00259	0.98952	-0.05687	0.66631	0.0356
120	0.00145	0.60452	-0.00719	0.00465	0.75862	-0.08741	0.71712	0.01378
130	0.000517742	0.190057	-0.44083	0	0.062492	-0.77833	0.615354	0.070891
140	6.05E-05	0.0312	0	0.002184	0.931127	-0.00983	0.636164	0
150	0.00201	0.84169	-0.0047	0.00093	0.66403	-0.02926	0.50503	0
160	0.007559062	0.629951	-0.36033	0.013826	0.498565	-0.16547	0.866838	0.038907
170	0.00119	0.38378	-0.00734	0.0051	0.67453	-0.09876	0.66589	0.00346
180	0.000113514	0.082553	-0.00198	0.002865	0.951018	-0.06094	0.824636	1.36E-12
190	0.00299	0.75656	-0.01162	0.00618	0.72023	-0.09141	0.5924	0.03863
210	0.00188	0.99211	-0.00749	0.00442	0.99999	-0.05802	0.67796	0.02629
220	0.00079	0.53366	-0.00247	0.00164	0.47508	-0.09998	0.68254	0.00289
230	0.001698903	0.209485	-0.61696	0.00077	0.574915	-0.00796	0.771938	0.034809
240	2.99E-04	8.80E-02	-3.80E-03	1.83E-04	1	-1.00E-01	5.02E-01	0
250	1.83E-04	5.15E-02	-2.53E-03	3.89E-04	9.79E-01	-1.58E-02	5.12E-01	9.02E-04
260	0.00119	0.68965	-0.00555	0.00546	0.57591	-0.0991	0.78486	0.01401
270	0.00091887	0.525606	-0.00467	0.011064	0.984838	-0.09588	0.728678	0.018106
280	3.18E-04	9.55E-02	-3.39E-03	4.28E-04	6.66E-01	-2.52E-02	5.05E-01	7.88E-17
290	0.00309	0.4631	-0.02615	0	0.97009	-0.09164	0.5616	0.003
300	2.13E-04	9.89E-02	-1.49E-03	2.20E-03	9.63E-01	-5.28E-02	6.18E-01	6.48E-03
310	0.00172	0.99745	-0.00569	0.00135	0.95323	-0.0198	0.65201	0.00472
320	0	0.995712	-0.92854	0.001917	1	-0.0081	0.778145	0.040888
330	0.00087	0.69063	-0.00189	0.00135	0.82151	-0.00698	0.75724	0
340	0.00685	0.66642	-0.06427	0.00489	0.84151	-0.09981	0.72185	0.04992
350	4.38E-05	0.00651	-0.00335	0.00775	0.999583	-0.08334	0.827317	0.05026
360	6.74E-05	0.001748	-0.00338	0.004161	1	-0.01764	0.664108	0.04571
370	0.00112	0.95707	-0.00542	0.00453	0.75228	-0.06917	0.83209	0.00721

ID	L_d	τ_d	r_d	L_t	τ_t	r_t	L_c	L_s
380	0.00069	0.53227	-0.00702	0.00754	0.89469	-0.09989	0.85182	0.01764
390	0.000384613	0.02044	-0.02503	3.20E-07	0.943345	-0.94673	0.638031	0.016382
400	0.000166502	0.046806	-0.00531	0.00507	0.868864	-0.05544	0.786619	0.006767
420	0.00922	0.67849	-0.03732	0.00316	0.93157	-0.07232	0.50211	0.09024
430	0.009251237	0.289335	-0.98716	0.010291	0.318563	-0.32413	0.865475	0.030299
440	0.00313	0.99457	-0.00847	0.00299	0.80982	-0.09938	0.49335	0.04935
450	0.006603296	0.536029	-0.94206	0	0.883799	-0.41128	0.539574	0.06418
460	6.88E-05	4.11E-06	-0.00394	0.00376	0.99919	-0.01846	0.703656	0.03917
470	0.00197374	0.656042	-0.39708	0.008111	0.348069	-0.14754	0.845523	0.03958
480	1.86E-04	6.02E-02	-2.67E-03	0	8.71E-01	-9.56E-02	5.12E-01	8.37E-13
490	0.00093	0.98564	-0.00173	0.00245	0.99799	-0.01779	0.75	0.01044
510	0.00889487	0.857261	-0.84191	0	0.654883	-0.83103	0.648771	0.087345
520	0.000255375	0.125598	-0.00418	0.01125	0.950714	-0.10378	0.794256	0.003281
530	1.60E-04	6.01E-02	-4.43E-03	5.96E-03	1.00E+00	-5.99E-02	7.95E-01	1.04E-02
540	0.00175	0.99995	-0.00988	0.00565	1	-0.09801	0.68124	0.02963
550	0.00146555	0.496544	-0.01045	0.007254	0.882725	-0.29459	0.710437	0.019951
560	0.00084	0.4617	-0.01837	0.00661	0.78251	-0.09858	0.87382	0.00752
570	9.76E-05	4.05E-02	-3.68E-03	3.57E-03	6.25E-01	-5.82E-02	8.11E-01	1.93E-02
580	0.001041238	0.000152	-0.03786	5.73E-16	0.357811	-0.74103	0.586641	0.041272
590	0.00013	0.04408	-0.00214	0.00242	0.00039	-0.09954	0.77489	0.01703
600	0.01	0.123067	-0.58316	0	0.589073	-0.80902	0.580597	0.059479
610	0.00108504	0.303564	-0.48482	0.013884	0.431421	-0.16559	0.814959	0.051275
630	0.00040894	0.000616	-0.02885	0.007883	1	-0.08967	0.737154	0.031962
650	0.00176	0.73626	-0.00825	0.00984	1	-0.0996	0.75338	0
660	0.00007	0.04351	-0.00493	0.00132	0.58631	-0.00934	0.79777	0.01396
670	0.0011	0.98728	-0.00526	0.0074	0.99294	-0.0875	0.82335	0.01352
680	0.00088	0.39534	-0.00923	0.00249	0.58195	-0.08265	0.79676	0.01158
690	0.0001941	0.064516	-0.00413	0.004786	0.853054	-0.06379	0.69173	0.001812
700	0.005662695	0.05832	-0.65593	0	0.669243	-0.5573	0.566607	0.062242
710	2.40E-04	8.83E-02	-8.11E-03	9.86E-03	1	-9.40E-02	7.81E-01	3.65E-02
720	0.003100758	0.521736	-0.90561	0.007032	0.98123	-0.20163	0.614845	0.069653
740	0.00171	0.75981	-0.00741	0.00128	0.66492	-0.02292	0.55498	0.03314
750	0.00157	0.58051	-0.01004	0.00251	0.24267	-0.0989	0.7136	0.0085
760	0.0006	0.17351	-0.01323	0.00667	0.8833	-0.09999	0.74585	0.00644
770	0.000105333	0.024559	-0.00242	0.000943	0.277997	-0.017	0.656958	1.45E-10
780	0.000163074	0.062516	-0.0011	0.00033	0.020207	-0.03582	0.564032	8.66E-15
790	0.004509291	0.198477	-0.78529	0.010872	1	-0.12226	0.888275	0.036165
800	0.00045	0.95116	-0.00033	0.00153	0.75663	-0.00384	0.73633	0.01817
810	0.00088	0.58018	-0.00738	0.00027	0.2045	-0.00979	0.69238	0.01092
820	7.87E-05	0.035429	0	0.000573	2.65E-18	-0.0481	0.628705	1.23E-18
830	0.00241	0.98928	-0.00776	0.0075	0.8534	-0.09256	0.66278	0.02412
840	0.007824734	0.702753	-0.70751	0.014026	0.177489	-0.31741	0.737333	0.058959

ID	L_d	τ_d	r_d	L_t	τ_t	r_t	L_c	L_s
850	0.00053	0.62077	-0.00162	0.01035	0.99461	-0.09943	0.80199	0.02386
870	0.000565661	0.294146	-0.00497	0.010803	0.971305	-0.0992	0.799953	0.013411
880	0.00105	0.33787	-0.01136	0.0042	0.9767	-0.08715	0.72651	0.00352
890	0.00115	0.50721	-0.00601	0.00003	0.79376	-0.01772	0.6597	0.02609
900	0.00196	1	-0.00946	0.00323	1	-0.09997	0.60135	0
910	0.003620863	0.966924	-0.46606	0	0.721551	-0.45682	0.579578	0.043292
920	0.00201	0.59814	-0.01117	0	0.64248	-0.02008	0.43502	0.02672
930	0.001580181	0.425833	-0.01388	0.001534	0.502334	-0.04567	0.709217	0.019713
940	0.00164	0.50318	-0.01289	0.00108	0.90606	-0.08595	0.57761	0.00582
960	0.00161	0.00221	-0.04859	0.0029	0.49495	-0.08273	0.70297	0.04844
970	0.00091	0.37097	-0.00296	0	0.92042	-0.0929	0.47413	0
980	0.000543824	0.025735	-0.02521	0.022248	1	-1	0.5791	0.01659
990	0.00082	0.26387	-0.00572	0.00032	1	-0.09993	0.49601	0
1000	0.00139	0.64984	-0.00442	0.0131	0.85884	-0.09434	0.71647	0.01429
1010	0.005472843	0.183301	-0.42473	0	0.597457	-0.83776	0.848704	0.046646
1020	0.00074	0.33917	-0.00467	0.00657	0.83814	-0.0997	0.79623	0.0005
1030	0.00095	0.28182	-0.01298	0.00315	0.59525	-0.03936	0.65065	0.07317
1040	0.0024	0.9971	-0.00446	0.00181	0.99646	-0.01719	0.48444	0.00557
1050	0.000776874	0.925196	-0.73085	0.015367	1	-0.1232	0.746583	0.056159
1060	0.00277	0.94383	-0.00864	0.00653	0.80458	-0.09886	0.58637	0.0086
1070	0.006155272	0.945248	-0.66887	0	0.260539	-0.26429	0.64887	0.043436
1080	0.005175296	0.565015	-0.86034	0	0.287392	-0.49533	0.605954	0.073187
1090	0.002874099	0.956776	-0.9005	0.018041	0.452555	-0.1863	0.873079	0.038052
1120	0.00734697	0.039253	-0.89186	0.00294	0.443191	-0.49739	0.737293	0.071801
1130	0.00131	0.75875	-0.00649	0.00345	0.69963	-0.07096	0.76176	0.00312
1140	0.000330313	0.098486	-0.00281	0.004117	0.905983	-0.08904	0.483236	0.019172
1150	0.00183	0.95672	-0.00667	0.00116	0.95626	-0.01615	0.63039	0.02346
1160	0.001607036	0.612998	-0.0174	0.027073	0.180766	-0.29587	0.838054	0.008618
1170	0.001046108	0.522711	-0.00549	0.001029	0.44403	-0.09983	0.587464	0.020619
1180	0.00175	0.91921	-0.00583	0.00388	0.935	-0.04776	0.66544	0.02436
1190	0.000139469	0.047065	-0.00248	0.002001	0.956503	-0.02517	0.631726	0.003806
1200	0.00108	0.46507	-0.0051	0.0065	0.74724	-0.09997	0.69544	0
1210	0.007730468	0.368779	-0.40436	0.005773	0.455134	-0.09851	0.821753	0.054164
1220	0.00158	0.89421	-0.01711	0.00648	1	-0.09121	0.85424	0.01989
1230	0.000169941	0.068692	-0.00075	0.000923	0.32733	-0.0208	0.51042	3.96E-06
1240	0.007924838	0.382941	-0.99294	0	0.824255	-0.95655	0.785832	0.047594
1250	0.006066421	0.876109	-0.05856	0.052019	0.703948	-0.20046	0.712214	0.02908
1260	0.00276	1	-0.02278	0.00079	0.57959	-0.09999	0.63069	0.06253
1270	0	0.5185	-0.09997	0.00062	0.80117	-0.02446	0.63468	0.06167
1280	0.00053	0.08896	-0.01484	0.00465	0.7394	-0.09985	0.65904	0.02187
1290	0.00737	0.74687	-0.0392	0.00611	0.99982	-0.09791	0.69991	0.06605
1300	3.50E-05	0.38184	-0.32794	0.053278	0.480724	-0.25765	0.749534	0.082759

ID	L_d	τ_d	r_d	L_t	τ_t	r_t	L_c	L_s
1310	0.00053	0.99831	0	0.00189	1	-0.00591	0.76252	0
1320	0.000157613	0.054669	-0.00381	0.003256	1	-0.02797	0.745285	0.000166
1330	0.002595669	0.544626	-0.28764	0.013419	0.938522	-0.23361	0.830256	0.039421
1340	0.009623261	0.122442	-0.34406	0	0.638697	-0.72387	0.835283	0.056774
1350	0.0008	0	-0.04204	0.00381	0.53293	-0.07085	0.79912	0.01795
1360	0.00175	0.5547	-0.00796	0.00304	0.9473	-0.0732	0.5615	0.01577
1380	0.006788296	0.760068	-0.36251	0.001231	0.493966	-0.00533	0.679927	0.000674
1400	0.00166	0.80208	-0.009	0.00604	0.85814	-0.09999	0.70282	0.00522
1410	0.009890646	0.35548	-0.23916	0.011418	0.858616	-0.1145	0.822087	0.059489
1420	0.000831587	0.276726	-0.0069	0.001164	0.822304	-0.01865	0.738855	0.004776
1430	0.0027	0.94348	-0.07665	0.00021	0.71184	-0.03603	0.5852	0.05077
1440	0.005451498	0.509417	-0.15559	0	0.916973	-0.7046	0.860895	0.043557
1450	0.000475139	2.93E-18	-0.02905	0.02055	0.905889	-0.14001	0.760985	0.023519
1460	0.000557024	0.345084	-0.00793	0.01186	0.867931	-0.12061	0.831913	0.027932
1480	0.001629417	0.994098	-0.00511	0.005071	0.994295	-0.06761	0.732077	0.012502
1490	0.009427282	0.91183	-1	0.001827	0.955446	-0.006	0.786115	0.037114
1500	0.000557858	0.101136	-0.31427	0.013326	0.78987	-0.13002	0.812731	0.061569
1510	0.00147	0.4437	-0.02401	0.00459	0.69911	-0.06724	0.81484	0.03978
1660	0.000232517	0.011617	-0.02267	0.014948	1	-0.12877	0.814363	0.026393
1670	0.00518	0.97043	-0.02405	0.00335	0.46808	-0.09956	0.49203	0
1680	0.00713	0.87049	-0.0585	0.00394	0.6739	-0.09814	0.76591	0.02578
1690	0.000185465	0.145871	-0.00029	0.099998	1.17E-09	-0.32405	0.814934	0.007841

Table 5. OLS Regression Results for L_c

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.071	0.515	-0.138	0.891
prop_poverty	-0.429	0.150	-2.860	0.005
prop_age_0_24	0.612	0.375	1.633	0.105
prop_age_25_39	0.535	0.208	2.566	0.012
prop_age_40_64	0.410	0.395	1.039	0.301
prop_edu	-0.141	0.879	-0.160	0.873
prop_employ	0.327	0.389	0.841	0.402
prop_R_Manuf	0.110	2.128	0.052	0.959
prop_R_Trade	-2.543	1.495	-1.701	0.092
prop_R_Edu	-0.268	0.975	-0.275	0.784
prop_R_Health	1.623	1.342	1.209	0.229
prop_W_Manuf	-0.038	0.131	-0.287	0.775
prop_W_Trade	0.013	0.017	0.754	0.452
prop_W_Edu	0.021	0.076	0.282	0.778
prop_W_Health	-0.001	0.005	-0.157	0.875
prop_white	0.185	0.099	1.863	0.065
prop_black	0.048	0.080	0.606	0.545
prop_indian.native	1.507	2.353	0.640	0.523
prop_asian	0.322	0.110	2.922	0.004
prop_residential	-0.036	0.124	-0.288	0.774
prop_commerical	-0.131	0.139	-0.942	0.348
prop_institute	-0.081	0.131	-0.617	0.538
prop_industrial	-0.370	0.160	-2.310	0.023
prop_transportation	-0.070	0.162	-0.430	0.668
prop_openspace	-0.149	0.110	-1.352	0.179
LUM	0.088	0.098	0.906	0.367

Table 6. OLS Regression Results for L_d

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.005	0.022	-0.212	0.832
prop_poverty	-0.001	0.006	-0.143	0.887
prop_age_0_24	0.009	0.016	0.556	0.579
prop_age_25_39	0.004	0.009	0.464	0.644
prop_age_40_64	-0.002	0.017	-0.104	0.918
prop_edu	-0.045	0.037	-1.217	0.226
prop_employ	0.011	0.016	0.693	0.490
prop_R_Manuf	-0.040	0.090	-0.442	0.659
prop_R_Trade	-0.107	0.063	-1.685	0.095
prop_R_Edu	0.070	0.041	1.697	0.092
prop_R_Health	0.003	0.057	0.046	0.964
prop_W_Manuf	-0.007	0.006	-1.201	0.232
prop_W_Trade	0.001	0.001	1.811	0.073
prop_W_Edu	-0.004	0.003	-1.405	0.163
prop_W_Health	0.000	0.000	0.250	0.803
prop_white	-0.005	0.004	-1.149	0.253
prop_black	-0.005	0.003	-1.613	0.110
prop_indian.native	-0.223	0.100	-2.233	0.027
prop_asian	0.000	0.005	-0.025	0.980
prop_residential	0.001	0.005	0.169	0.866
prop_commerical	0.002	0.006	0.303	0.763
prop_institute	0.005	0.006	0.852	0.396
prop_industrial	0.004	0.007	0.639	0.524
prop_transportation	0.007	0.007	0.954	0.342
prop_openspace	0.006	0.005	1.331	0.186
LUM	0.001	0.004	0.169	0.866

Table 7. OLS Regression Results for τ_d

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.445	2.818	-0.513	0.609
prop_poverty	0.741	0.821	0.903	0.368
prop_age_0_24	2.593	2.049	1.265	0.208
prop_age_25_39	1.813	1.139	1.592	0.114
prop_age_40_64	2.039	2.158	0.945	0.347
prop_edu	-6.106	4.806	-1.271	0.206
prop_employ	0.107	2.126	0.050	0.960
prop_R_Manuf	5.150	11.634	0.443	0.659
prop_R_Trade	-12.623	8.172	-1.545	0.125
prop_R_Edu	5.254	5.332	0.985	0.327
prop_R_Health	3.086	7.340	0.420	0.675
prop_W_Manuf	0.758	0.718	1.056	0.293
prop_W_Trade	0.116	0.092	1.266	0.208
prop_W_Edu	-0.356	0.413	-0.862	0.391
prop_W_Health	0.024	0.029	0.821	0.414
prop_white	0.149	0.544	0.274	0.784
prop_black	-0.385	0.437	-0.882	0.379
prop_indian.native	-8.292	12.868	-0.644	0.521
prop_asian	0.571	0.602	0.948	0.345
prop_residential	-0.673	0.679	-0.992	0.323
prop_commerical	-0.703	0.758	-0.927	0.356
prop_institute	-0.517	0.719	-0.719	0.474
prop_industrial	-0.760	0.876	-0.867	0.388
prop_transportation	-0.338	0.888	-0.380	0.704
prop_openspace	0.514	0.603	0.853	0.396
LUM	0.613	0.534	1.149	0.253

Table 8. OLS Regression Results for r_d

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.810	2.198	0.823	0.412
prop_poverty	0.354	0.640	0.554	0.581
prop_age_0_24	-1.110	1.598	-0.695	0.489
prop_age_25_39	-0.908	0.888	-1.022	0.309
prop_age_40_64	-0.020	1.683	-0.012	0.991
prop_edu	3.435	3.748	0.916	0.361
prop_employ	-0.981	1.658	-0.592	0.555
prop_R_Manuf	-2.713	9.073	-0.299	0.765
prop_R_Trade	10.405	6.374	1.632	0.105
prop_R_Edu	-6.620	4.159	-1.592	0.114
prop_R_Health	0.402	5.725	0.070	0.944
prop_W_Manuf	0.613	0.560	1.095	0.276
prop_W_Trade	-0.195	0.072	-2.719	0.008
prop_W_Edu	0.441	0.322	1.368	0.174
prop_W_Health	-0.005	0.023	-0.203	0.840
prop_white	-0.108	0.424	-0.255	0.799
prop_black	-0.411	0.340	-1.208	0.230
prop_indian.native	8.524	10.036	0.849	0.397
prop_asian	-0.543	0.470	-1.155	0.250
prop_residential	-1.138	0.529	-2.149	0.034
prop_commerical	-0.922	0.591	-1.559	0.122
prop_institute	-0.932	0.561	-1.663	0.099
prop_industrial	-0.855	0.683	-1.251	0.213
prop_transportation	-1.332	0.693	-1.923	0.057
prop_openspace	-1.161	0.470	-2.467	0.015
LUM	0.142	0.416	0.342	0.733

Table 9. OLS Regression Results for L_t

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0276	0.0846	0.3269	0.7444
prop_poverty	0.0212	0.0246	0.8593	0.3920
prop_age_0_24	-0.0294	0.0615	-0.4782	0.6334
prop_age_25_39	-0.0109	0.0342	-0.3187	0.7506
prop_age_40_64	0.0242	0.0648	0.3732	0.7097
prop_edu	0.0189	0.1442	0.1314	0.8957
prop_employ	-0.0524	0.0638	-0.8215	0.4130
prop_R_Manuf	-0.1308	0.3491	-0.3746	0.7086
prop_R_Trade	-0.3310	0.2452	-1.3498	0.1797
prop_R_Edu	0.3789	0.1600	2.3679	0.0196
prop_R_Health	0.0451	0.2203	0.2046	0.8382
prop_W_Manuf	-0.0038	0.0215	-0.1786	0.8586
prop_W_Trade	0.0003	0.0028	0.1195	0.9051
prop_W_Edu	-0.0111	0.0124	-0.8951	0.3726
prop_W_Health	0.0008	0.0009	0.9296	0.3545
prop_white	0.0082	0.0163	0.5044	0.6149
prop_black	-0.0065	0.0131	-0.4973	0.6199
prop_indian.native	-0.4632	0.3861	-1.1996	0.2328
prop_asian	0.0136	0.0181	0.7551	0.4517
prop_residential	0.0130	0.0204	0.6358	0.5262
prop_commerical	0.0596	0.0228	2.6194	0.0100
prop_institute	0.0232	0.0216	1.0777	0.2834
prop_industrial	0.0021	0.0263	0.0796	0.9367
prop_transportation	0.0335	0.0267	1.2560	0.2116
prop_openspace	0.0088	0.0181	0.4866	0.6275
LUM	0.0095	0.0160	0.5912	0.5555

Table 10. OLS Regression Results for τ_t

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.083	2.248	1.372	0.173
prop_poverty	0.232	0.654	0.355	0.723
prop_age_0_24	-0.970	1.635	-0.593	0.554
prop_age_25_39	-0.154	0.909	-0.170	0.866
prop_age_40_64	-0.024	1.721	-0.014	0.989
prop_edu	2.481	3.833	0.647	0.519
prop_employ	-1.663	1.696	-0.981	0.329
prop_R_Manuf	-16.648	9.279	-1.794	0.075
prop_R_Trade	20.749	6.518	3.183	0.002
prop_R_Edu	3.532	4.253	0.830	0.408
prop_R_Health	-11.161	5.855	-1.906	0.059
prop_W_Manuf	0.052	0.573	0.091	0.928
prop_W_Trade	-0.116	0.073	-1.589	0.115
prop_W_Edu	0.455	0.330	1.380	0.170
prop_W_Health	0.010	0.023	0.422	0.674
prop_white	-0.374	0.434	-0.861	0.391
prop_black	-0.277	0.348	-0.797	0.427
prop_indian.native	-11.660	10.263	-1.136	0.258
prop_asian	-0.195	0.480	-0.405	0.686
prop_residential	-0.051	0.541	-0.094	0.925
prop_commerical	0.090	0.605	0.148	0.882
prop_institute	-0.054	0.573	-0.094	0.926
prop_industrial	0.463	0.699	0.662	0.509
prop_transportation	0.025	0.708	0.036	0.971
prop_openspace	0.057	0.481	0.118	0.906
LUM	-0.856	0.426	-2.012	0.047

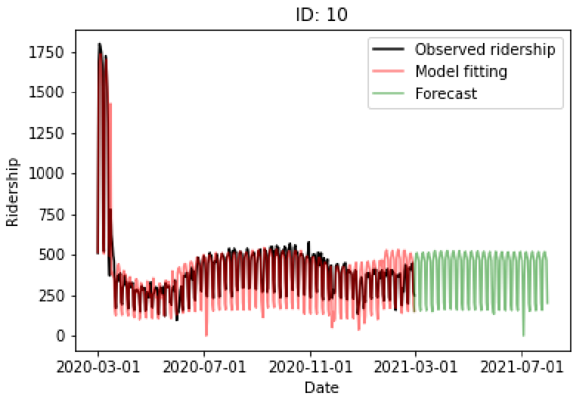
Table 11. OLS Regression Results for r_t

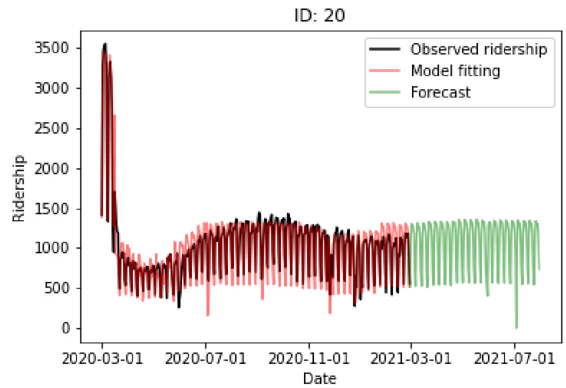
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.9527	1.7869	0.5331	0.5950
prop_poverty	0.8635	0.5202	1.6599	0.0997
prop_age_0_24	-1.2670	1.2994	-0.9750	0.3316
prop_age_25_39	-0.9783	0.7223	-1.3545	0.1782
prop_age_40_64	-2.0133	1.3684	-1.4712	0.1440
prop_edu	0.2824	3.0470	0.0927	0.9263
prop_employ	-0.3002	1.3479	-0.2227	0.8242
prop_R_Manuf	0.2390	7.3762	0.0324	0.9742
prop_R_Trade	9.7921	5.1815	1.8898	0.0613
prop_R_Edu	-1.7430	3.3810	-0.5155	0.6072
prop_R_Health	-4.3945	4.6540	-0.9442	0.3470
prop_W_Manuf	0.2947	0.4552	0.6475	0.5186
prop_W_Trade	-0.0781	0.0582	-1.3411	0.1825
prop_W_Edu	0.2720	0.2621	1.0379	0.3015
prop_W_Health	0.0051	0.0183	0.2799	0.7800
prop_white	0.2330	0.3450	0.6754	0.5008
prop_black	0.0992	0.2768	0.3584	0.7207
prop_indian.native	5.3460	8.1586	0.6553	0.5136
prop_asian	0.1284	0.3818	0.3363	0.7373
prop_residential	0.2324	0.4304	0.5399	0.5903
prop_commerical	0.4635	0.4807	0.9641	0.3370
prop_institute	0.1385	0.4557	0.3038	0.7618
prop_industrial	0.6188	0.5556	1.1138	0.2677
prop_transportation	0.0821	0.5631	0.1458	0.8843
prop_openspace	0.2109	0.3823	0.5517	0.5823
LUM	-0.3886	0.3383	-1.1488	0.2530

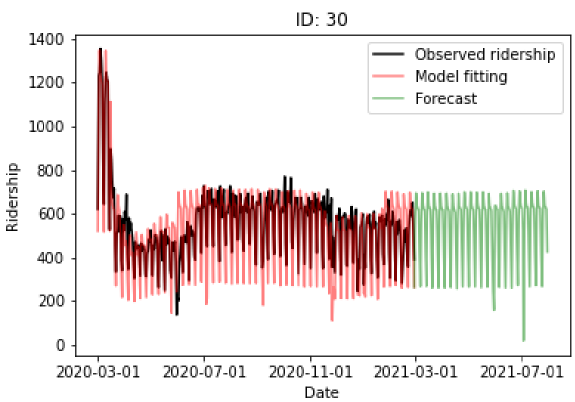
Table 12. OLS Regression Results for L_s

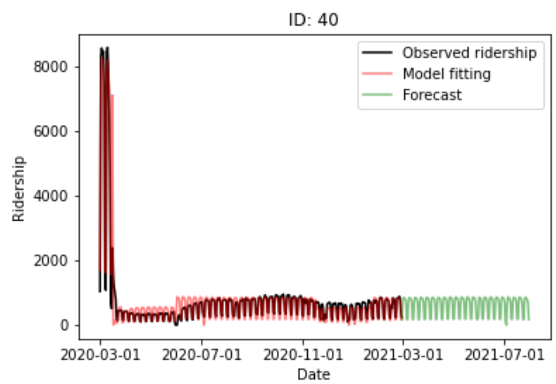
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.43	0.188	2.31	0.02
prop_poverty	-0.12	0.055	-2.20	0.03
prop_age_0_24	-0.20	0.137	-1.45	0.15
prop_age_25_39	-0.01	0.076	-0.08	0.93
prop_age_40_64	-0.14	0.144	-0.97	0.34
prop_edu	0.37	0.321	1.15	0.25
prop_employ	-0.27	0.142	-1.92	0.06
prop_R_Manuf	0.16	0.778	0.20	0.84
prop_R_Trade	-0.46	0.546	-0.85	0.40
prop_R_Edu	0.34	0.356	0.94	0.35
prop_R_Health	0.08	0.491	0.17	0.86
prop_W_Manuf	-0.04	0.048	-0.89	0.38
prop_W_Trade	0.01	0.006	1.38	0.17
prop_W_Edu	-0.05	0.028	-1.88	0.06
prop_W_Health	0.00	0.002	0.53	0.60
prop_white	-0.10	0.036	-2.70	0.01
prop_black	-0.04	0.029	-1.43	0.15
prop_indian.native	-0.09	0.860	-0.11	0.91
prop_asian	-0.04	0.040	-0.94	0.35
prop_residential	0.02	0.045	0.39	0.70
prop_commerical	0.02	0.051	0.30	0.77
prop_institute	0.09	0.048	1.78	0.08
prop_industrial	0.01	0.059	0.22	0.83
prop_transportation	0.04	0.059	0.66	0.51
prop_openspace	0.05	0.040	1.34	0.18
LUM	-0.04	0.036	-1.08	0.28

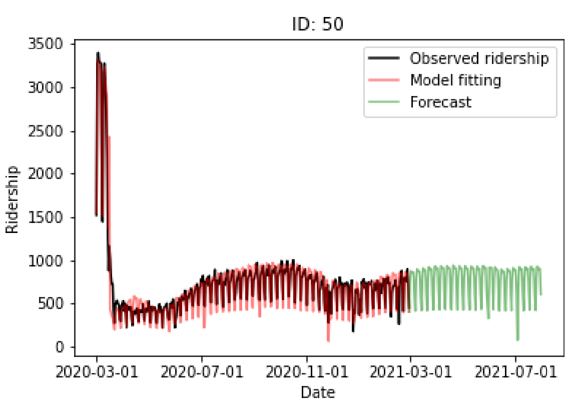
All the fitted curves fitted with the dynamics models for ridership reduction, along with their forecasts are presented below. The name of each figure represents its station ID.

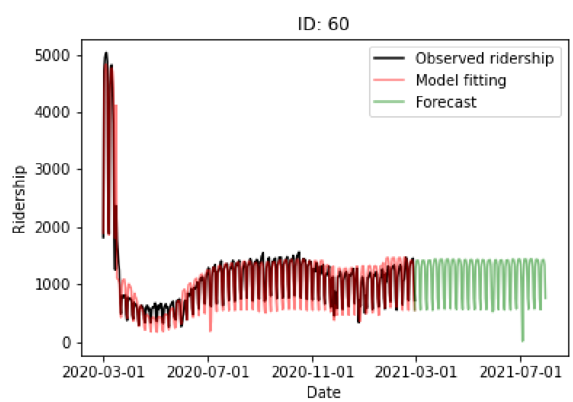


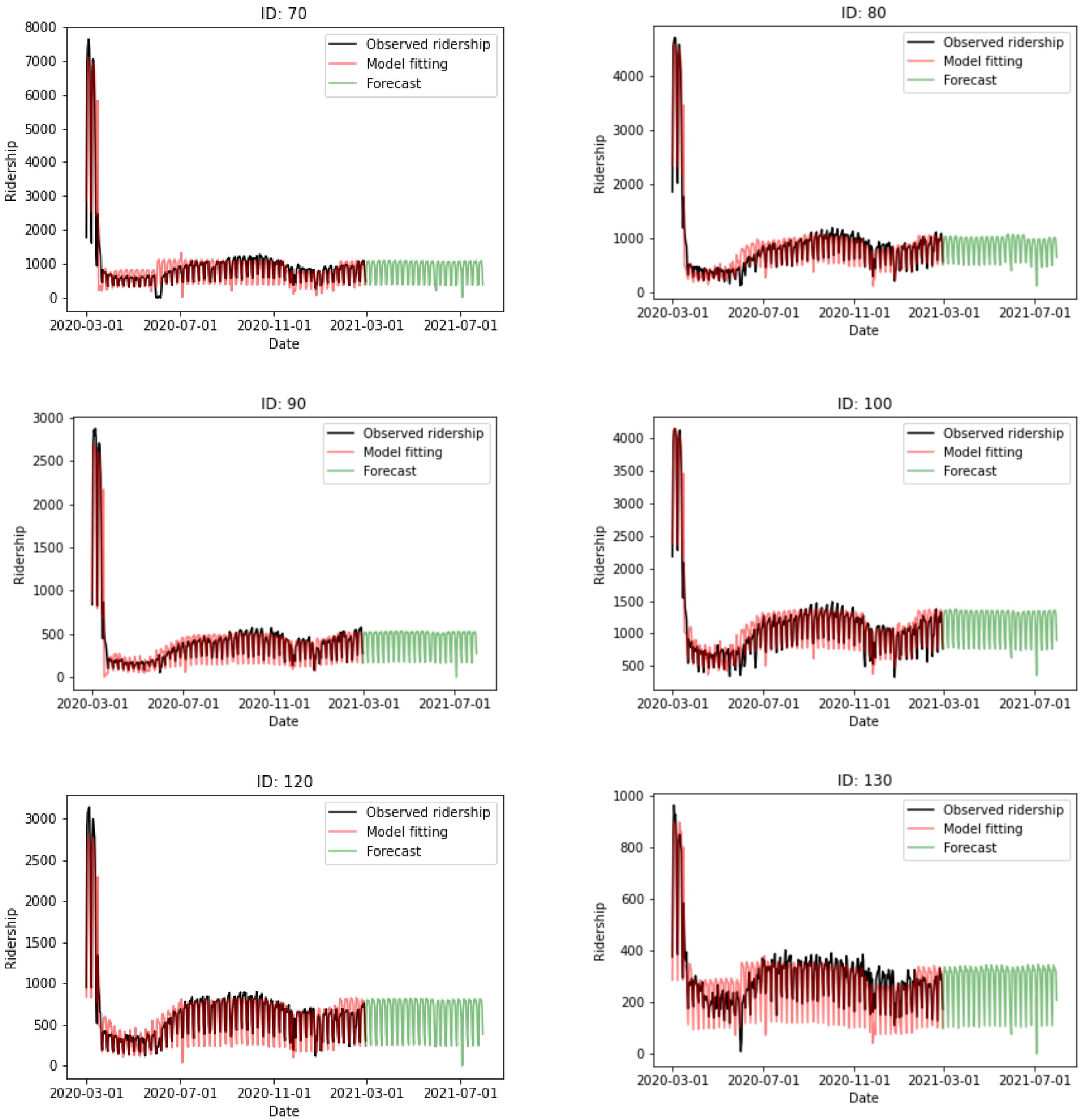








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Forecast
Ridership
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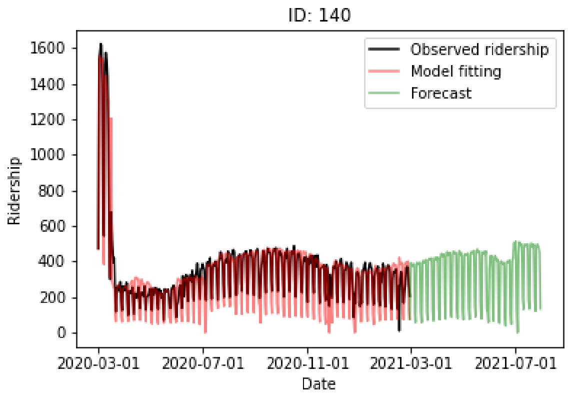
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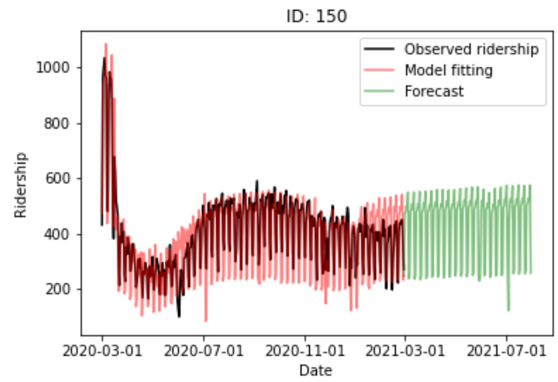
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Forecast
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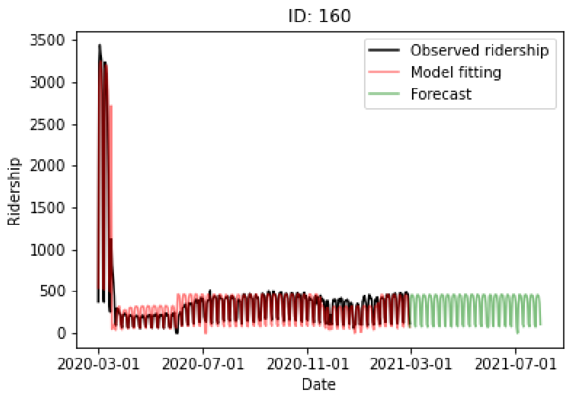
2021-07-01


ID: 160
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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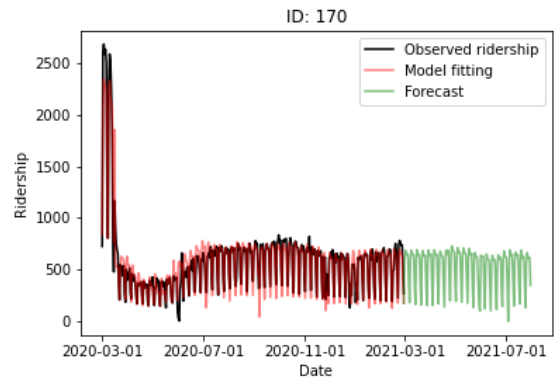
2021-07-01


ID: 170
Observed ridership
Model fitting
Forecast
Ridership
Date
2020-03-01
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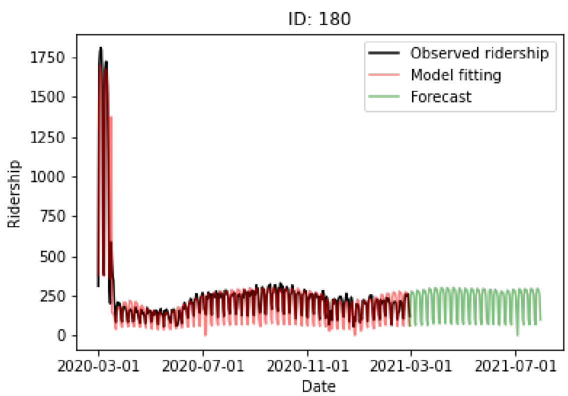
ID: 180
Observed ridership
Model fitting
Forecast
Ridership
Date
2020-03-01
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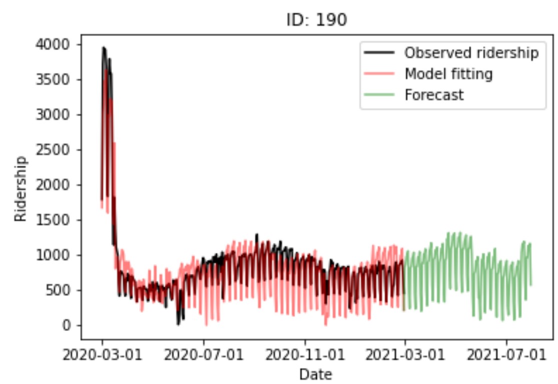
ID: 190
Observed ridership
Model fitting
Forecast
Ridership
Date
2020-03-01
2020-07-01
2020-11-01
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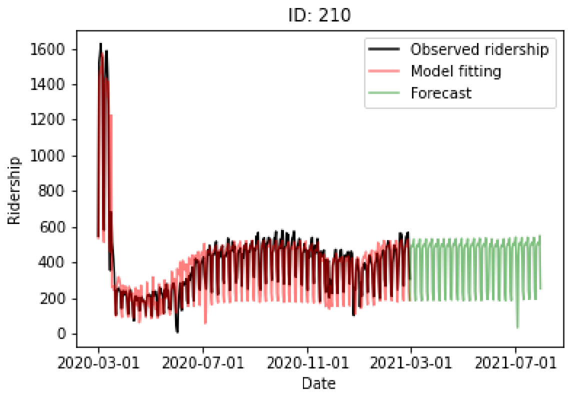
ID: 210
Observed ridership
Model fitting
Forecast
Ridership
Date
0
200
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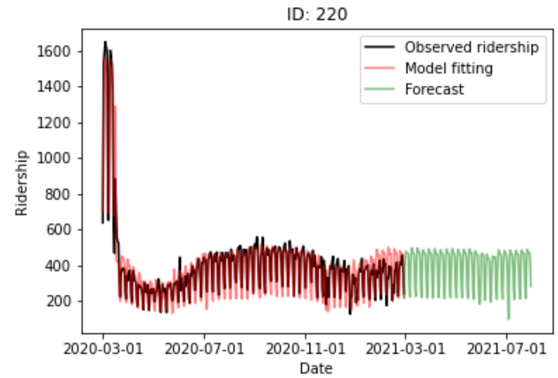
2020-11-01
2021-03-01
2021-07-01


ID: 220
Observed ridership
Model fitting
Forecast
Ridership
Date
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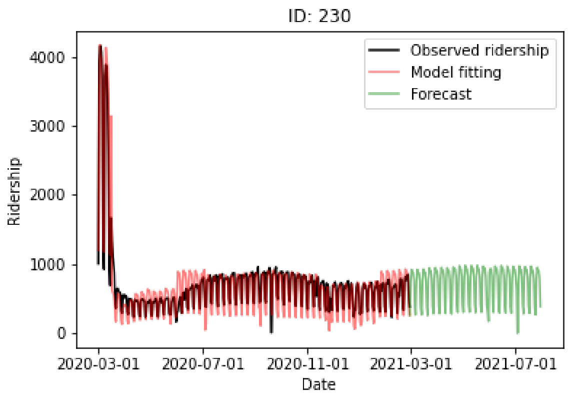
2021-07-01


ID: 230
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-03-01
2020-07-01
2020-11-01
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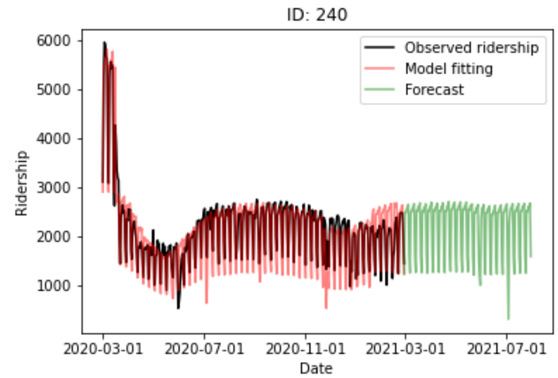
2021-07-01


ID: 240
Observed ridership
Model fitting
Forecast
Ridership
Date
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4000
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2020-11-01
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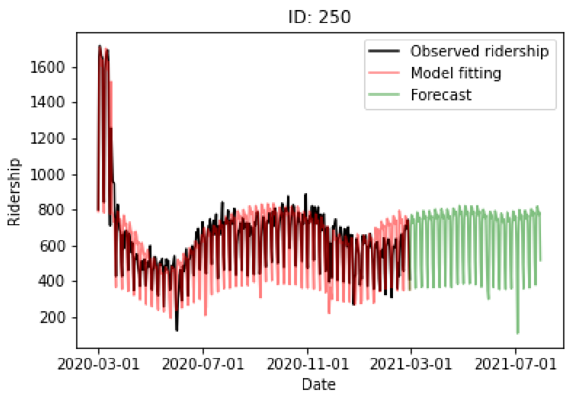
2021-07-01


ID: 250
Observed ridership
Model fitting
Forecast
Ridership
Date
200
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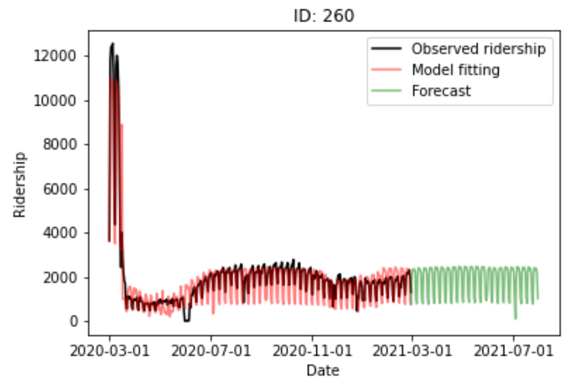
2021-03-01
2021-07-01


ID: 260
Observed ridership
Model fitting
Forecast
Ridership
Date
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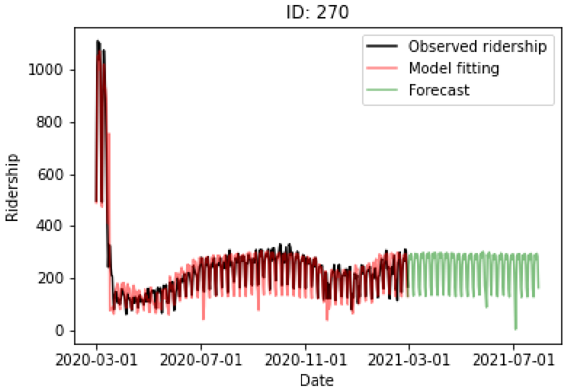
2021-07-01


ID: 270
Observed ridership
Model fitting
Forecast
Ridership
Date
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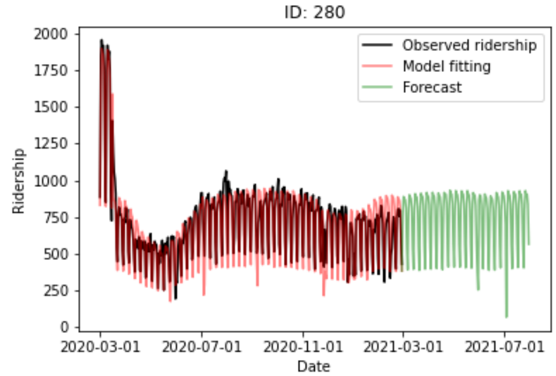
2021-07-01


ID: 280
Observed ridership
Model fitting
Forecast
Ridership
Date
0
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1750
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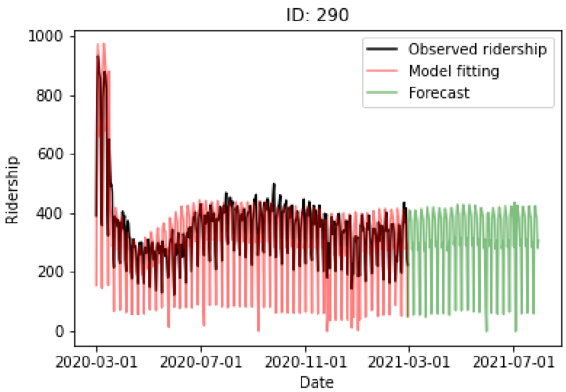
2020-11-01
2021-03-01
2021-07-01


ID: 290
Observed ridership
Model fitting
Forecast
Ridership
Date
0
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2020-03-01
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2020-11-01
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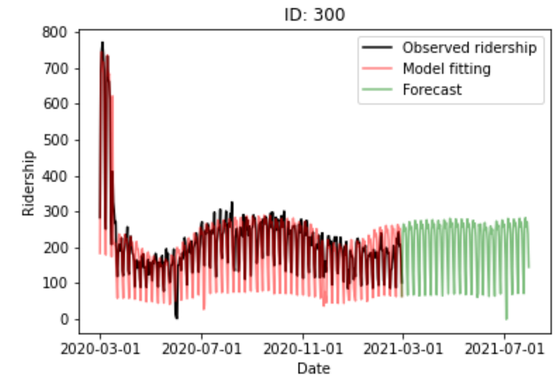
2021-07-01


ID: 300
Observed ridership
Model fitting
Forecast
Ridership
Date
0
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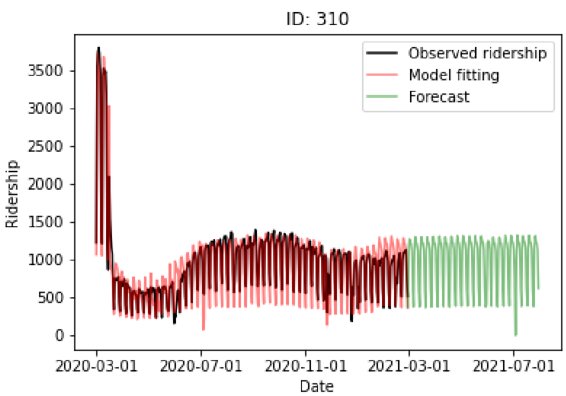
2020-11-01
2021-03-01
2021-07-01


ID: 310
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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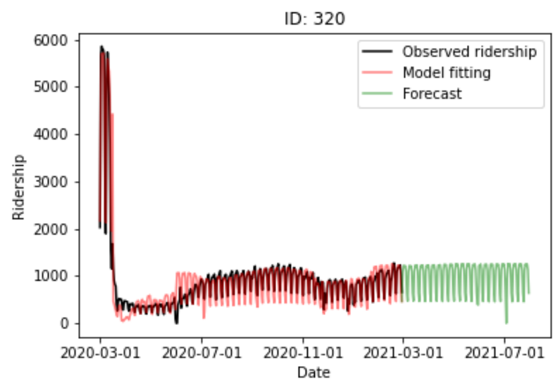
2021-07-01


ID: 320
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-03-01
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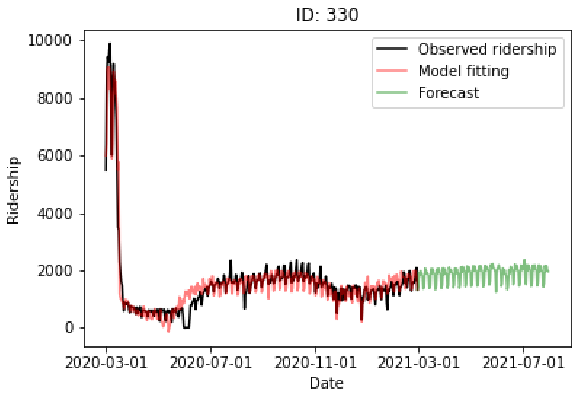
2021-03-01
2021-07-01


ID: 330
Observed ridership
Model fitting
Forecast
Ridership
10000
8000
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4000
2000
0
2020-03-01
2020-07-01
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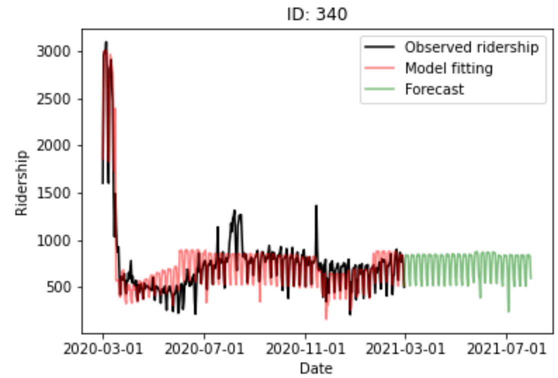
2021-07-01
Date


ID: 340
Observed ridership
Model fitting
Forecast
Ridership
3000
2500
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1500
1000
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2020-11-01
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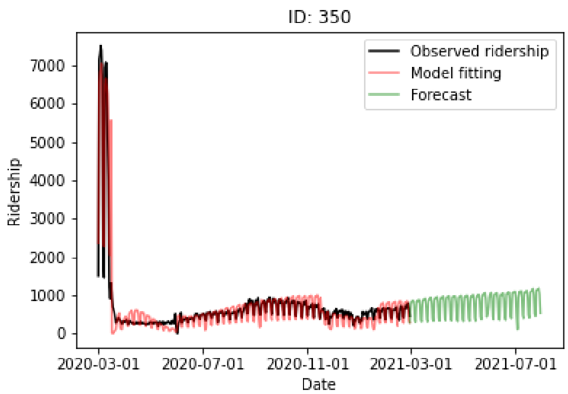
2021-07-01
Date


ID: 350
Observed ridership
Model fitting
Forecast
Ridership
7000
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5000
4000
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2000
1000
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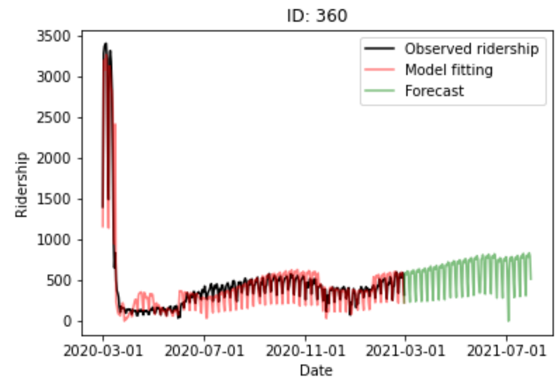
2021-07-01
Date


ID: 360
Observed ridership
Model fitting
Forecast
Ridership
3500
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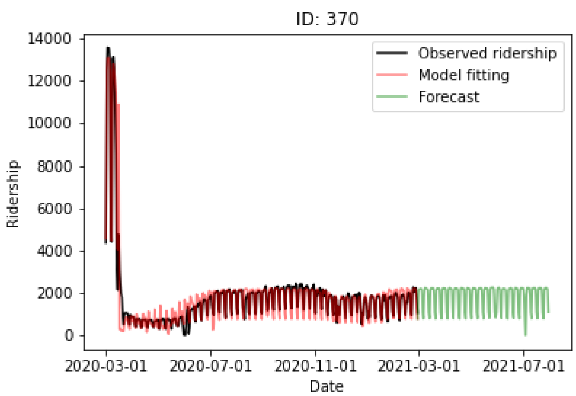
2021-07-01
Date


ID: 370
Observed ridership
Model fitting
Forecast
Ridership
14000
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4000
2000
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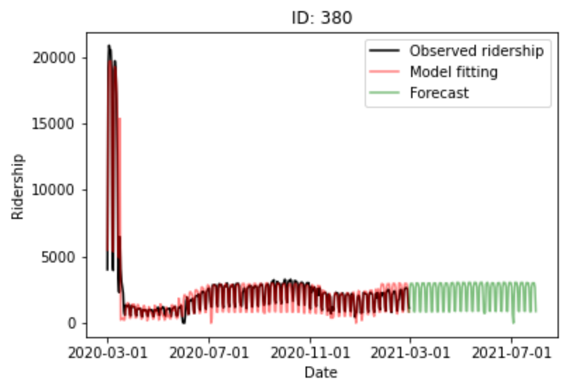
2021-07-01
Date


ID: 380
Observed ridership
Model fitting
Forecast
Ridership
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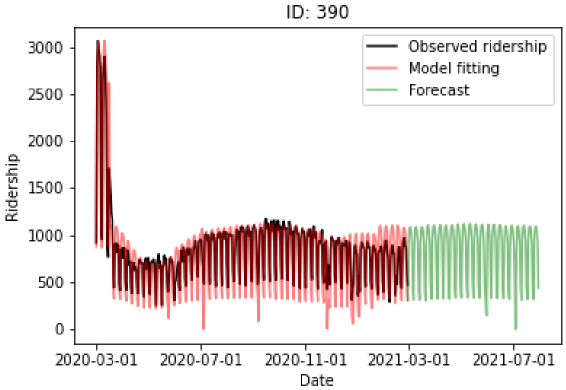
2021-07-01
Date


ID: 390
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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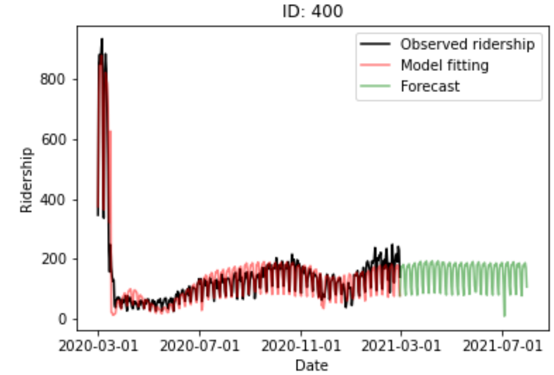
2021-07-01


ID: 400
Observed ridership
Model fitting
Forecast
Ridership
Date
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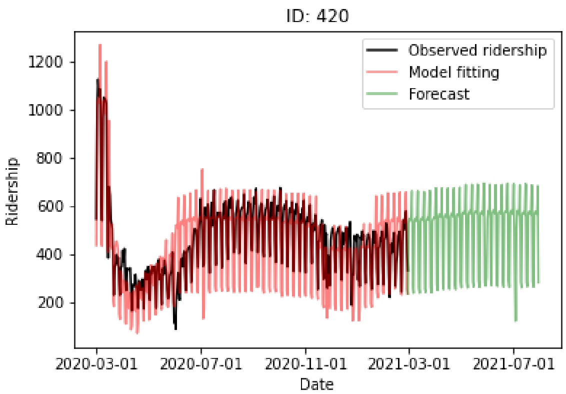
2021-07-01


ID: 420
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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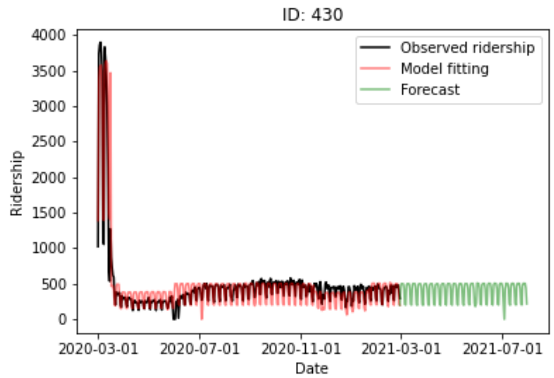
ID: 430
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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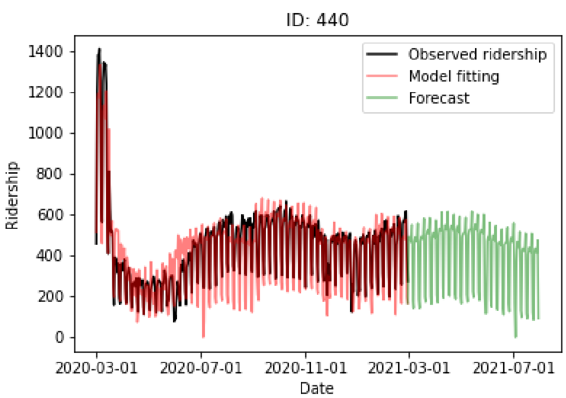
ID: 440
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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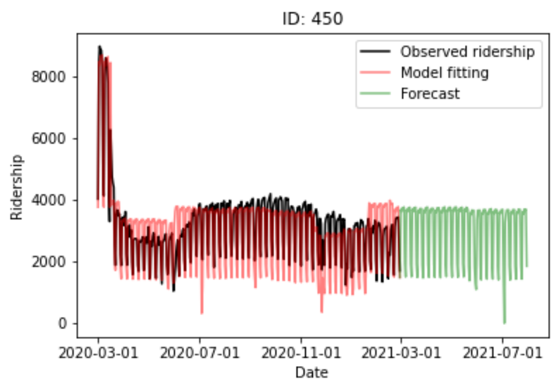
ID: 450
Observed ridership
Model fitting
Forecast
Ridership
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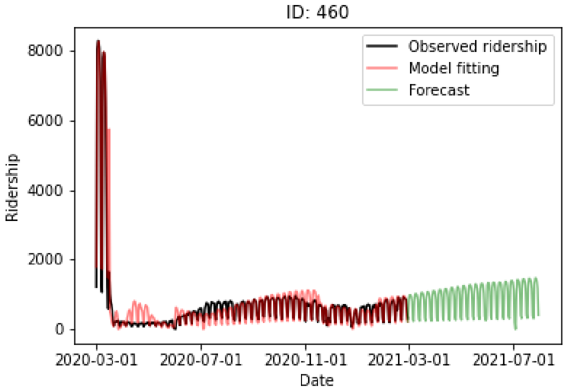
ID: 460
Observed ridership
Model fitting
Forecast
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2021-07-01
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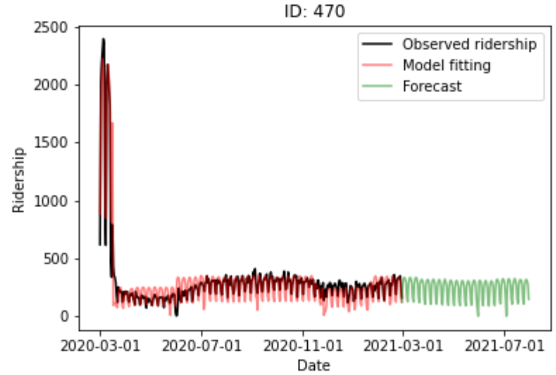
ID: 470
Observed ridership
Model fitting
Forecast
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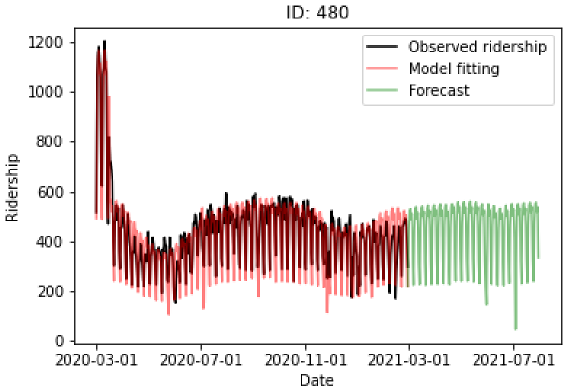
ID: 480
Observed ridership
Model fitting
Forecast
Ridership
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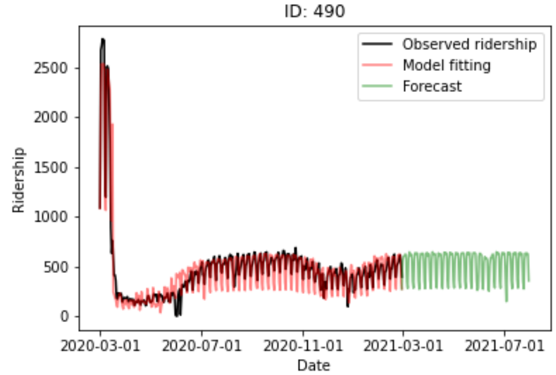
ID: 490
Observed ridership
Model fitting
Forecast
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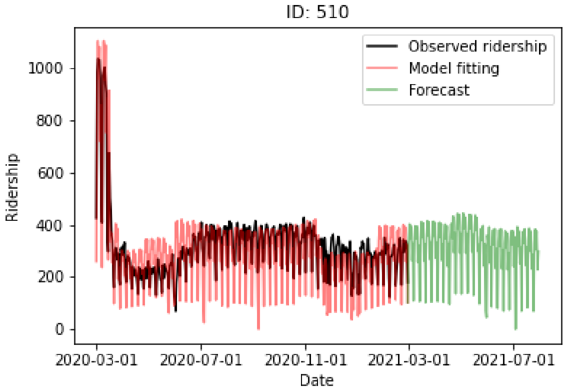
ID: 510
Observed ridership
Model fitting
Forecast
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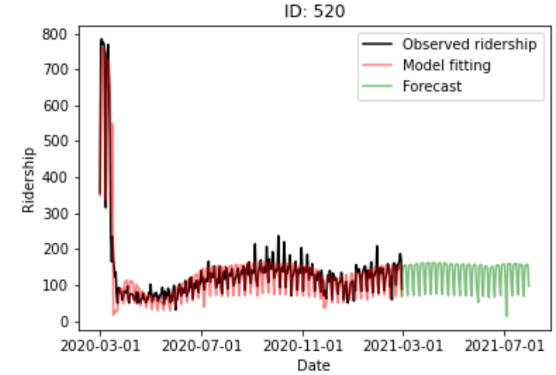
ID: 520
Observed ridership
Model fitting
Forecast
Ridership
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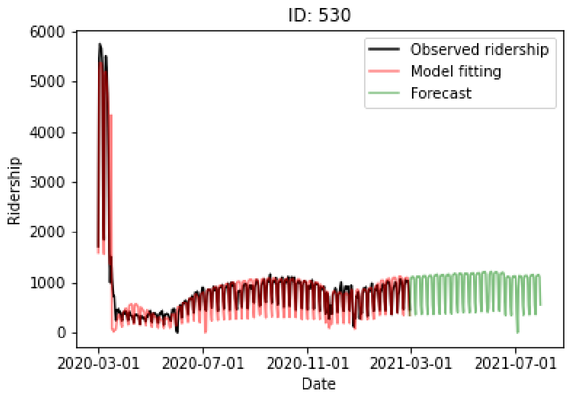
Date


ID: 530
Observed ridership
Model fitting
Forecast
Ridership
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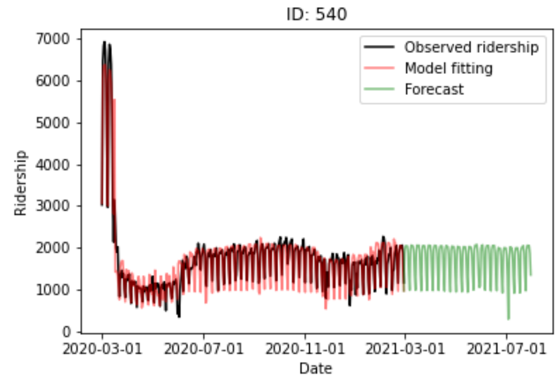
Date


ID: 540
Observed ridership
Model fitting
Forecast
Ridership
0
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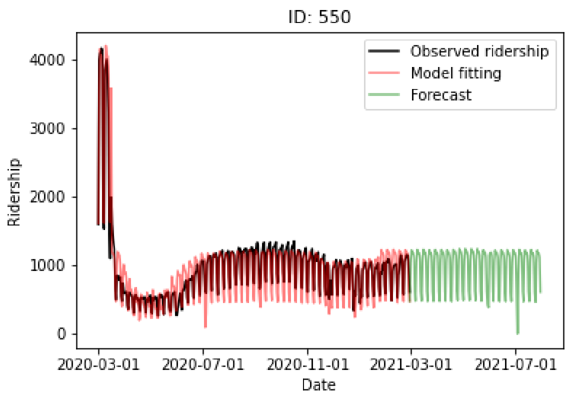
2021-07-01
Date


ID: 550
Observed ridership
Model fitting
Forecast
Ridership
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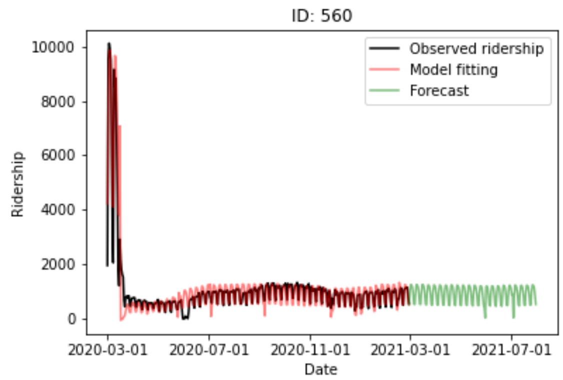
2021-07-01
Date


ID: 560
Observed ridership
Model fitting
Forecast
Ridership
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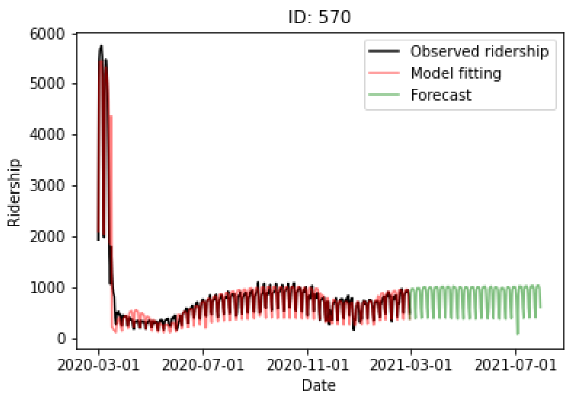
ID: 570
Observed ridership
Model fitting
Forecast
Ridership
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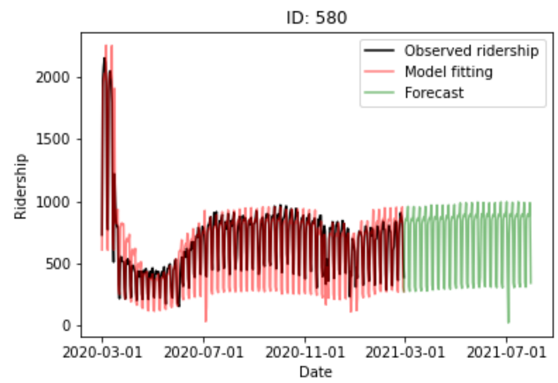
ID: 580
Observed ridership
Model fitting
Forecast
Ridership
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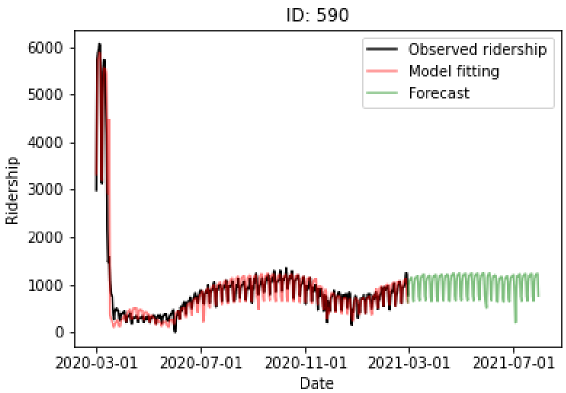
Date


ID: 590
Observed ridership
Model fitting
Forecast
Ridership
Date
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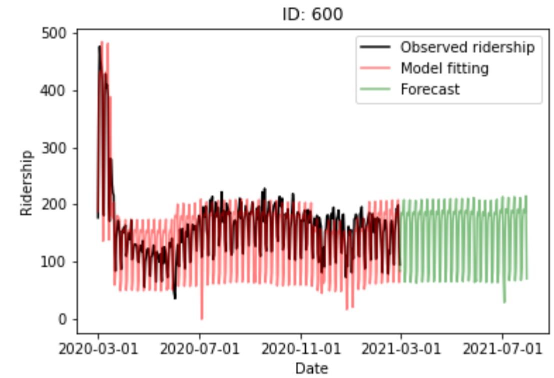
ID: 600
Observed ridership
Model fitting
Forecast
Ridership
Date
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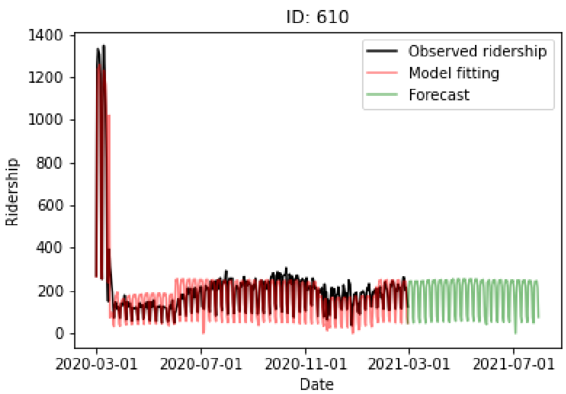
ID: 610
Observed ridership
Model fitting
Forecast
Ridership
Date
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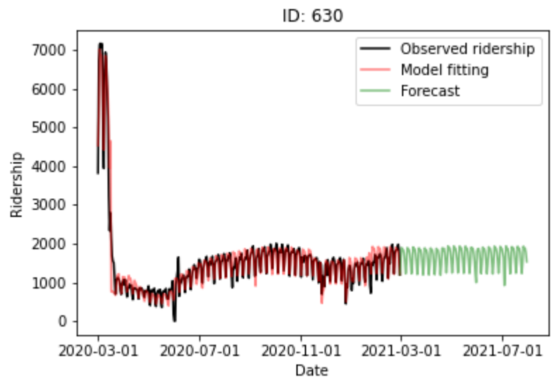
ID: 630
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-11-01
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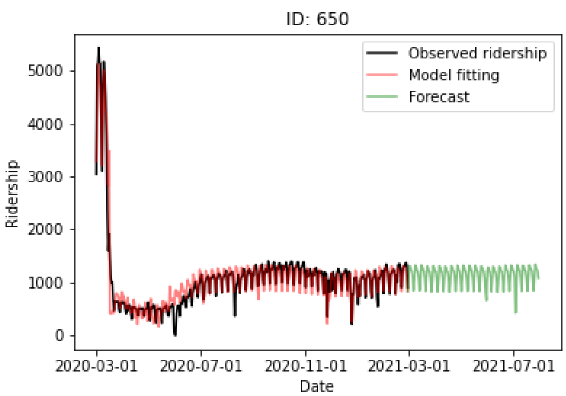
ID: 650
Observed ridership
Model fitting
Forecast
Ridership
Date
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2020-07-01
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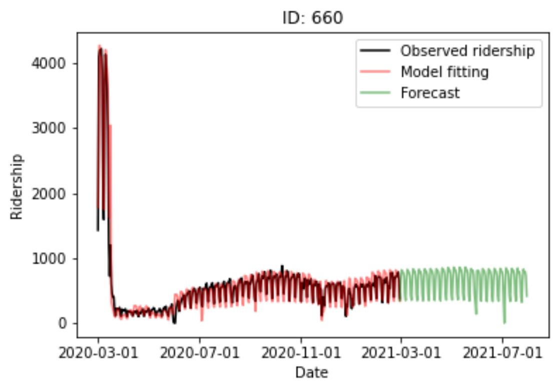
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Observed ridership
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Forecast
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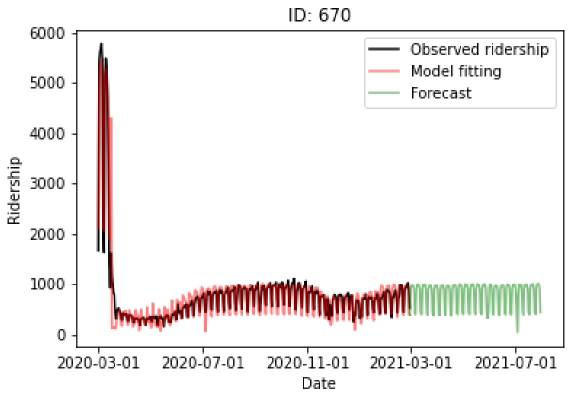
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Model fitting
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Ridership
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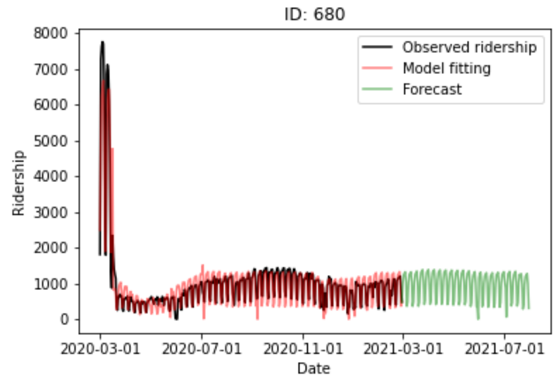
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Model fitting
Forecast
Ridership
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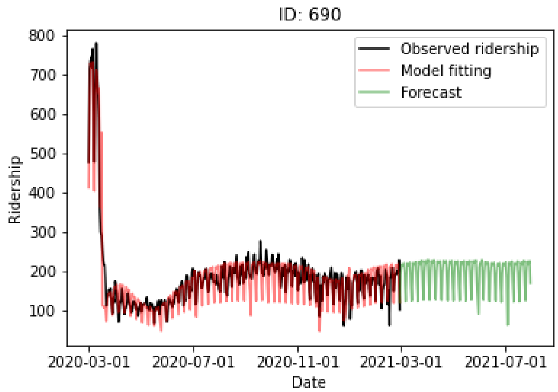
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Model fitting
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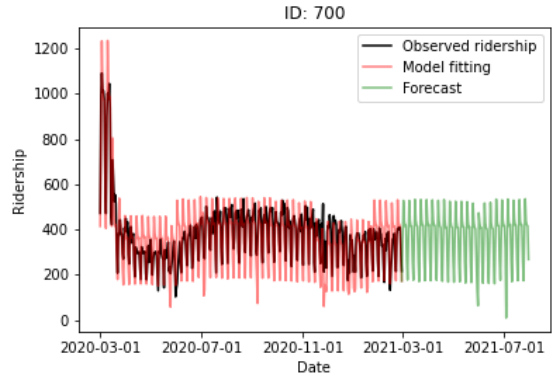
Ridership
Date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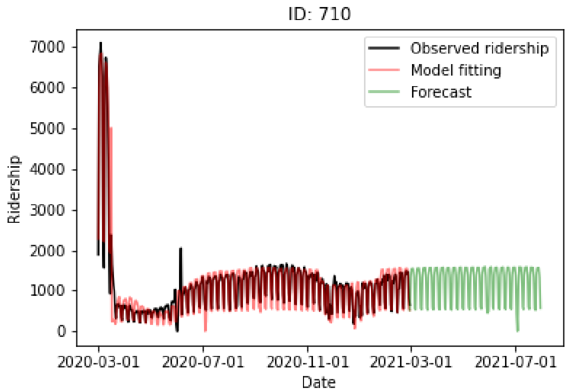
Ridership
Date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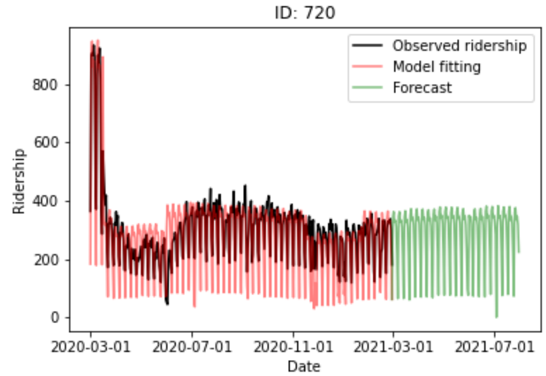
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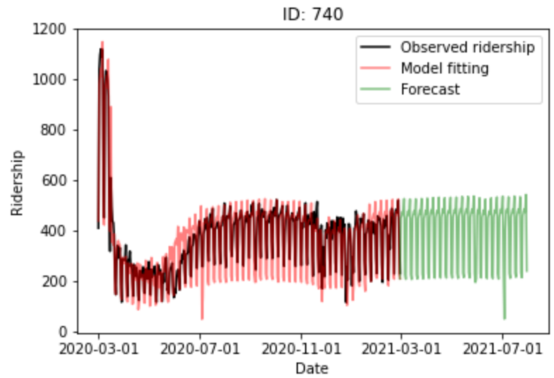
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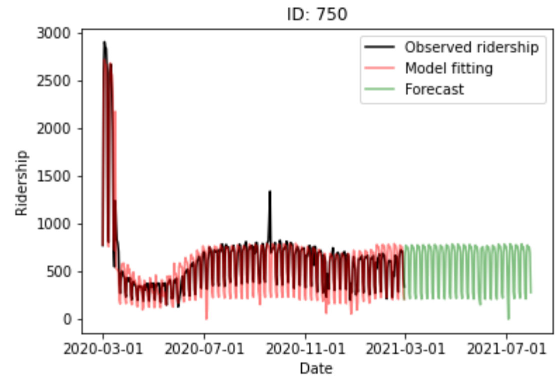
Model fitting
Forecast
Ridership
Date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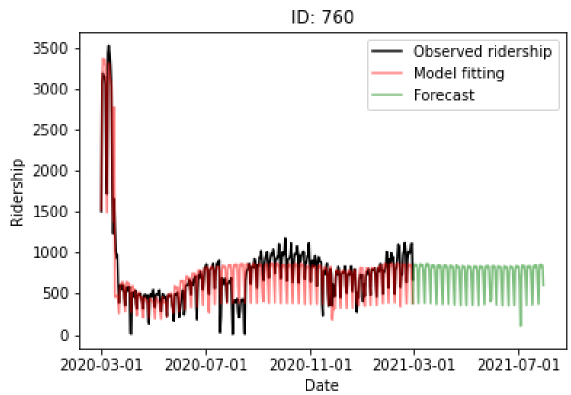
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Ridership
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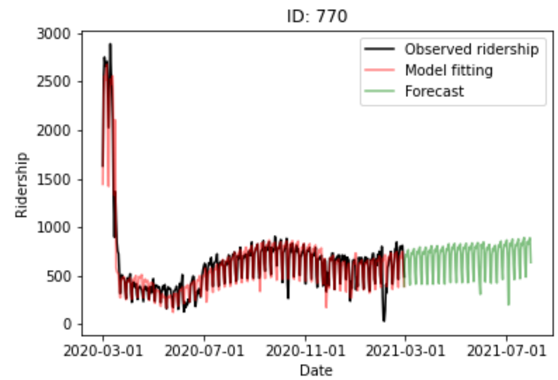
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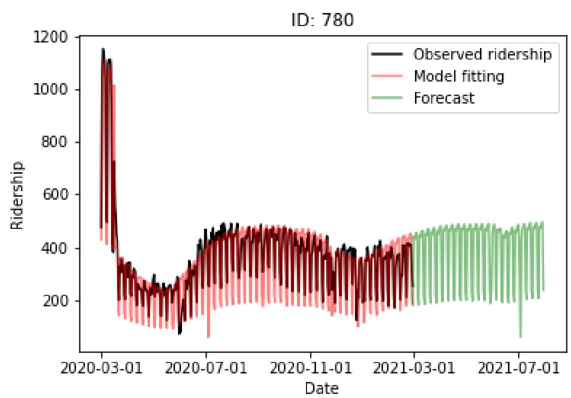
Model fitting
Forecast
Ridership
Date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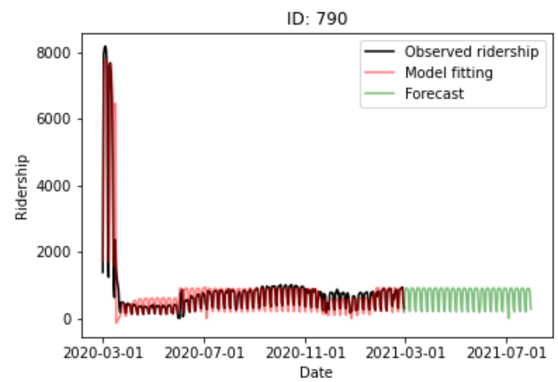
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Model fitting
Forecast
Ridership
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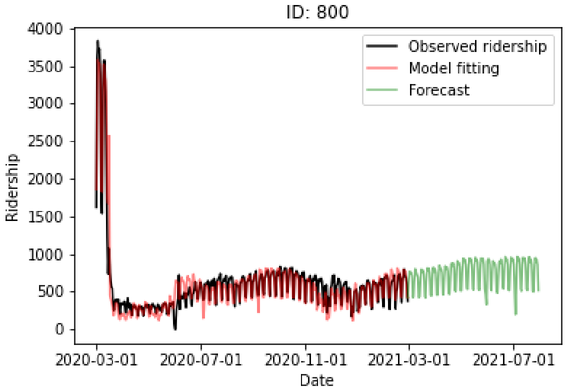
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Model fitting
Forecast
Ridership
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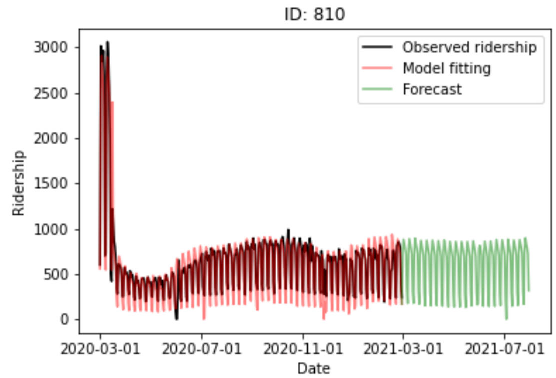
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Model fitting
Forecast
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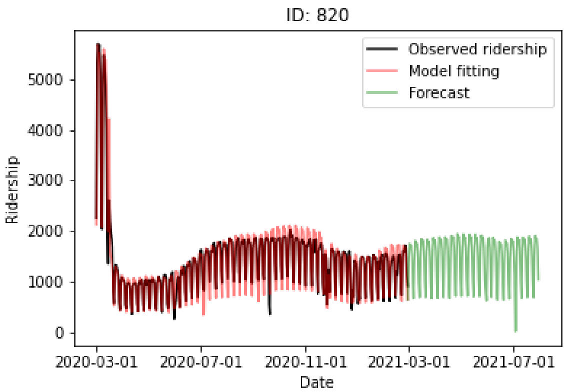
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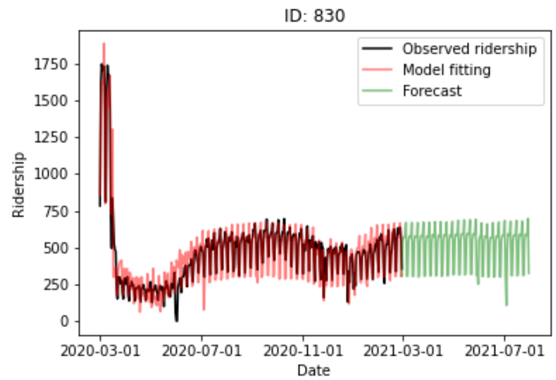
ID: 830
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Model fitting
Forecast
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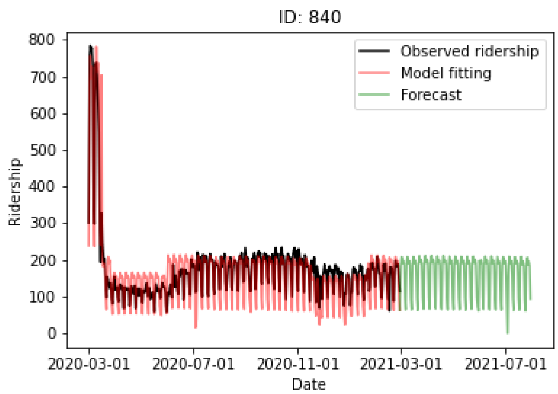
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Observed ridership
Model fitting
Forecast
Ridership
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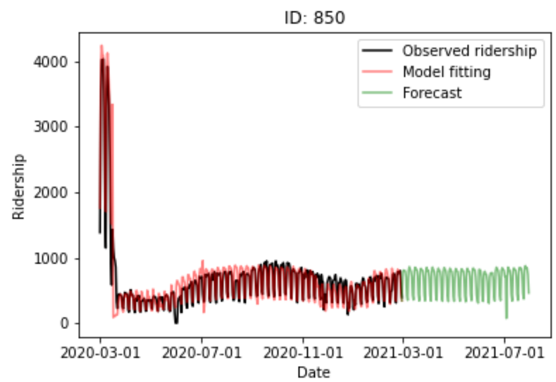
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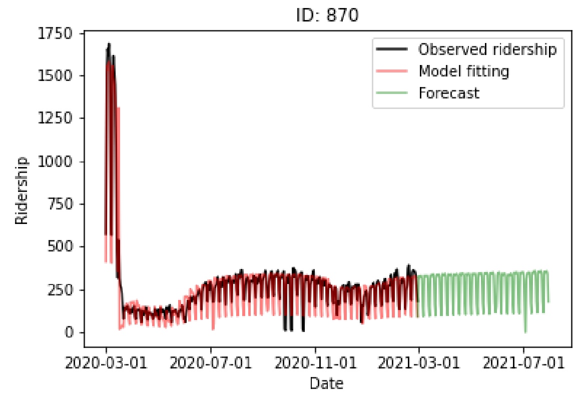
ID: 870
Observed ridership
Model fitting
Forecast
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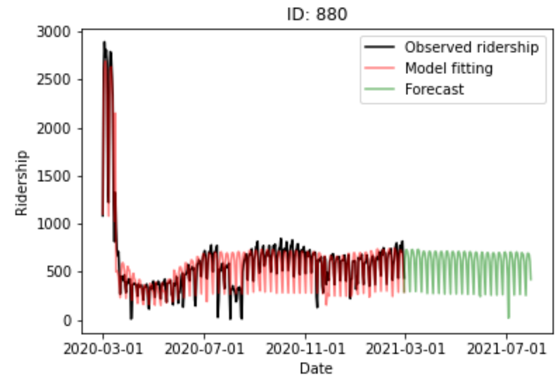
ID: 880
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Model fitting
Forecast
Ridership
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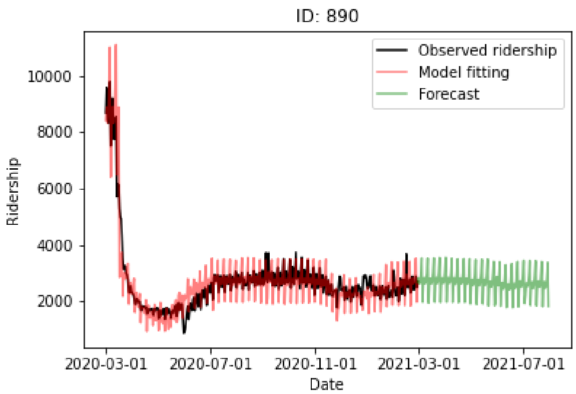
ID: 890
Observed ridership
Model fitting
Forecast
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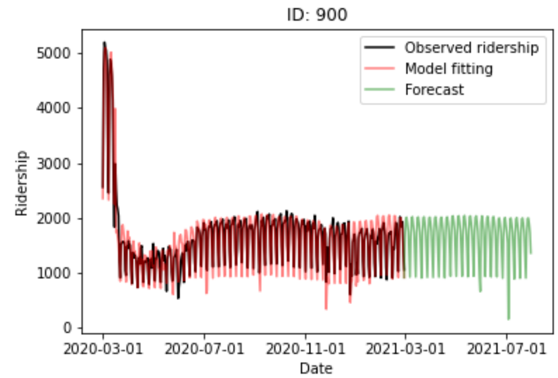
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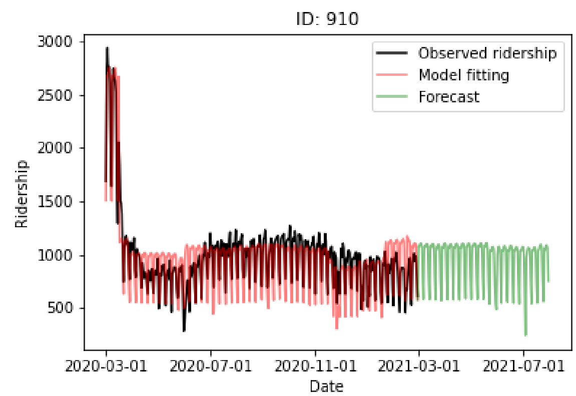
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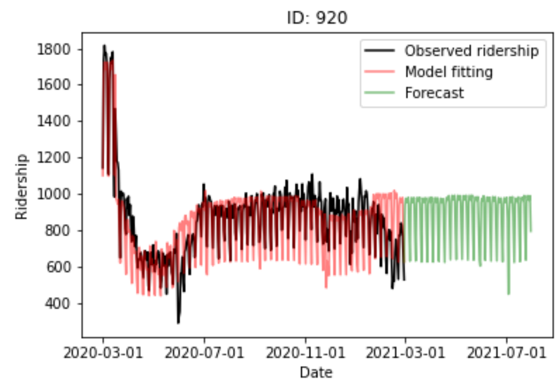
ID: 920
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Model fitting
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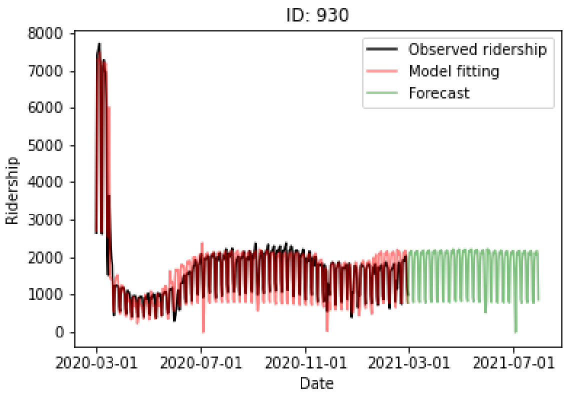
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Observed ridership
Model fitting
Forecast
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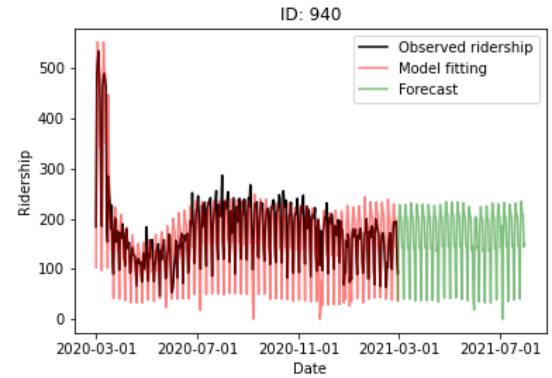
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Observed ridership
Model fitting
Forecast
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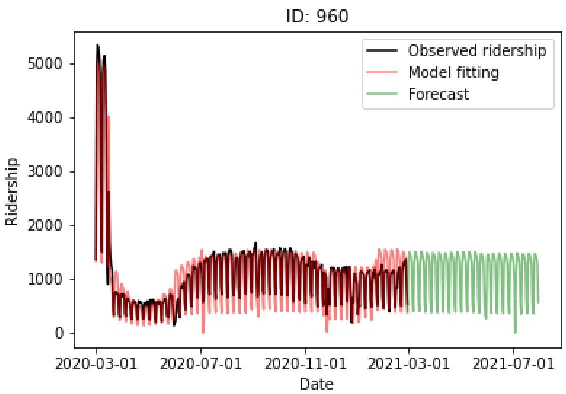
ID: 960
Observed ridership
Model fitting
Forecast
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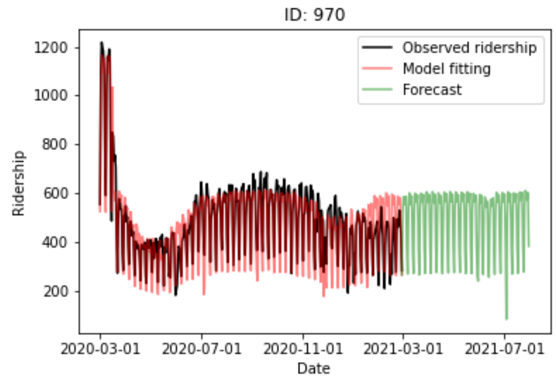
ID: 970
Observed ridership
Model fitting
Forecast
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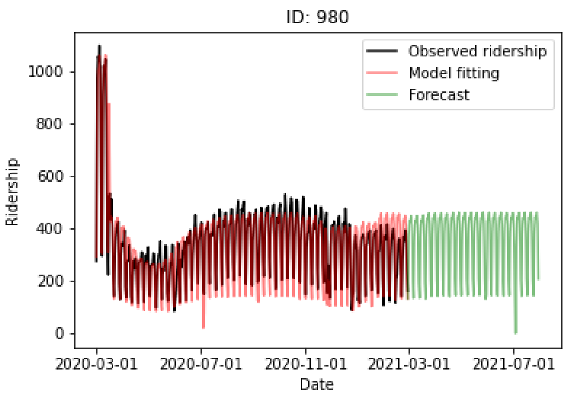
ID: 980
Observed ridership
Model fitting
Forecast
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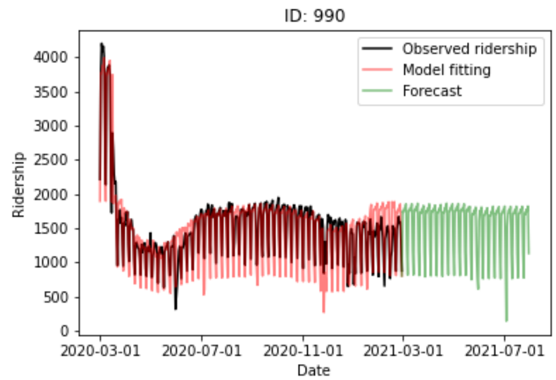
ID: 990
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Model fitting
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Ridership
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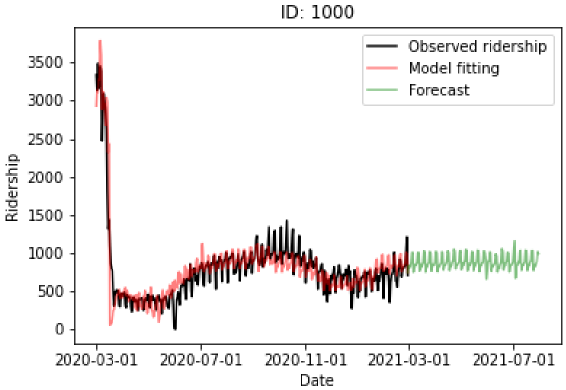
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Model fitting
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Ridership
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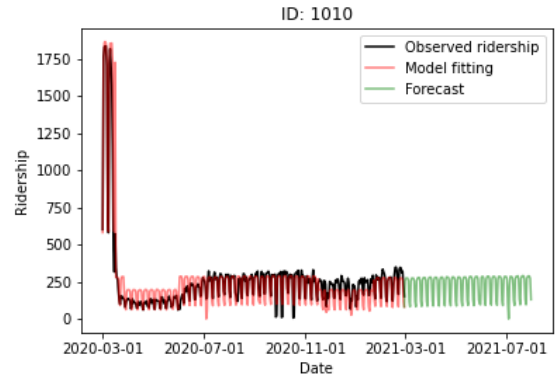
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Forecast
Ridership
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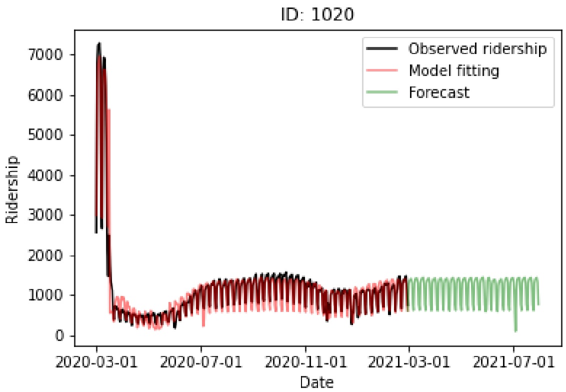
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Model fitting
Forecast
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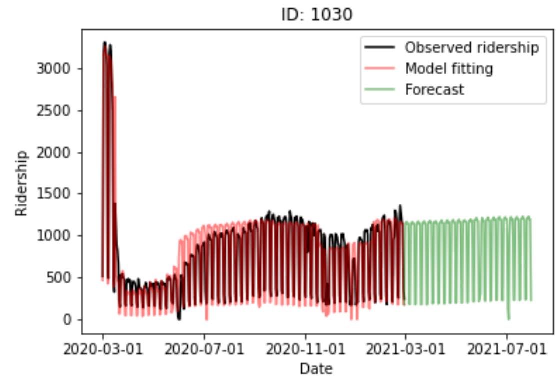
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Model fitting
Forecast
Ridership
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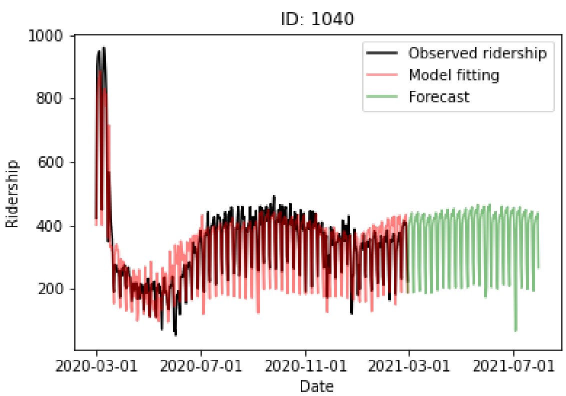
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Model fitting
Forecast
Ridership
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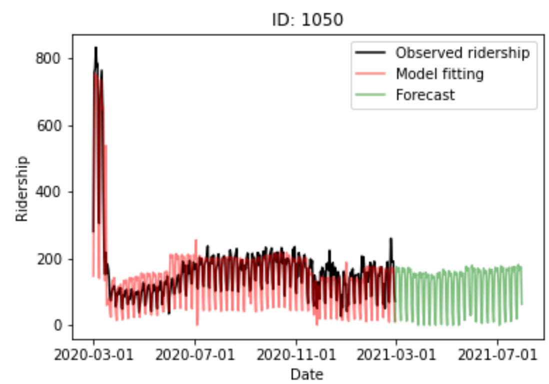
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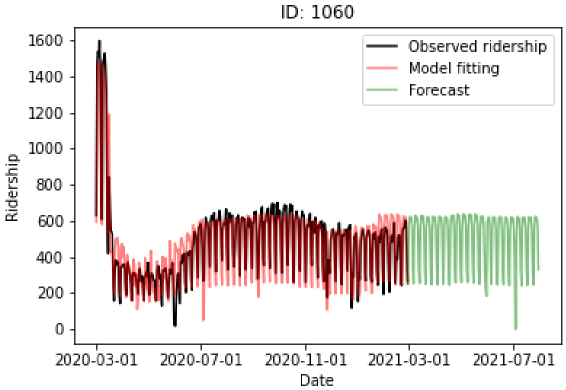
Model fitting
Forecast
Ridership
Date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Observed ridership
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Forecast
Ridership
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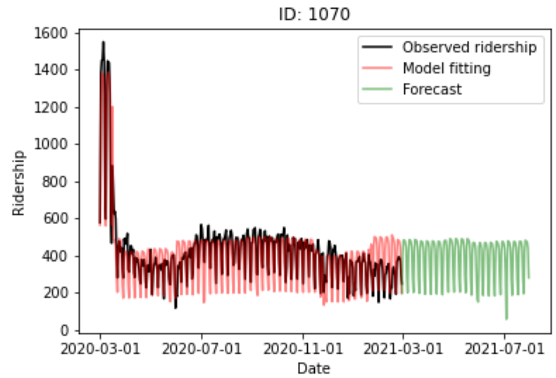
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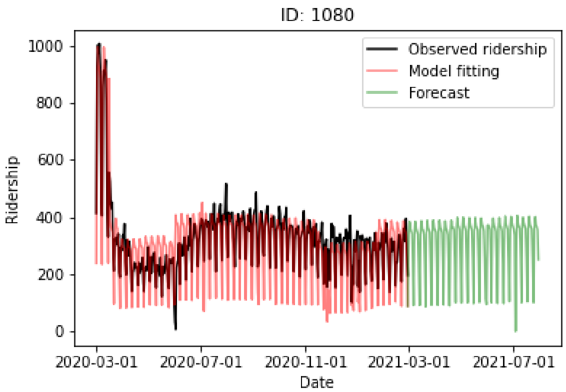
ID: 1080
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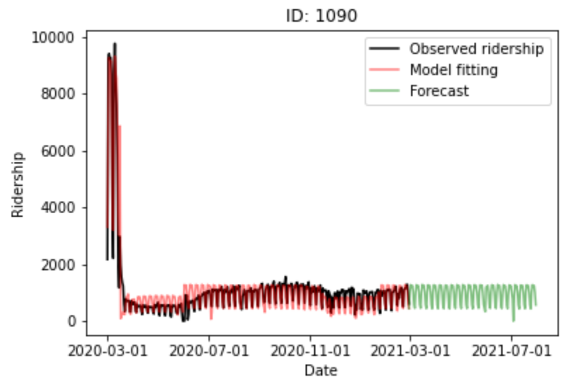
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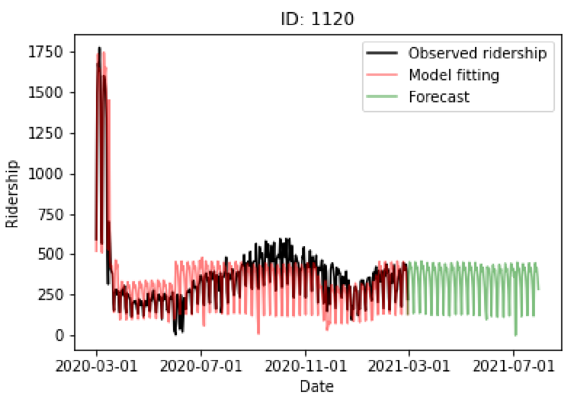
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Forecast
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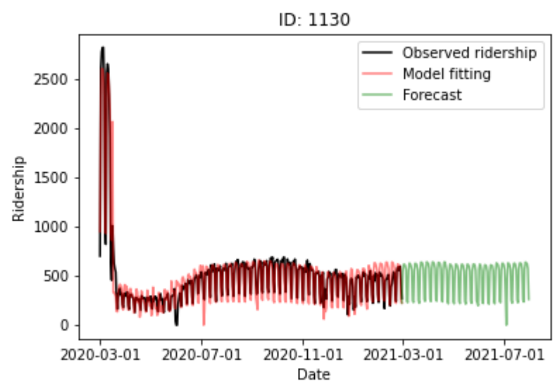
ID: 1130
Observed ridership
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Forecast
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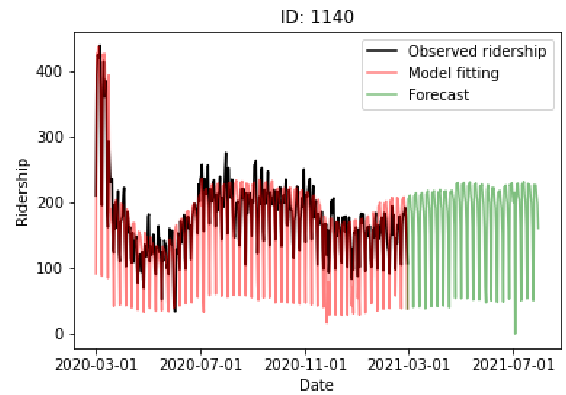
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Model fitting
Forecast
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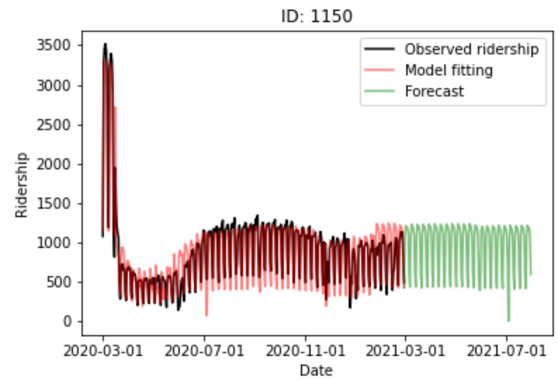
ID: 1150
Observed ridership
Model fitting
Forecast
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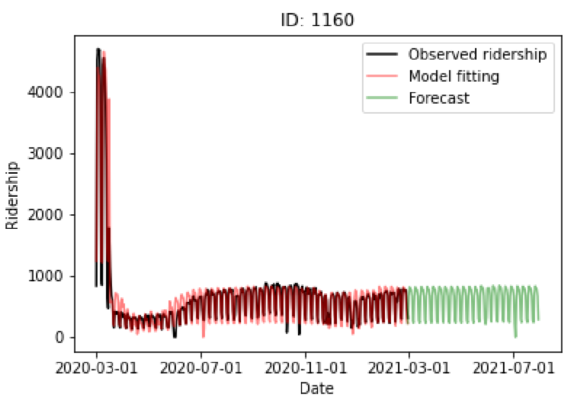
ID: 1160
Observed ridership
Model fitting
Forecast
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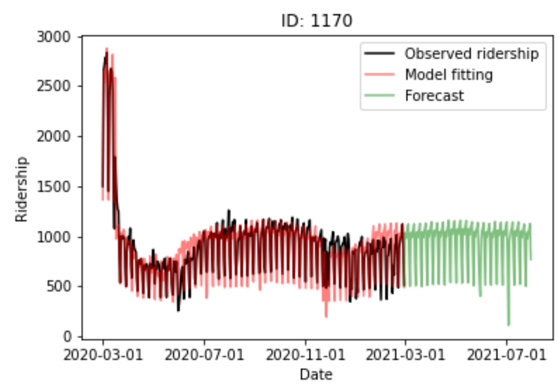
ID: 1170
Observed ridership
Model fitting
Forecast
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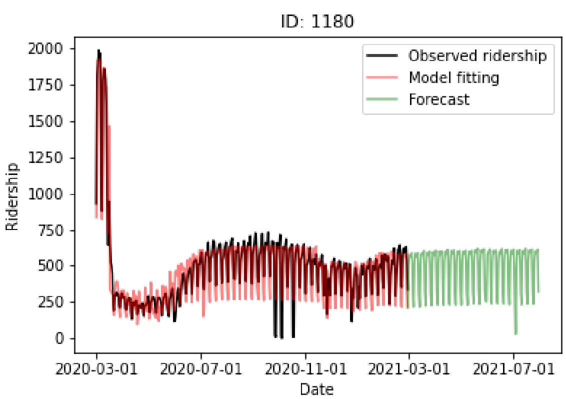
ID: 1180
Observed ridership
Model fitting
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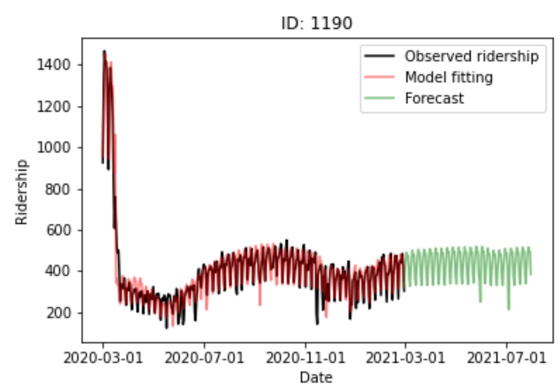
ID: 1190
Observed ridership
Model fitting
Forecast
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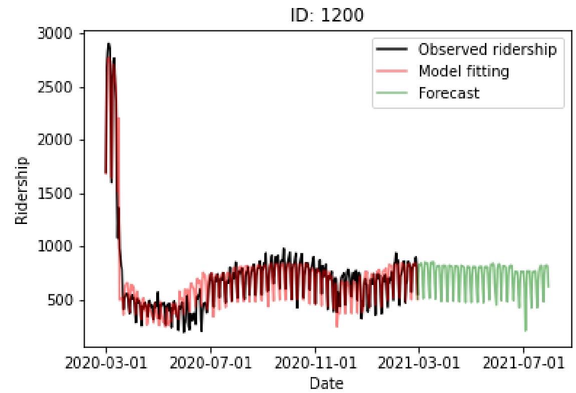
2021-07-01
Date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Observed ridership
Model fitting
Forecast
Ridership
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2021-07-01
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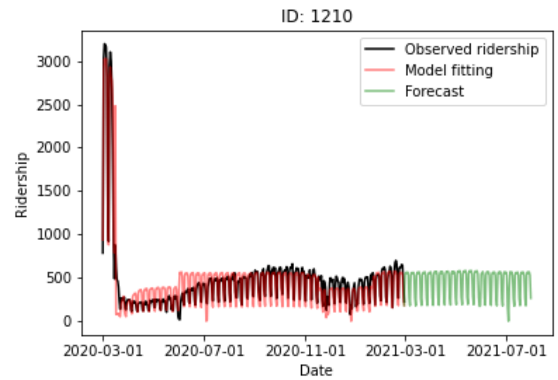
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Observed ridership
Model fitting
Forecast
Ridership
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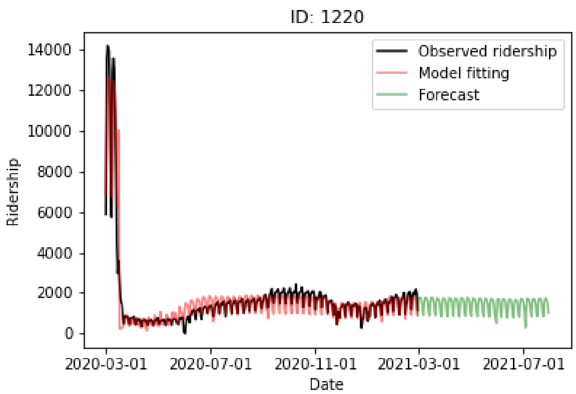
ID: 1220
Observed ridership
Model fitting
Forecast
Ridership
14000
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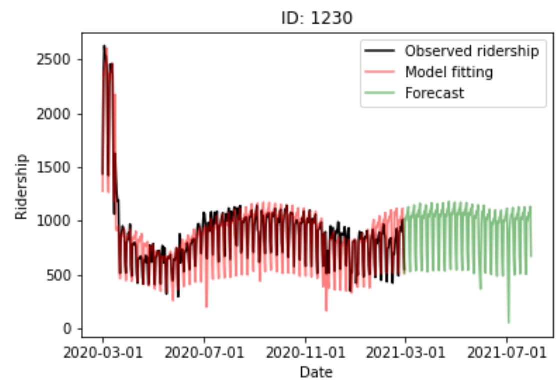
Date


ID: 1230
Observed ridership
Model fitting
Forecast
Ridership
2500
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500
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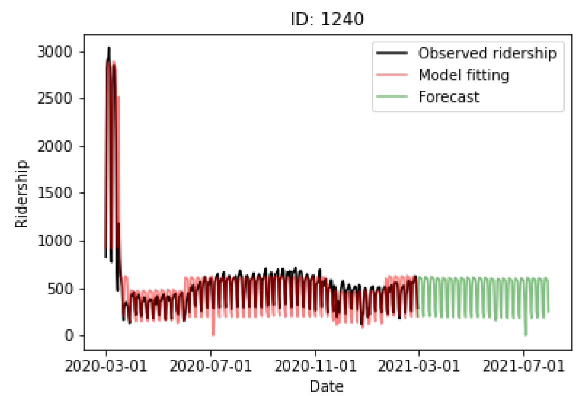
2021-07-01
Date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Observed ridership
Model fitting
Forecast
Ridership
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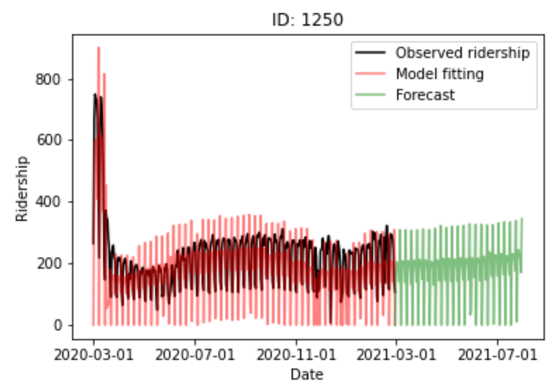
ID: 1250
Observed ridership
Model fitting
Forecast
Ridership
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400
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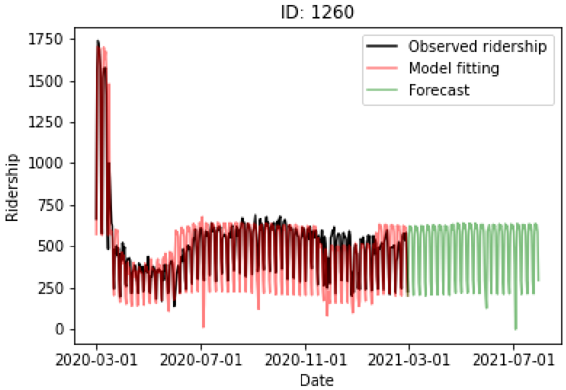
Date


ID: 1260
Observed ridership
Model fitting
Forecast
Ridership
1750
1500
1250
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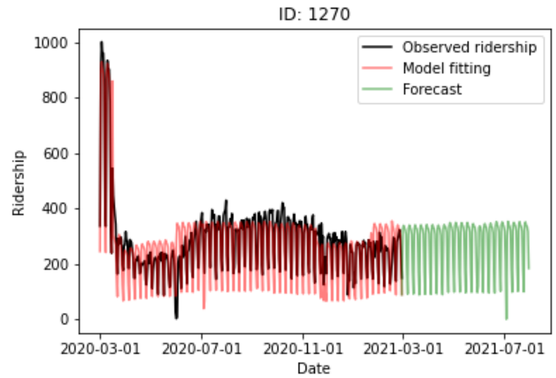
2021-07-01
Date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Observed ridership
Model fitting
Forecast
Ridership
1000
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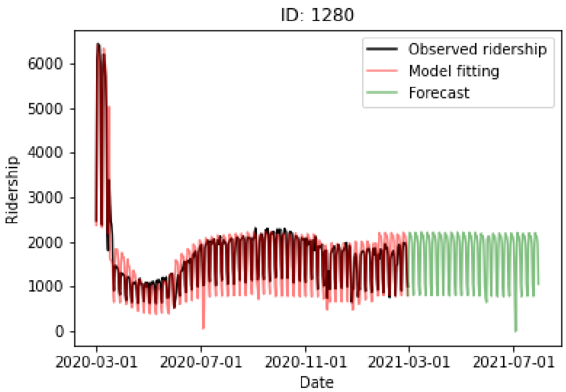
2021-07-01
Date


ID: 1280
Observed ridership
Model fitting
Forecast
Ridership
6000
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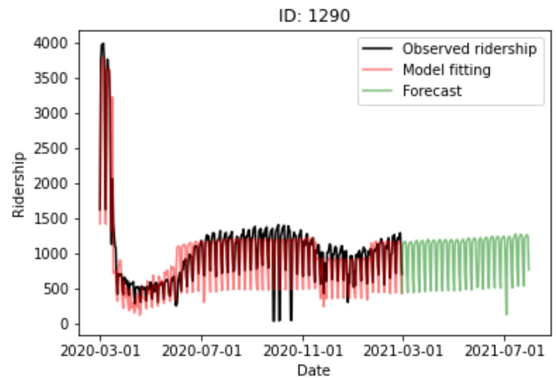
2021-07-01
Date


ID: 1290
Observed ridership
Model fitting
Forecast
Ridership
4000
3500
3000
2500
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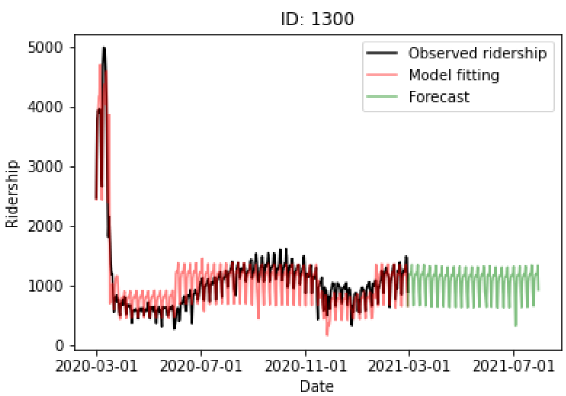
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Model fitting
Forecast
Ridership
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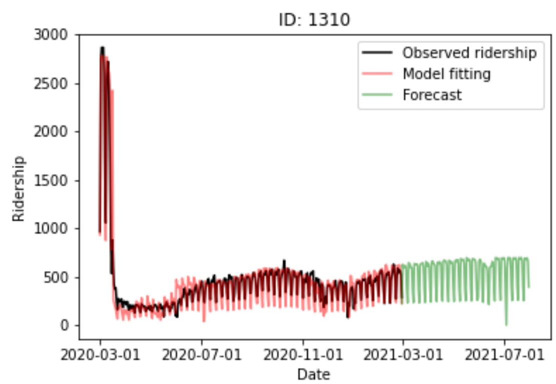
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Observed ridership
Model fitting
Forecast
Ridership
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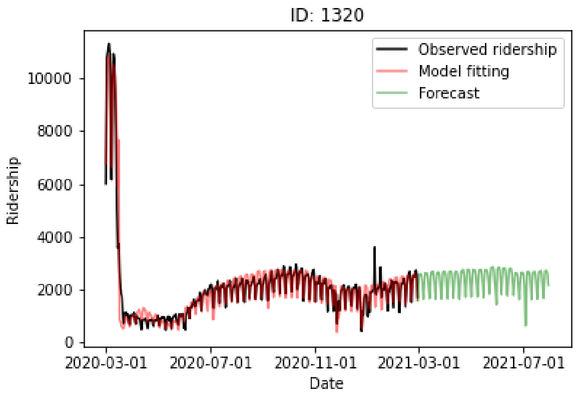
2021-07-01
Date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Observed ridership
Model fitting
Forecast
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2021-07-01
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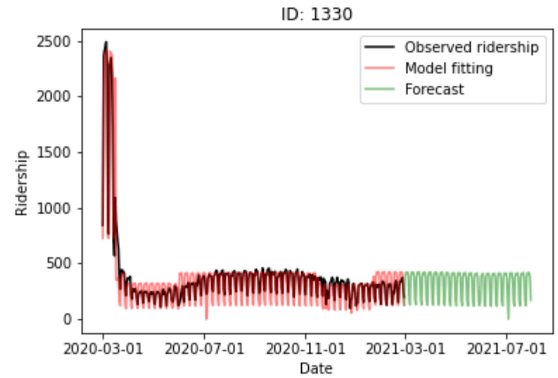
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Observed ridership
Model fitting
Forecast
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2021-07-01
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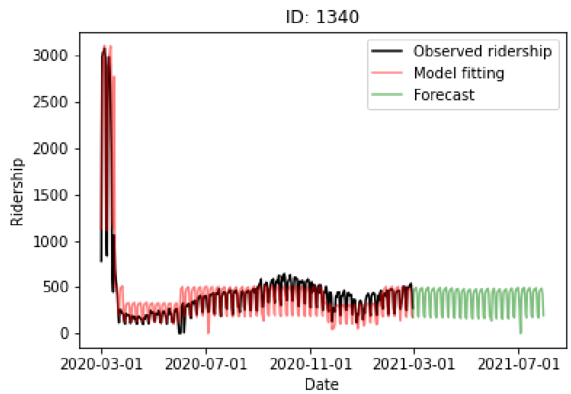
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Observed ridership
Model fitting
Forecast
Ridership
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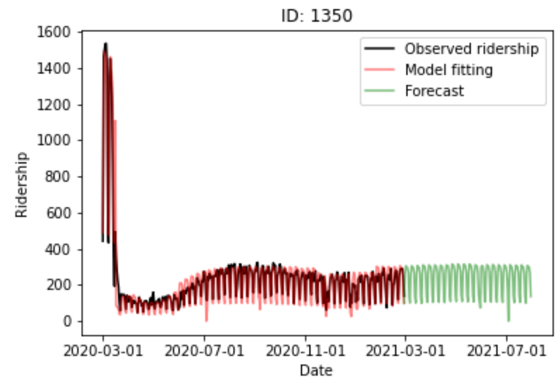
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Observed ridership
Model fitting
Forecast
Ridership
1600
1400
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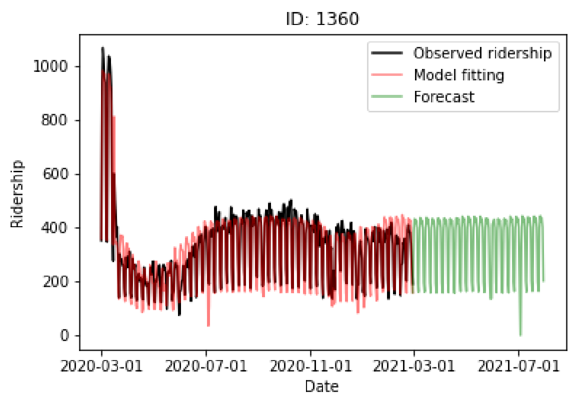
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Observed ridership
Model fitting
Forecast
Ridership
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2021-07-01
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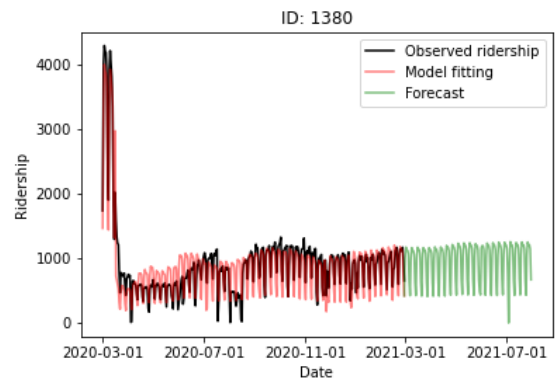
ID: 1380
Observed ridership
Model fitting
Forecast
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2021-07-01
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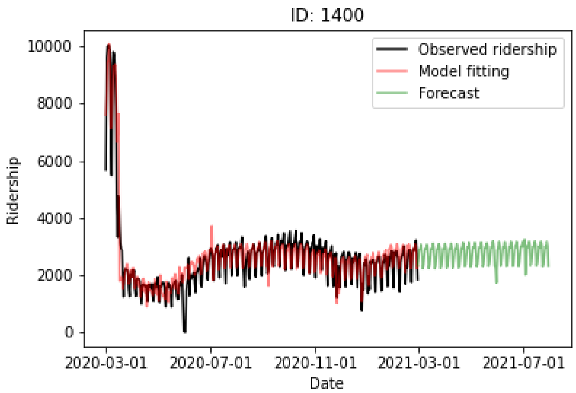
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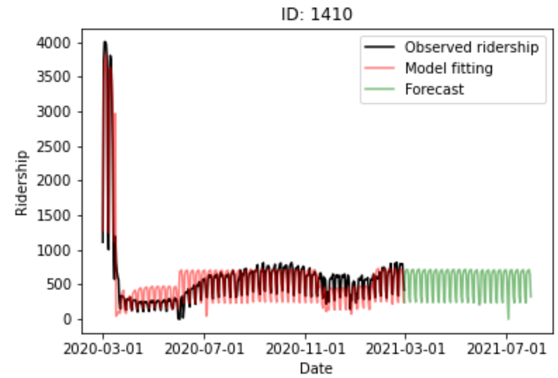
Model fitting
Forecast
Ridership
Date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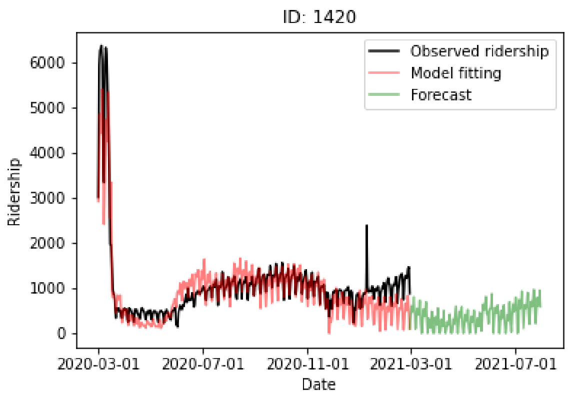
Model fitting
Forecast
Ridership
Date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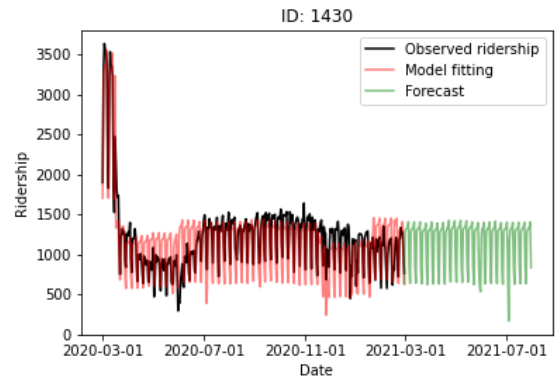
Model fitting
Forecast
Ridership
Date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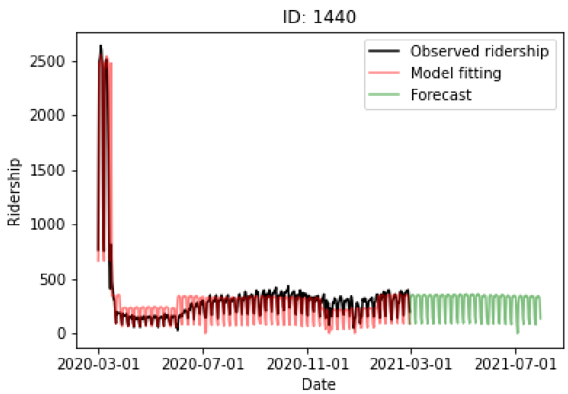
Observed ridership
Model fitting
Forecast
Ridership
Date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Model fitting
Forecast
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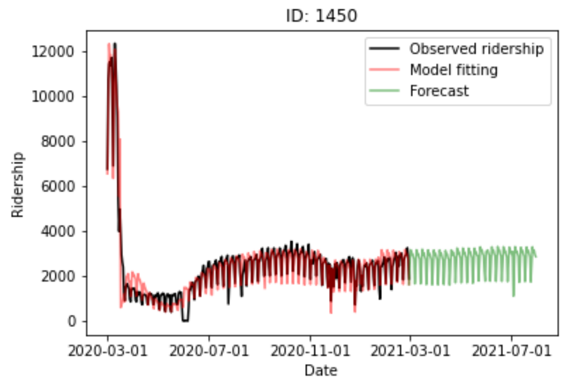
Date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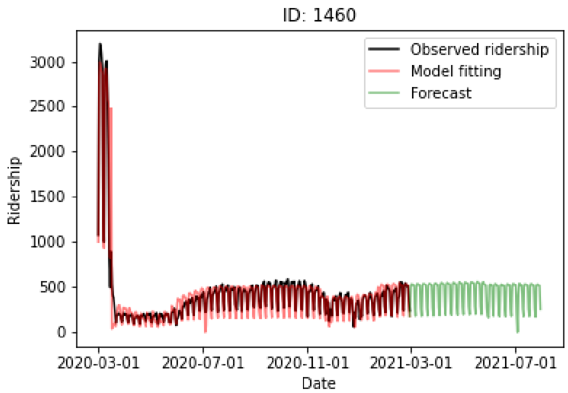
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Observed ridership
Model fitting
Forecast
Ridership
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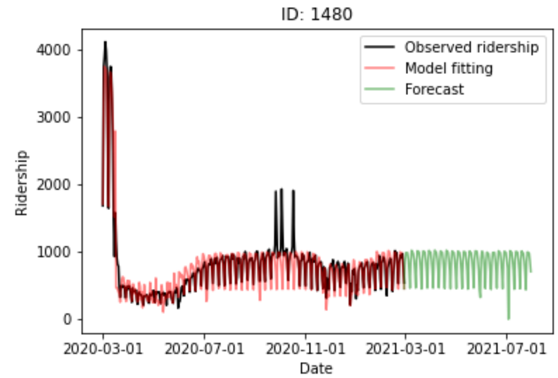
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Observed ridership
Model fitting
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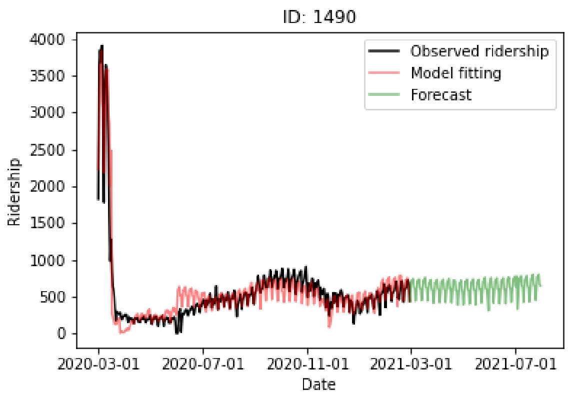
ID: 1490
Observed ridership
Model fitting
Forecast
Ridership
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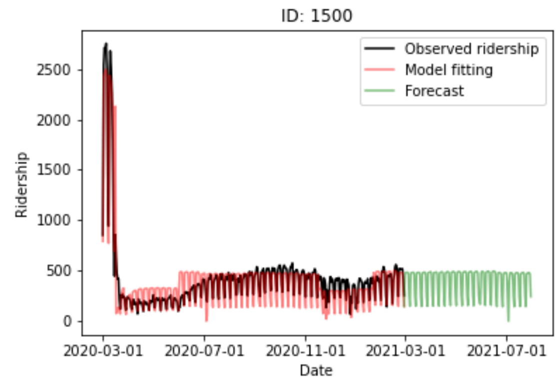
ID: 1500
Observed ridership
Model fitting
Forecast
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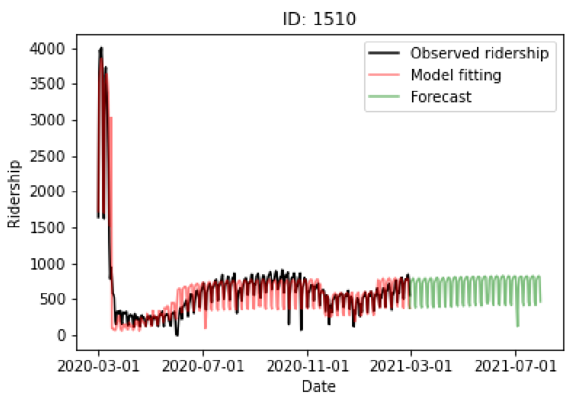
ID: 1510
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Model fitting
Forecast
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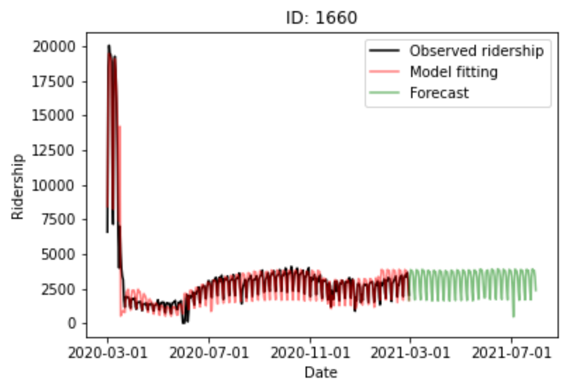
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Model fitting
Forecast
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5000
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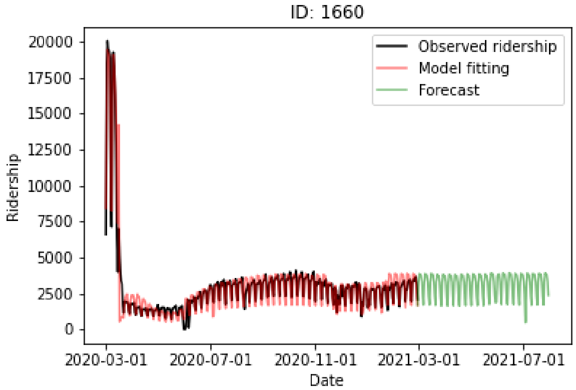
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Model fitting
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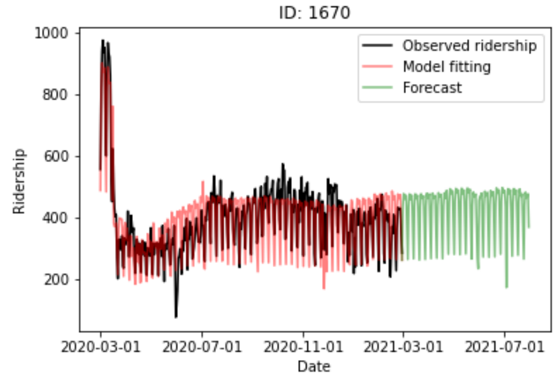
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Model fitting
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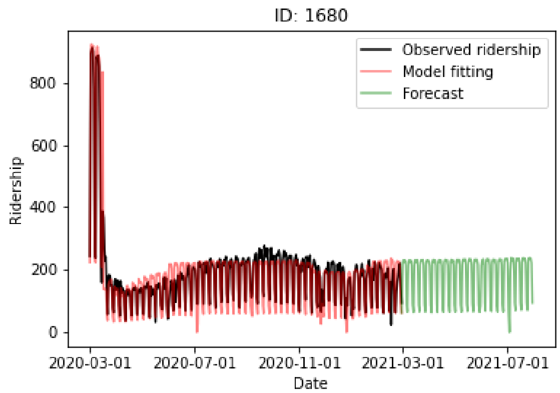
Date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Observed ridership
Model fitting
Forecast
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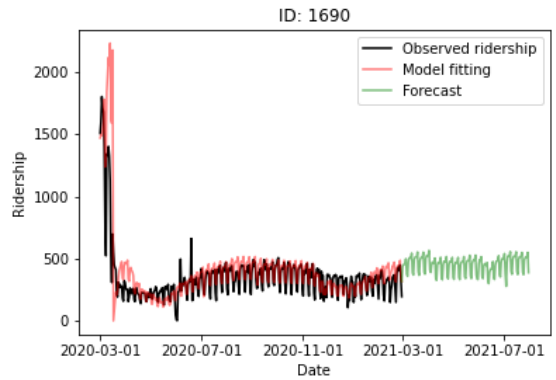
ID: 1690
Observed ridership
Model fitting
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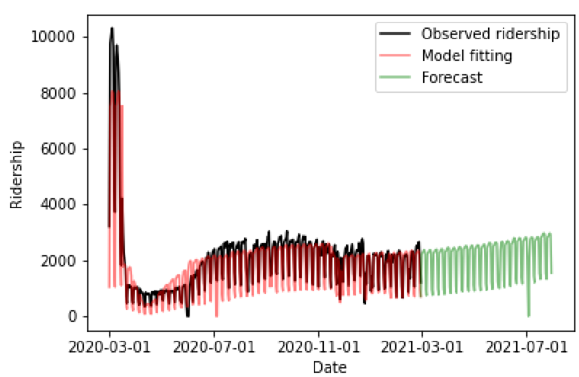
Observed ridership
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Date

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