

**A COMPARISON OF TIME SERIES
METHODS FOR POST-COVID
TRANSIT RIDERSHIP FORECASTING**

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Degree
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ABSTRACT

Transit agencies conduct system level ridership forecasting for planning, budgeting, and administrative purposes. The COVID-19 pandemic introduced substantial changes to transit ridership levels and patterns, which has impacted the performance of ridership forecasting. Although time series methods are commonly used for forecasting transportation demand, they have received limited use in practice for ridership forecasting. This thesis compares the performance of seven time series methods for univariate forecasts of system-wide, monthly transit ridership for heavy rail agencies in the continental US. The forecasting methods are: ETS, ARIMA, STL-ETS, STL-ARIMA, TBATS, neural network, and a hybrid model. Ridership was forecasted for pre- and post-COVID periods (pre- and post- March 2020) as well as for the full series (January 2002 to December 2023). The MAPE and MASE were used to compare forecast performance. About half of the pre-COVID forecasts produced a MAPE below 5% and about 90% produced a MAPE below 10%. Most of the full-series and post-COVID models underperformed by comparison, with only about 10% producing a MAPE below 5% and under half producing a MAPE below 10%. The hybrid method performed relatively well for each time period. The neural network underperformed for the pre-COVID and full series periods, but performed relatively well for the post-COVID period. Based on these findings, time series forecasting is an efficient method to forecast ridership with stable seasonality, periodicity, and trends, which was typical of pre-pandemic ridership. However, the results suggest that these stable ridership patterns have not yet returned at many US heavy rail agencies.

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CHAPTER ONE

INTRODUCTION

Transit agencies need system-level ridership forecasts for various planning and administrative functions, such as creating their operating budget, prioritizing long-term investments, and planning service frequency (*Boyle 2006; Plotch 2022*). Transit agencies historically have forecasted ridership using various methods such as professional judgement, rules of thumb, direct ridership models, and the four-step or activity-based travel demand model (*Boyle 2006*). However, these forecasting methods might not be suitable in the wake of the COVID-19 pandemic due to its continued impacts on travel behavior (*Miller 2023*). The pandemic has introduced more uncertainty to transit ridership patterns and possibly has even permanently changed previously well-established features of transit ridership, such as the presence of strong seasonality, daily peaks, and strong commuter ridership (*Rowlands and Loh 2023*). Therefore, transit agencies may want to consider different methods to forecast ridership. This study aims to explore the performance of one potential method: time series forecasting.

Even prior to the pandemic, transit agencies stood to gain advantages by considering alternative methods of ridership forecasting. Prior to the pandemic, the most widely-used methods of ridership forecasting in practice tended to be the four-step and activity-based travel demand models, which are time consuming to set up, require extensive calibration, and are not suited to sub-regional forecasting (*Cervero 2006; Miller 2023; Pougala, Hillel and Bierlaire 2022*). While more simple methods of ridership forecasting exist and are capable of achieving a finer resolution, for example, linear regression models (*Cervero 2006*), time series models are particularly easy to set up due to their ability to produce univariate forecasts; agencies only need to know their previous ridership in order to begin forecasting. Given that most agencies already report their ridership levels to the Federal Transit Administration, they likely already have the data they need to produce time series forecasts. By using free, open-source software packages to automatically optimize the parameters of a time series model, agencies could quickly, frequently, and cheaply produce reasonably accurate forecasts for their planning and budgeting purposes.

Time series forecasting methods are well-defined, and have been long-used in many disciplines including transportation. The moving average and autoregressive methods, which are the basis of half of the methods used in this study, were first introduced in the 1920s (*Yule 1921; Yule 1927*), and have been used for transportation forecasting since at least 1976 (*Polhemus 1976*). The exponential smoothing method, which is the basis of the other half of the methods used in this study, was introduced in the late 1950s (*Hyndman and Athanasopoulos 2018d*), and has been used to examine problems in transportation since at least 1973 (*Craw 1973*). Prior studies have applied time series analysis to forecast demand in different transportation sectors including roadways, airlines, and freight (*Babcock, Lu and Norton 1999; Jayanthi and Jothilakshmi 2021; Nihan and Holmesland 1980; Washington et al. 2020; Wickham 1995; Zheng and Wei 2020*). Time series analyses typically depend on understanding the data generating mechanism to predict future values. This feature gives time series methods an advantage over other methods in the wake of the COVID-19 pandemic, since the assumptions used for other methods (e.g. ridership elasticities that

depend on the relationship between ridership and other variables) may not be consistent during or after COVID-19.

This study seeks to compare the performance of several classical and some newer, more complex time series methods to forecast rail ridership in the United States (US) in the wake of the COVID-19 pandemic. Monthly ridership for the 14 heavy rail agencies in the continental US was forecasted using seven different time series methods. Three time series periods were used. In the first time period, a baseline was established for pre-COVID forecast performance. In the second time period, the models were trained through the onset of the pandemic to examine the usefulness of pre-COVID data in post-COVID forecasts. In the third time period, the models were trained only on post-COVID data in order to test the ability of the models to identify trends and patterns in post-COVID ridership. In order to gain a more comprehensive understanding of the performance of the models, a moving window was used to see the changing performance of the forecasts over time. This study can help inform transit agencies as they explore various forecasting approaches that could handle uncertainty in the post-COVID era.

The thesis proceeds as follows. In Chapter 2, a literature review is presented which explains the recent trends in US rail ridership, factors that have been shown to have a relationship with rail ridership, and traditional methods of forecasting transit ridership. A review of the recent studies that have forecasted post-COVID transit ridership using time series methods is also presented. In Chapter 3, the forecasting software, data, time series methods, and performance measures are explained. In Chapters 4 and 5, the results of the pre-COVID (before March 2020), full series (from January 2002 to December 2023), and post-COVID (after March 2020) analyses are presented. In Chapter 4, a moving window was used to generate about 3,000 time series models for 12-month forecasts, which demonstrate the changing performance of the seven time series methods over time and due to the pandemic. In Chapter 5, the most recent time series analyses from each time period are shown in order to compare the performance of the seven models at the 14 agencies. In Chapter 6, conclusions and areas for future research are discussed.

This study demonstrates the applicability of time series forecasting for post-COVID transit ridership demand. The code used to complete the analysis of this study has been published publicly on Github (https://github.com/ashley2876/forecasting_repo), so that the time series methods used in this study may be immediately accessible to transit agencies and practitioners. Additionally, a web application has been developed by Minneapolis Metro Transit (<https://metrotransitm.n.shinyapps.io/route-trends/>), which is user-friendly and will allow for similarly accessible time series forecasts.

CHAPTER TWO

LITERATURE REVIEW

This section discusses 1) the recent trends in rail ridership in the US and factors that contribute to changes in rail ridership levels, 2) methods to forecast ridership demand other than time series forecasting, and 3) the findings of prior studies that used time series methods to explore transit ridership, particularly since the start of the COVID-19 pandemic. The literature review is presented in three sections. First, the recent changes in rail ridership and driving factors are discussed. Next, studies that used classical travel demand models, such as the four-step travel demand model or regression models, are discussed. Last, the details of prior studies that used time series forecasting for transit ridership, particularly post-COVID ridership, are summarized.

Recent Changes in Rail Ridership and Influencing Factors

Prior to the COVID-19 pandemic, overall transit ridership in the US was in decline (see Table 2-1). Most US transit agencies saw a peak in ridership after the Great Recession, where ridership reached a high at many agencies in the early-to-mid 2010s, and then steadily declined over the course of the rest of the decade. The COVID-19 pandemic caused substantial ridership decreases worldwide due to reduced service, stay-at-home orders, and fears of infection, among other reasons. More than three years after the onset of the COVID-19 pandemic, urban transit ridership at nearly all US agencies in metro areas with more than 500,000 people has still not recovered (*Hammon 2023*), likely due to factors such as the increased popularity of telework, changes in travel patterns (e.g., increases in off-peak and weekend travel) (*Rowlands and Loh 2023*), and service disruptions due to operator shortages (*Ziedan, Brakewood and Watkins 2023*). At the same time, trips made by other modes in the US such as air travel and interstate travel have recovered (*OAG N.D.; USAFacts 2023*). In order to understand the potential reasons why urban transit ridership has not recovered, context is required. This section of the literature review explores the recent trends in rail ridership and the factors that have been found to influence rail ridership, which can provide insights into the current patterns in transit ridership today.

There have been numerous studies that looked into the causes of the nationwide decline in transit ridership during the 2010s, and a summary of the most relevant papers is provided in Table 2-1. Although the studies have tended to look at similar variables, they have sometimes resulted in different findings, likely due to using slightly different datasets and periods of analysis.

The first study examined total bus and rail ridership in 215 US Metropolitan Statistical Areas (MSAs) using National Transit Database (NTD) data. Ridership in unlinked passenger trips from 2002 to 2018 were used to estimate and validate a fixed-effects panel data regression model. The results showed that the causes of rail ridership decline included: higher incomes, car ownership, rates of remote work, and fares; and lower gas prices. The study also noted that ridehailing services have little effect on rail ridership in the largest metropolitan areas, but were found to decrease rail ridership by 10% in mid-sized metropolitan areas (*Erhardt et al. 2022*).

Another study used data from the American Community Survey (ACS), NTD, and the American Public Transportation Association (APTA) to create five clustered regions, and trend analysis was

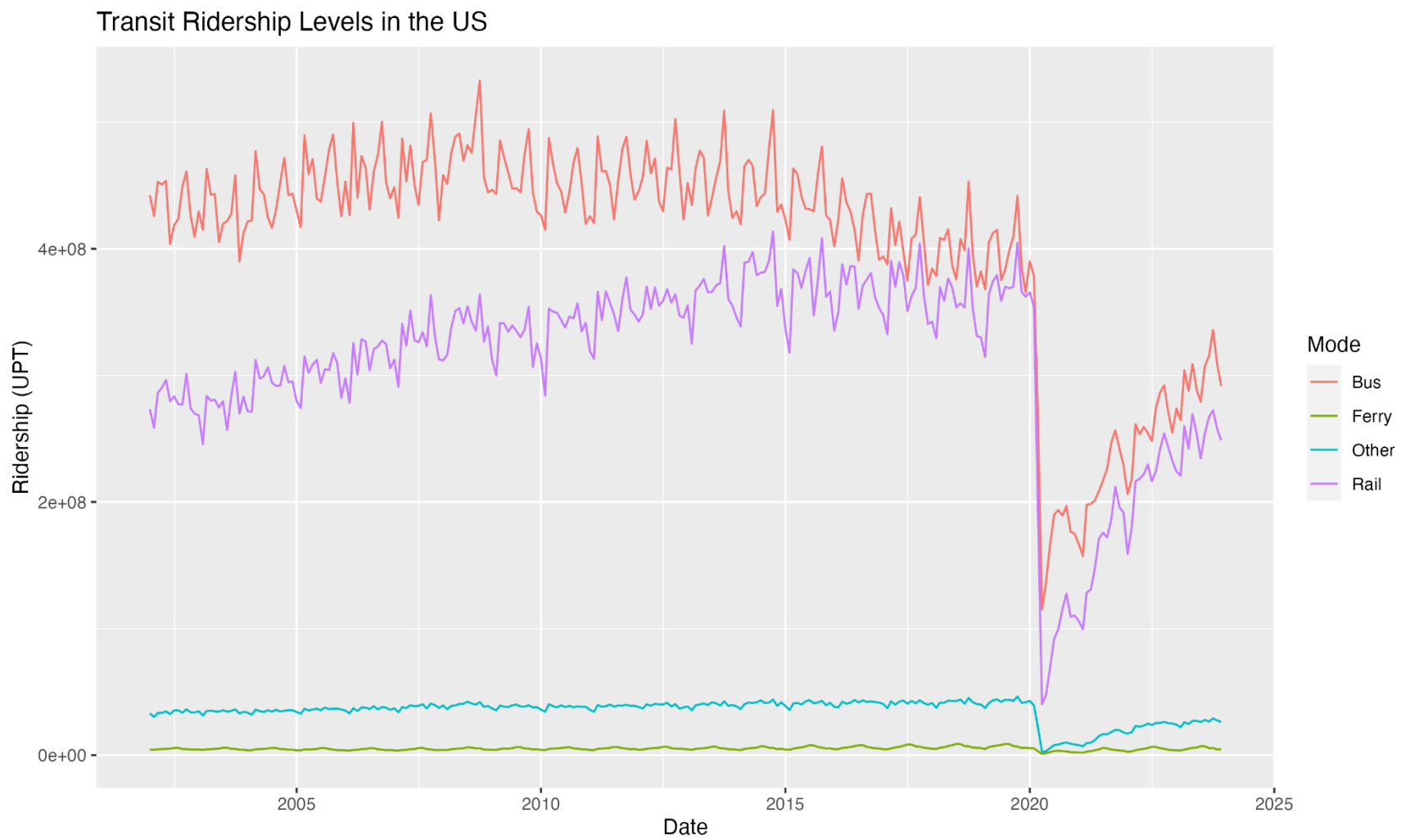


Figure 2-1 National Transit Ridership in the US by Mode (January 2002 to December 2023)

Table 2-1 Explanatory Variables of the Decreases in Rail Ridership in the 2010s in the US

Relationship to Rail Ridership	Explanatory Variables
Positive Relationship	<ul style="list-style-type: none"> • Share of young, transit-affinitive population groups (<i>Driscoll et al. 2018</i>) • Age (<i>Driscoll et al. 2018</i>) • Decreased costs of driving (<i>Lee and Lee 2022</i>) • Share of zero-vehicle households, especially among young households (<i>Lee and Lee 2022</i>) • Gas prices (<i>Erhardt et al. 2022</i>) • Changes in service levels, especially in denser transit-oriented regions (<i>Watkins et al. 2020</i>) • Change in population (<i>Watkins et al. 2020</i>) • Presence of bike share companies (<i>Graehler, Mucci and Erhardt 2019</i>)
Weak Positive Relationship	<ul style="list-style-type: none"> • Presence of ridehailing services (<i>Lee and Lee 2022</i>)
Weak Negative Relationship	<ul style="list-style-type: none"> • Presence of Transportation Networking Companies (TNCs) (<i>Graehler, Mucci and Erhardt 2019</i>) • Cost of fare (<i>Lee and Lee 2022</i>) • Gentrification (<i>Lee and Lee 2022</i>)
Negative Relationship	<ul style="list-style-type: none"> • Income (<i>Erhardt et al. 2022</i>) • Car ownership (<i>Erhardt et al. 2022</i>) • Remote work (<i>Erhardt et al. 2022</i>) • Cost of fare (<i>Erhardt et al. 2022</i>) • Presence of ridehailing services (for mid-sized cities only) (<i>Erhardt et al. 2022</i>) • Share of poor households in high-density neighborhoods, when in excess of 20% (<i>Lee and Lee 2022</i>) • Unemployment rate, especially in excess of 6% (<i>Lee and Lee 2022</i>) • Access to a private vehicle (<i>Lee and Lee 2022</i>)
No Relationship	<ul style="list-style-type: none"> • Change in zero-vehicle households (<i>Watkins et al. 2020</i>) • Share of young adults 18-34 (<i>Lee and Lee 2022</i>)

applied to identify relationships. The results showed a moderate relationship between change in rail ridership and 1) change in service levels and 2) change in population. Change in zero-vehicle households was found to have no relationship to rail ridership. The study concluded that strategies to increase ridership include increasing service levels, adding new mobility options such as demand-response service or partnerships with transportation networking companies (TNCs), and to improve technology and customer amenities (*Watkins et al. 2020*).

Similarly, an APTA report was released in 2018 that explained in more detail the causes of the nationwide decline in public transit ridership during the 2010s. Data were gathered for the top nine MSAs and included metrics such as: population, real gasoline price, real income, vehicle miles traveled, and the traffic congestion index. Four common themes were associated with ridership declines: 1) erosion of time competitiveness due to traffic congestion caused by densification, delivery services, addition of street enhancements and safety standards, and TNCs; 2) reduced customer affinity and loyalty as well as reduction in monthly pass purchases due to remote work, alternative work schedules, and increase in online commerce; 3) cost competitiveness due to lower cost of auto ownership and cheap TNC fares; and 4) external factors such as parking availability and movement of major amenities to locations outside of the service area that are more difficult to serve with high quality transit (*Grisby, Dickens and Hughes-Cromwick 2018*).

Another study examined 19 of the largest urban areas in the US using data sources such as the NTD, the Bureau of Labor Statistics, Federal Highway Administration (FHWA) Highway Statistics, US Census Data, Uber Entry data, and the ACS. A gradient boosting decision tree was used with counterfactual simulations to identify relationships between the explanatory variables and annual transit ridership in unlinked passenger trips. The factors that contributed to decreases in rail ridership were found to be the decreasing costs of driving, increased access to private vehicles, increased fares, and gentrification in high-density neighborhoods. The relationship between the share of carless households and rail ridership was positive, especially for carless young households. Ridehailing services were found to have a barely positive relationship with rail ridership. When the share of low-income households in high-density neighborhoods was greater than 20%, a negative relationship with rail ridership was found; this may indicate gain in rail ridership at the expense of bus ridership. The unemployment rate, especially when over 6%, was found to have a negative relationship with rail ridership. The share of young adults was not found to have a clear relationship to rail ridership (*Lee and Lee 2022*).

One study posited that changes in service levels, gas price, and auto ownership are insufficient to explain the ridership declines. NTD data segmented by mode for unlinked passenger trips in 22 major North American cities were used to carry out a longitudinal analysis of the determinants of public transit ridership. The introduction of bike share in a city was associated with increased heavy rail ridership. However, when TNCs are introduced to a market, heavy rail ridership was found to decline by 1.3% every year and build with each passing year. The study suggested that service increases alone would need to be substantial in order to simply maintain the then-current level of ridership. In order to implement efficient policies, it was recommended that agencies partner with cities to consider supplementary strategies such as congestion pricing or the reallocation of right-of-way on urban streets from private vehicles to transit (*Graehler, Mucci and Erhardt 2019*).

A 2018 study looked more generally at ridership trends from the past 50-plus years to determine if demographic changes could be responsible for some of the decline in transit ridership in the US. The study used National Household Travel Survey (NHTS) data and ACS data to examine ridership data over time among different population groups and metro areas. Ridership estimates were modeled based off the data and compared to actual ridership. The results revealed that, while ridership from 1980 to 2018 had peaked and declined seven different times, ridership per capita had decreased by 15%. Two demographic phenomena were found to have a strong relationship to ridership decline, which were: the share of young, transit-using population groups was decreasing due to an aging population, and population was decreasing in counties with high transit service quality and use. Generally, the NHTS data showed that people tend to take fewer trips as they get older, regardless of which mode they may use to make trips (*Driscoll et al. 2018*).

Methods of Forecasting Transit Ridership

At this time, few transit agencies in the United States appear to be using time series methods to forecast transit demand. Rather, the preferred methods used by the Federal Transit Administration, metropolitan planning organizations, and state Departments of Transportation to forecast transit ridership appear to be the four-step travel demand model (*Central Transportation Planning Staff N.D.; Connecticut Department of Transportation N.D.; Federal Transit Administration 2020; Metropolitan Washington Council of Governments N.D.; Sound Transit 2015*) or the activity-based model (*Chicago Metropolitan Agency for Planning N.D.; Greenwood 2023; Miami-Dade Transportation Planning Organization 2024; New York Metropolitan Transportation Council N.D.; Twin Cities Metropolitan Council N.D.*). Some agencies also use a GIS-based modeling software and simulation tool developed by the Florida Department of Transportation, called TBEST, although the tool is calibrated to be transferrable only to cities in Florida; the tool can be re-calibrated for other states/cities, but the calibration process is complex (*Bunner and Catala 2023*). More recently, several studies have looked into alternatives to the four-step and activity-based models, such as direct demand models. This section of the literature review will examine the requirements of the four-step, activity-based, and direct demand models in order to compare them to time series methods in the context of COVID-19.

The four-step travel demand model is typically used for long term regional planning; the primary unit of analysis is the Traffic Analysis Zone (TAZ), which may have too low of a resolution for sub-regional planning (*Cervero 2006*). However, the Federal Transit Administration has developed a software called STOPS that uses a modified four-step model to generate transit demand estimations using data from the 2000 Census, General Transit Feed Specification data, and data from an agency's local regional travel demand model. FTA states that capable travel-forecasting professionals may expect two to three weeks of effort to install, calibrate, and prepare forecasts for straightforward projects, and for more complex projects, they may need two to three additional weeks of effort (*Federal Transit Administration 2020*).

Activity-based models have been proposed as an improved alternative to the four-step model, since they are able to model more complex travel patterns by factoring in elements of human behavior (*McNally and Rindt 2008*). However, like the four-step model, the activity-based model is computationally complex and complicated in design, and requires fine-tuning to suit the local context (*Miller 2023*). The amount of data required for the estimation of stable and significant

parameters can be prohibitive (*Pougala, Hillel and Bierlaire 2022*). In the context of COVID-19, both the four-step model and activity-based model may be challenged due to potential violations of the assumptions upon which the models depend. The pandemic may have introduced a “new normal” which may require adjustments in the models’ fixed constants (*Miller 2023*). Due to these limitations, some agencies are choosing to rely on pre-pandemic travel demand estimates rather than producing new forecasts, see for example (*Greenwood 2023*).

Direct ridership models are another commonly used method of forecasting transit ridership. These models typically use regression to estimate ridership as a function of station environments and transit service features, and produce a high-resolution output suitable for examining relationships between transit ridership and the built environment. In particular, direct ridership models have been proposed as supplementary methods to the four-step model, used for the purpose of producing order-of-magnitude estimates for the impacts of new policies on transit ridership, for example, transit-oriented development (*Cervero 2006*). In a 2018 study, direct ridership models were evaluated for their ability to predict ridership beyond the estimation data set. The study used daily, directional route-stop-level ridership for the dependent variable. Many independent variables were used for the potential demand and transit supply at a stop, and included factors like employment, population, and number of zero-vehicle households within walking distance of a stop, as well as the frequency of service and number of nearby competing stops. The results showed that the forecasted rail ridership was in the correct direction, but the magnitude of the change was underestimated (*Mucci and Erhardt 2018*).

More generally, a recent study compiled data from 164 unique transit projects in the US in order to evaluate the overall accuracy of transit forecasts. The specific methods used to carry out the travel demand forecasts for these 164 projects was not stated, but given that the projects span five decades (from the 1970s to the 2010s), it may be reasonable to expect that these projects represent a variety of forecasting methods, traditional and otherwise. To quantify the forecast accuracy, the study compared the system- or project-level average weekday ridership using a simple percent difference between observed and forecasted ridership. Quantile regression formulation was used to test the sensitivity of the forecast accuracy against the explanatory variables. The results showed that forecast accuracy varied by mode, service characteristics, ramp-up period, and timespan, and has been improving over the years. Almost 80% of the projects had actual ridership that was below the forecasted levels. Post-2000 forecasted ridership was about 28% higher than the observed average ridership, but pre-2000, the forecasts were about 108% higher than actual ridership. The forecasts for heavy rail projects were highly optimistic, perhaps due to the scope of their service and the potential for high variability in their demand (*Hoque et al. 2023*).

In summary, four-step and activity-based travel demand models are common methods of estimating transit ridership demand in practice, as are regression-based direct ridership models. However, the four-step and activity-based models have some drawbacks; for example, they have extensive calibration requirements which can be time-consuming to complete, are best suited for the regional scale, and their assumptions may not hold for post-COVID ridership modeling. Direct ridership models provide a high resolution ridership forecast, for example, at the station-level, and they can be used to estimate the potential impact of a new transit policy or evaluate the relationship between transit ridership and features of the surrounding built environment. However, direct ridership models require multiple variables in order to be set up, may require fine-tuning regarding

which variables should and should not be included, and are best-suited as “sketch models” to produce order-of-magnitude estimates of potential transit ridership. In comparison, time series models only require a single variable, previous ridership, in order to be set up. Similar to direct ridership models, they can also take additional variables into consideration, as long as those variables are able to be represented as a time series with the same seasonality and number of observations as the ridership variable. Time series forecasts can be modeled at any level of resolution, from route- or station-level to system-level. As will be discussed in the next chapter, by taking advantage of existing forecasting packages that are capable of optimizing the model parameters automatically, time series forecasts are extremely user friendly, cost effective, and time efficient methods that can be used to quickly generate ridership forecasts. For these reasons, time series methods are proposed in this study for the purpose of generating short- or medium-term forecasts for budgeting, planning, and administrative purposes.

Time Series Methods for Transit Ridership Forecasting

As discussed in the previous section, many pre-COVID studies of transit ridership have explored the performance and applicability of a variety of forecasting methods, for example, time series multiple regression models (*Doi and Allen 1986*), ordinary least squares regression models (*Mucci and Erhardt 2018*), and mode choice models (*Chen and Naylor 2011*). Some studies have explored the accuracy of pre-COVID transit forecasts and have generally found a tendency towards optimism bias, or forecasts that overestimate ridership, regardless of the method used (*Hoque et al. 2023; Perry 2017*). Numerous prior studies have examined time series methods specifically to forecast pre-COVID transit ridership, using for example, autoregressive integrated moving average (ARIMA) (*Ding et al. 2018; Kyte, Stoner and Cryer 1988; Wang et al. 2018*), exponential smoothing (*Ge, Zheng and Hou 2013*), and machine learning (*Chen, Zhang and Jiang 2020; Chiang, Russell and Urban 2011; Egu and Bonnel 2021*). In this section, the details of prior studies that examined the application of time series methods to transit ridership forecasting are summarized. Particular attention is paid to studies that have used post-COVID (after March 2020) ridership data in their training and/or testing series.

The first relevant post-COVID study sought to forecast daily ridership from January 1, 2021 to May 31, 2021 at “L” train stations in downtown Chicago using a random forest model. The training data was from March 1, 2020 through December 31, 2020, and the testing dataset was from January 1, 2021 through May 31, 2021. The data were used to forecast out five months. The results showed that the daily ridership forecasts were accurate for the first month, but the performance of the forecasts decreased as the forecast horizon increased. The researchers also found that the average temperature had an impact on ridership, more so than the stay-at-home executive order (*Azimian and Jiao 2021*).

A 2022 publication examined forecasting daily turnstile data from January 2019 to July 2020 for the New York City subway using piecewise stationary time series methods. The goal was to produce a non-stationary time series model using several independent ARIMA models to bridge between “break points,” or points where the data become non-stationary due to anomalies caused by unforeseen events. Station-level subway data taken at four-hour increments were used to measure ridership. As a baseline measure, an ARIMA model was applied to the entire dataset, ignoring the break points. A machine learning algorithm was used to detect break points in the

ridership dataset, which were generally found to be around March 12th or 13th, 2020. Then, the dataset was separated into two, with the break point being the boundary, and an ARIMA model was applied to each dataset. The piecewise ARIMA model was found to have performed substantially better than the baseline ARIMA method (*Moghimi et al. 2022*).

A 2023 study predicted the impacts of the COVID-19 pandemic on US transit ridership in the five most populous cities in the US (New York City, Los Angeles, Chicago, Houston, and Philadelphia) using monthly transit ridership data and epidemic data from March 2020 to April 2022. The researchers used the ARIMA and Prophet models to forecast ridership given COVID infections. The forecasting accuracy of the ARIMA model was found to be between 6-10%, and the forecasting accuracy of the Prophet model was found to be between 8-12%. The researchers stated that the insufficient stationarity, periodicity, and seasonality of the time series contributed to the difficulty in refining the Prophet model (*Gao et al. 2023*).

Another 2023 study developed a neural architecture and feature search approach to automatically fine-tune the architecture and features of a deep learning neural network to predict any given route-level public transit ridership. The approach utilized a randomized local hyper-parameter search to find a set of parameters that would minimize both the prediction errors and the model complexity. The approach was tested on automatic passenger count data from five routes of the Chattanooga Area Regional Transportation Authority using data from January 2019 to October 2021. The study found that optimizing neural networks for each route significantly improved their performance compared to generic neural networks (*Ayman et al. 2022*).

One last relevant study from 2023 produced real-time, one-day ahead forecasts at 147 bus rapid transit stations in Bogota, Columbia using data from August 2015 to May 2021, during which time there existed highly dynamic and uncertain conditions (COVID-19 and a month-long protest). The researchers developed an open-source infrastructure with five forecasting methods: ARIMA, seasonal ARIMA, multilayer perceptron (MLP), convolutional neural networks (CNN), and long-short-term memory (LSTM). The models were applied using two learning strategies: static (estimated using only the test data) and online (model was re-trained as new data became available). Under stable conditions, all models had similar performance, although the static CNN model consistently underperformed, and the online LSTM outperformed the other models. For COVID-19 conditions, the online LSTM outperformed the other models. All models performed substantially worse under the dynamic conditions compared to the stable conditions. The researchers also noted that it took the machine learning models one and a half months to learn the new demand patterns (*Caicedo, González and Walker 2023*).

This review shows that transit ridership forecasting is an important and challenging task for transit agencies, departments of transportation, regional planners, and other practitioners. The forecasting methods used in practice, e.g., the four-step model, tend to be demanding, time-consuming, and are often limited in their scope and by the context of the study area. The pandemic has introduced potentially permanent changes to transit rider behavior, which may require the reevaluation of the assumptions upon which travel demand models like the four-step model rely. Transit agencies stand to benefit substantially from a forecasting method which is less demanding, expensive, and time consuming in comparison, and a flexible method like time series forecasting could be one solution. Time series models require only one variable (previous ridership) in order to be

estimated, but can also incorporate covariates associated with transit ridership, e.g., the price of gas, change in population, fare changes, and income levels. Time series methods have been used in a limited number of studies to forecast transit ridership in the wake of the COVID-19 pandemic. However, no study to-date has compared the forecasting performance of time series methods for all of the heavy rail agencies in the continental US individually, which could provide insight into the general suitability of time series forecasting for heavy rail, as well as any changes to ridership patterns on heavy rail as a result of the pandemic. Additionally, this study compares statistical, machine learning, and hybrid time series methods, while other post-COVID studies have mostly compared only pure statistical and pure machine learning methods. The results of this study could inform transit agencies on methods of forecasting with minimal complexity relative to the methods used in practice, especially for the purpose of making short-/medium-term, system-level, heavy rail forecasts.

CHAPTER THREE

DATA AND METHODS

In this section, the data source and methods used in this study are discussed in four parts. First, the ridership data used in this study are explained, and recent ridership changes observed at the agencies in this study are briefly discussed. Next, information regarding the software and code used to develop the models is provided. Then, the time series methods used in this study are described. Last, the measures used to evaluate the forecasting performance are explained.

Data and Period of Analysis

Monthly ridership data in terms of unlinked passenger trips (UPT) were downloaded from the National Transit Database website (*Federal Transit Administration N.D.*). It should be noted when using this dataset that the data may be adjusted over time; for this reason, the entire time series data must be refreshed when adding additional ridership observations to an analysis. The dataset used in this study included ridership for heavy rail in the continental US. The fourteen agencies used in this study are shown in Table 3-1. In Table 3-1, the minimum, maximum, and average monthly unlinked passenger trips on heavy rail are shown for pre- and post-COVID periods. The percent recovery in ridership as of the last observation available at the time of this writing (December 2023) was also found; ridership recoveries were found to range from about 40% to 80%.

Prior to the pandemic, ridership at many agencies was already declining, but the onset of the pandemic led to dramatic decreases in ridership. The effects of the pandemic on heavy rail ridership were first apparent in March of 2020, which was when many American states and cities initially implemented a mandatory or advisory stay-at-home order (*Moreland et al. 2020*). The pre-pandemic downward trend and the effect of the pandemic on transit ridership can be seen in Figure 3-1 (for the largest heavy rail agency in the US), Figure 3-2 (for the nine mid-sized heavy rail agencies), and Figure 3-3 (for the four smallest heavy rail agencies). The agencies are placed on separate plots according to the scale of their ridership so that the trends and ridership changes are clearly visible. At most agencies there is a clear decrease in ridership starting approximately around 2015, although the ridership decline started earlier at some agencies. An exception to the trend is the agencies in and around the New York City area; the ridership levels at these agencies appear to have had minimal decreases. However, all agencies had dramatic ridership decreases in March and April of 2020. From February to March of 2020, ridership declines at the 14 heavy rail agencies ranged from 32-55%, and from February to April ridership declines ranged from 55-94%. Therefore, February 2020 was considered to be the last pre-COVID month, and April 2020 was considered to be the first post-COVID month. The periods of analysis were selected based on these findings.

Models with multiple time periods were tested in this study in order to: 1) compare forecasting performance pre- and post-COVID, 2) investigate the impact of the number of observations on the forecasting performance, and 3) isolate the effects of the pandemic on post-COVID ridership trends and patterns. Figure 3-4 shows a visualization of the three time periods selected for analysis. The first time period used in this study was the pre-COVID period, which included data from

Table 3-1 Heavy Rail Agencies in the Continental US Showing Minimum, Maximum, and Average Unlinked Passenger Trips (UPT) Pre- and Post-COVID

Agency Name	Pre-COVID (before March 2020)			Post-COVID (after March 2020)			Recovery in Ridership from Dec 2019 to Dec 2023		
	Mean	Min	Max	Mean	Min	Max	Trips in Dec 2019	Trips in Dec 2023	2023 / 2019
Chicago Transit Authority	17,568,046	13,265,040	22,663,990	7,386,012	2,235,078	11,509,844	15,923,640	8,766,560	55.1%
County of Miami-Dade	1,532,757	1,079,749	1,996,221	902,467	287,803	1,239,336	1,433,928	1,177,272	82.1%
Los Angeles County MTA	3,599,656	616,954	4,629,231	1,934,341	1,132,356	2,528,557	3,401,148	1,724,702	50.7%
Maryland Transit Administration	1,058,714	124,877	1,367,600	185,900	84,936	352,425	579,668	293,169	50.6%
Massachusetts Bay Transportation Authority	12,876,889	9,359,700	16,679,922	5,686,246	1,182,140	7,882,855	11,545,872	6,397,500	55.4%
Metropolitan Atlanta Rapid Transit Authority	6,027,105	4,401,906	7,982,627	2,095,629	993,578	2,906,653	4,428,131	2,410,636	54.4%
MTA New York City Transit	205,182,028	148,267,939	253,609,943	125,865,343	20,254,269	183,903,625	236,357,677	173,256,395	73.3%
Port Authority Trans-Hudson Corporation	6,625,755	2,687,713	8,620,158	3,242,174	414,576	5,236,791	7,080,358	4,561,550	64.4%
Port Authority Transit Corporation	839,383	663,580	1,044,748	346,943	83,152	500,393	895,747	451,425	50.4%
San Francisco Bay Area Rapid Transit District	9,674,381	7,203,696	12,556,439	2,936,377	656,653	4,845,494	9,309,469	3,919,728	42.1%
Southeastern Pennsylvania Transportation Authority	7,774,345	5,432,593	9,821,204	3,742,342	1,263,591	5,220,404	7,717,104	4,010,239	52.0%
Staten Island Rapid Transit Operating Authority	611,521	368,986	828,475	284,901	35,979	506,733	604,767	412,352	68.2%
The Greater Cleveland Regional Transit Authority	505,912	223,497	851,608	229,188	159,213	328,061	460,306	305,495	66.4%
Washington Metropolitan Area Transit Authority	21,884,752	16,023,750	27,860,355	7,077,317	1,182,655	13,872,488	17,783,221	10,814,219	60.8%
Data Source: National Transit Database, December 2023 Adjusted Database (<i>Federal Transit Administration N.D.</i>)									



Figure 3-1 Ridership at MTA New York City Transit from January 2002 to December 2023

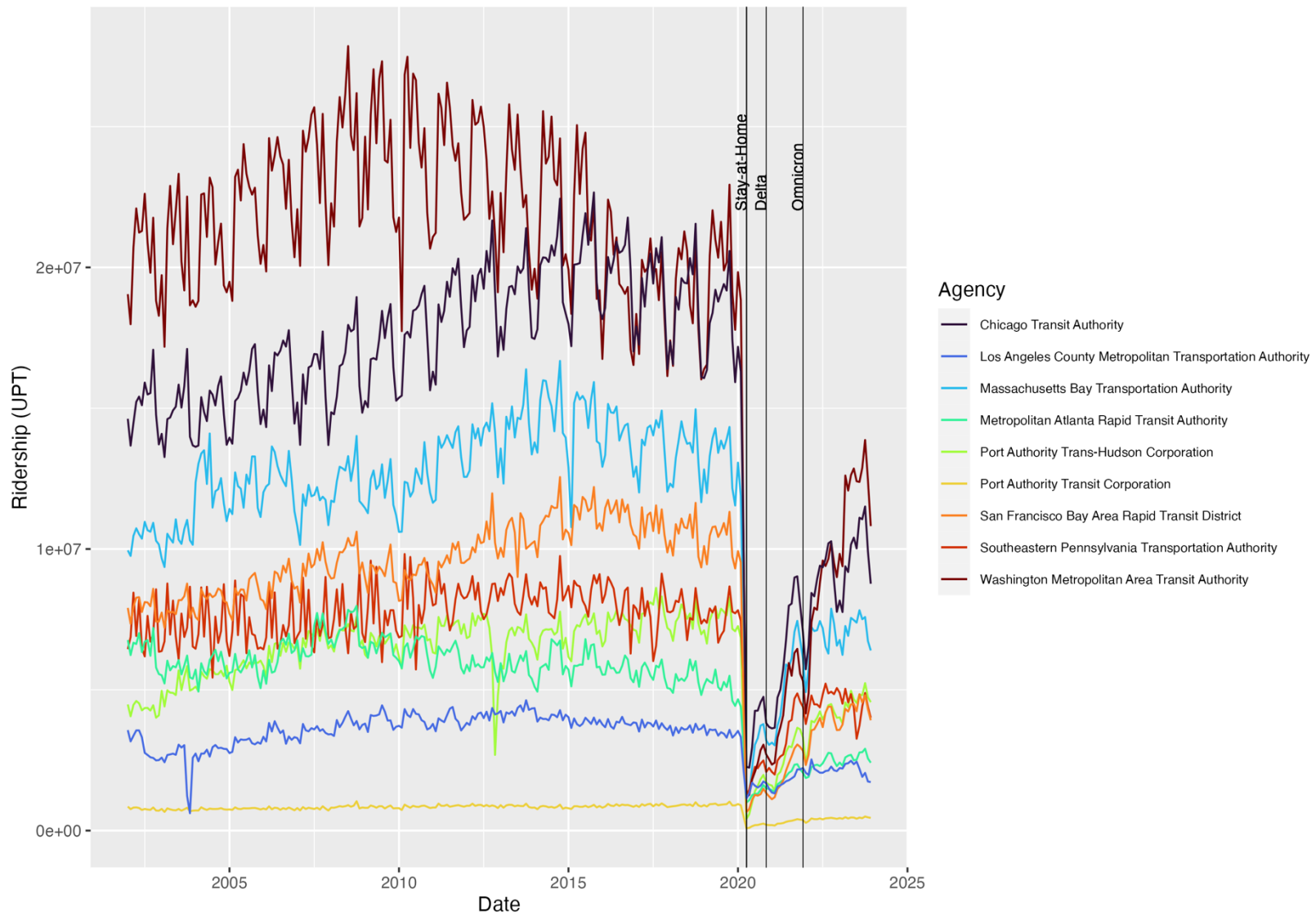


Figure 3-2 Ridership at Larger Heavy Rail Agencies from January 2002 to December 2023

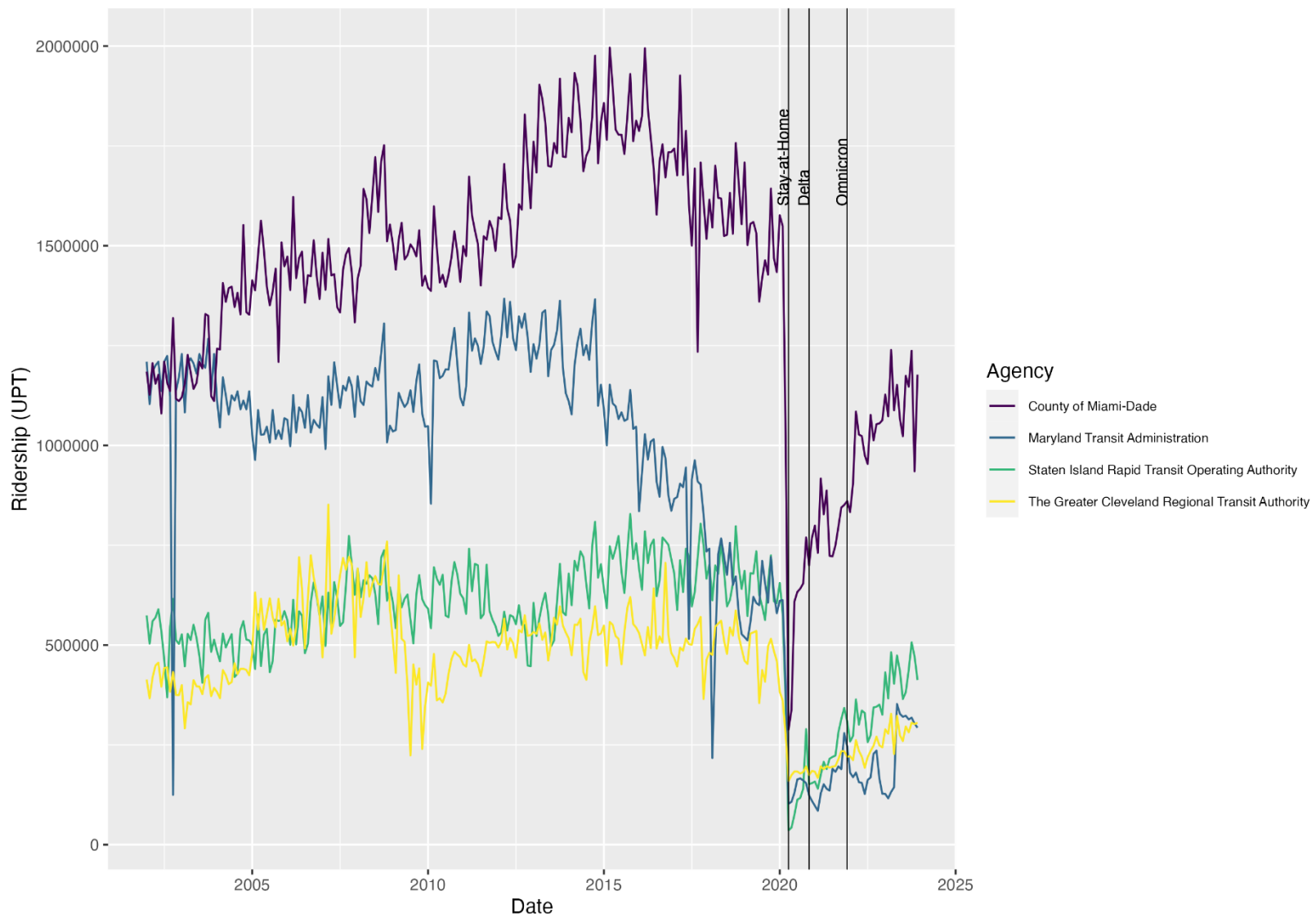


Figure 3-3 Ridership at Smaller Heavy Rail Agencies from January 2002 to December 2023

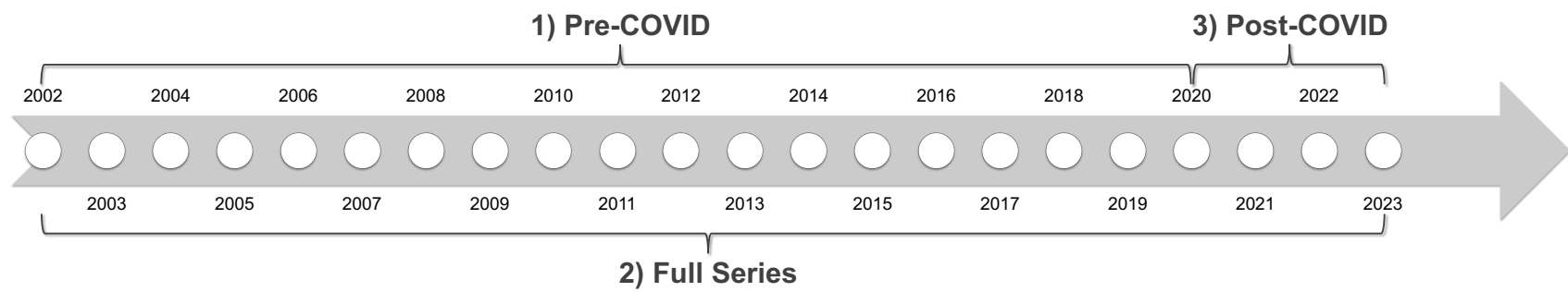


Figure 3-4 The Three Forecasting Time Periods Used in this Study

January 2002 to February 2020. This time period was used to establish a baseline performance for the seven forecasting methods under “normal” conditions. The second time period was the full data series, which included data from January 2002 to December 2023. This time period was used to forecast post-COVID ridership while incorporating pre-pandemic ridership patterns. The third time period was the post-COVID period, which included data from April 2020 to December 2023. This time period was used to evaluate the performance of the forecasting methods under the “new normal” conditions, without considering prior patterns in transit ridership. December 2023 was the latest available observation at the time of this writing. All forecasts and testing datasets contained data points for the same 12 months in order to evaluate the forecast performance by comparing the estimated ridership to the actual ridership.

Software

The software used in this thesis initially was based on a web application called Route Trends and Info created by staff from Minneapolis Metro Transit (*Minneapolis Metro Transit N.D.*). The application runs off R Software (*R Core Team 2013*). Metro Transit’s application supports seven forecasting methods: (1) exponential smoothing (ETS); (2) autoregressive integrated moving average (ARIMA); (3) and (4) Seasonal and Trend Decomposition using LOESS, using ETS or ARIMA (STL-ETS and STL-ARIMA); (5) the exponential smoothing state space model with trigonometric seasonality, Box-Cox transform, ARMA errors, trend, and seasonal periods (TBATS); (6) a feed-forward autoregressive neural network with a single hidden layer (NNET); and (7) a hybrid model with equal weights of the ETS, STL-ARIMA, TBATS, and NNET methods (*Hyndman and Athanasopoulos 2018d; Minneapolis Metro Transit N.D.*).

The source code for Minneapolis Metro’s application is available to the public on GitHub (*Lind, Reid and Ky 2019*). The source code was modified substantially by the author of this thesis and used directly in R (v4.3.1) in order to change the model parameters, output additional performance measures (e.g., mean absolute scaled error), and output customized graphs (*R Core Team 2013*). For example, Minneapolis Metro’s application uses the ETS method in their hybrid model, but in this study, the ARIMA method was used because it decreased the mean absolute percent error of many of the post-COVID forecasts by over one percentage point. Also, the original GitHub code produces a single interactive plot using the “dygraphs” package (*Vanderkam et al. 2018*), but these were changed to non-interactive plots with seven graphs using the “ggplot2” package (*Wickham 2016*). The functions used to produce the forecasts in this study have been made publicly available on Github at the following web address: https://github.com/ashley2876/forecasting_repo.

Time Series Models

Seven time series models were estimated in this study, also shown below in Figure 3-5: ETS, ARIMA, STL-ETS, STL-ARIMA, TBATS, NNET, and a hybrid model with equal weights of the ARIMA, NNET, STL, and TBATS methods (Hybrid ANST). This study focused on the first four classical time series models because they are widely established, well understood, and familiar to academics and some practitioners. The last three models were selected due to their ability to handle complex seasonality in time series using non-linear functions. This study does not focus on other machine learning methods or deep learning methods for several reasons. First, the short length of the data used in this study is not likely to be suitable to such methods. Second, to the best of the

Time Series Methods Used

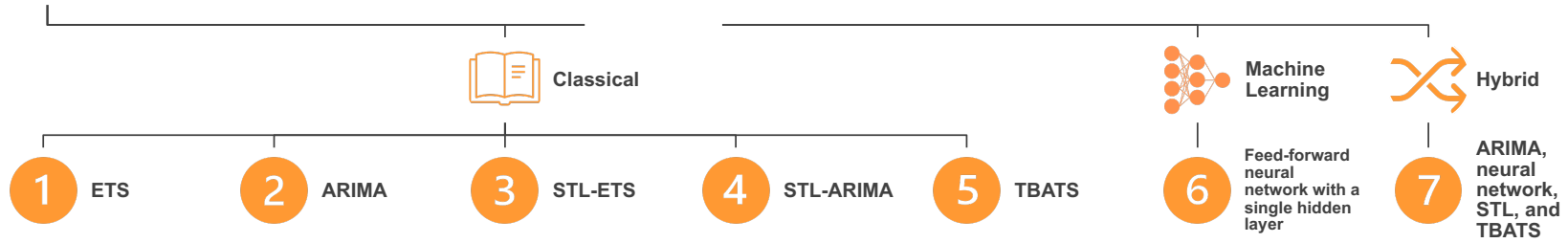


Figure 3-5 Types of Forecasting Methods Used in this Study

author's knowledge, no US transit agency is using other machine learning or deep learning methods to conduct ridership forecasts, and this study is intended to be aimed at practitioners. Last, machine learning methods, especially deep learning methods, are expensive to conduct, require extensive set up, and the results are more difficult to interpret.

Each of the chosen forecasting methods are briefly discussed below. The equations have been omitted for brevity but interested readers are referred to the following references (*Hyndman and Athanasopoulos 2018d; Livera, Hyndman and Snyder 2011*).

Exponential Smoothing (ETS)

ETS is the exponential smoothing state space model. This method is computationally simple but the least robust among the methods used in this thesis. There are 18 potential equations for an ETS model. A general notation can be denoted as ETS(error, trend, seasonal), and each component has multiple possibilities. Errors can be “A” additive or “M” multiplicative. Trends can be “N” none, “A” additive, or “Ad” additive damped. Seasonal components can be “N” none, “A” additive, or “M” multiplicative. By using the “ets()” function in the “forecast” package, the best fit model was selected from the 18 options by minimizing the corrected Akaike information criterion (AICc) (*Hyndman et al. 2021; Hyndman and Khandakar 2008; Hyndman and Athanasopoulos 2018e*). For more details on the ETS method, readers are referred to (*Hyndman and Athanasopoulos 2018e*).

Autoregressive Integrated Moving Average (ARIMA)

ARIMA is a state space model which is relatively computationally simple but assumes linear data to generate forecasts. There exist a potentially infinite number of possible equations for an ARIMA model. A general notation for a non-seasonal ARIMA model is ARIMA(p, d, q). The “p” is the order of the autoregressive (AR) part, the “d” is the degree of first differencing (the integrated (I) part), and the “q” is the order of the moving average (MA) part. A general notation for a seasonal ARIMA model is ARIMA(p, d, q)(P, D, Q)_m, where “P,” “D,” and “Q” are the seasonal AR, differencing, and MA orders, respectively, and “m” is the number of observations per year. In this study, the number of observations per year is always 12. Using the “auto.arima()” function from the “forecast” package with the argument “stepwise = FALSE,” R automatically chose the best fit ARIMA model based on a combination of the following criteria: unit root tests, minimizing the AICc, and minimizing the maximum likelihood estimation (*Hyndman and Athanasopoulos 2018a; Hyndman et al. 2021; Hyndman and Khandakar 2008*). For more details on the ARIMA method, readers are referred to (*Hyndman and Athanasopoulos 2018a*).

Seasonal and Trend Decomposition Using Locally Estimated Scatterplot Smoothing (LOESS) (STL) with ETS or ARIMA

STL is a method to decompose a time series into the seasonal, trend-cycle, and remainder components, where LOESS is a method of evaluating nonlinear relationships. The STL method allows the seasonal component to change over time and can be robust to outliers, but it does not automatically handle calendar variation. In this study, the STL method was used to de-seasonalize the data. This is useful for transit ridership data because transit ridership tends to vary substantially by season. The seasonal component “S_t” is forecasted separately from the non-seasonal

components “ T_t ” and “ R_t ” using the seasonal naïve method. A seasonal naïve forecast means all forecasts were set equal to the last observed value from the same season (Hyndman and Athanasopoulos 2018d). The non-seasonal components can then be forecast using any non-seasonal forecasting method (Hyndman and Athanasopoulos 2018d). The “`stlm()`” function from the “forecast” package was used to forecast using the STL-ETS and STL-ARIMA methods (Hyndman et al. 2021; Hyndman and Khandakar 2008; Hyndman and Athanasopoulos 2018b). For more details about STL decomposition, readers are referred to (Hyndman and Athanasopoulos 2018b).

Exponential Smoothing State Space Model with Trigonometric Seasonality, Box-Cox Transform, Autoregressive Moving Average Errors, Trend, and Seasonal Periods (TBATS)

The TBATS model is an exponential smoothing state-space model capable of modelling complex seasonality; this method also allows the seasonal component to change slowly over time. TBATS can consider a Box-Cox transformation to handle non-linearity in the data, the autoregressive moving average model to de-correlate the residuals, trend components for long- and short-term trend (with and without dampening), and trigonometric functions based on Fourier representations with time-varying components to handle complex seasonality (Livera, Hyndman and Snyder 2011). By using the “`tbats()`” function in the “forecast” package, R selected the best fit model by adjusting the above parameters to find a model configuration that minimized the Akaike information criterion (AIC) (Razbash and Hyndman N.D.). This method has a long computation time relative to the other state space models used in this study. For more details on the TBATS model, readers are referred to (Livera, Hyndman and Snyder 2011).

Feed-Forward Autoregressive Neural Network with a Single Hidden Layer (NNET)

The neural network used in this thesis is capable of handling data with complex nonlinear relationships. R's `nnetar()` function from the “forecast” package was used to estimate a feed-forward autoregressive neural network with a single hidden layer (Hyndman et al. 2021). In order to ensure reproducibility, a random seed should be set, because the neural network randomly selects the initial parameters which cause the performance measures for the same forecasts to vary slightly from run to run (Hyndman 2017). The seed was set to “1234” in this study; however, it should be noted that the moving window method of producing forecasts described in the next chapter appears to interfere with the seed. A seasonal neural network model is represented by $NNAR(p,P,k)_m$, where “ P ”, the number of seasonal lags, defaults to one, “ p ”, the number of non-seasonal lags, is selected from the optimal linear model fitted to the seasonally adjusted data, “ k ”, the number of neurons in the hidden layer, is equal to $(p + P + 1)/2$, and “ m ” is the number of observations per year (always 12 in this study). Prediction intervals were derived for the neural network forecasts by setting the `forecast()` function to simulate 1,000 future sample paths (Hyndman and Athanasopoulos 2018c; Hyndman and Athanasopoulos 2018d). With a larger data set, the performance of the forecasts may be improved when “ P ,” the number of seasonal lags, is set to a context-appropriate value (e.g., 12 for monthly data). However, the short length of the data in this study caused the neural network to overfit the model when “ P ” was set to 12, so the default of one was used. This method is one of the more computationally complex methods in this thesis, and as such, has a longer computation time. For more details on the neural network model, readers are referred to (Hyndman and Athanasopoulos 2018c).

Hybrid (ARIMA, NNET, STL-ARIMA, TBATS)

Hybrid models produce forecasts by combining several methods to produce a single forecast result. The `hybridModel()` function from the “forecastHybrid” package was used to estimate a hybrid (ensemble) model with equal weights of the ARIMA, NNET, STL-ARIMA, and TBATS methods. Minneapolis Metro’s hybrid model uses ETS instead of ARIMA; for this study, the ARIMA model was selected instead because it improved the performance of many the post-COVID forecasts by decreasing the value of the mean absolute percent error by over one percentage point. The method for the STL component of the hybrid model was ARIMA. Parallel processing was used between models to shorten the computation time. The weights of each model were set to be equal because this has been shown empirically to give good performance. This method is the most computationally complex method in this thesis, and as such, has the longest computation time. For more details on the hybrid model, readers are referred to (Shaub 2020).

Performance Measures

The performance measures used in this thesis were the mean absolute percent error (MAPE) and the mean absolute scaled error (MASE) of the testing data. The MAPE is a percentage error and is unitless. Therefore, the MAPE is a good measure to compare between datasets that have different scales. The MASE is a scaled error and can be used to compare between datasets with different units. A MASE less than one indicates that, according to the mean absolute error (MAE), the forecast performed better than the average naïve forecast. In the case of seasonal data, a naïve forecast means all forecasts were set equal to the last observed value from the same season (Hyndman and Athanasopoulos 2018d). The MAPE and MASE for the testing data were recorded to provide a measure of the forecast accuracy (Hyndman and Athanasopoulos 2018d). The formula for the MAPE is provided in Equation 1. The formula for the MASE for a seasonal forecast is given in Equation 2.

$$MAPE = mean\left(\left|\frac{100e_t}{y_t}\right|\right) \quad 1)$$

Where

t = time (in months)

y_t = the fitted values (ridership in UPT)

e_t = the forecast error (the difference between an observed value and its forecast) (Hyndman and Athanasopoulos 2018d).

$$MASE = mean\left(\left|\frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^T |y_t - y_{t-m}|}\right|\right) \quad 2)$$

Where

t = time (in months)

m = number of observations per year (always 12 in this study)

y_t = the fitted values (ridership in UPT)

y_{t-m} = the fitted values from the previous season (ridership in UPT)

T = time at the last observation

e_j = the forecast error (the difference between an observed value and its forecast) (*Hyndman and Athanasopoulos 2018d*).

CHAPTER FOUR

RESULTS AND DISCUSSION OF THE MOVING WINDOW FORECASTS

Over the course of this thesis, forecasts for many different time periods were estimated as new observations became available for inclusion. Initially, forecasts were estimated using very little post-COVID data; the seven time series methods in this study performed well when used for one-step-ahead forecasts, but for 12-month forecasts, the methods underperformed. With more observations, the performance of the post-COVID and full series forecasts appeared to improve, with both forecasting periods producing similar performance. However, it was observed that even for forecasting periods that were very close in time (e.g., 12-month testing data starting in September 2022 versus 12-month testing data starting just four months later in January 2023), the overall model performance would change, even when comparing the same time periods (i.e., the full series period vs. the post-COVID period). The results appeared counter-intuitive; one may assume that as more training data become available, the overall forecasting performance would improve, especially as post-COVID ridership trends and patterns stabilize. However, the changes observed in the overall model performance were mixed; for example, for both the post-COVID and full series time periods, when updating the training data to include observations through December 2022 instead of just through August 2022, there were more forecasts with good performance and fewer forecasts with acceptable performance (based on the MAPE being below 5% and 10%, respectively). In order to get a more comprehensive insight into the seven time series methods' overall forecasting performance for heavy rail ridership in the US, a consecutive series of 12-month forecasts were estimated using a moving window.

In this chapter, forecasts for each time period were estimated for a consecutive series of 12-month-long forecasting horizons using moving windows. The mean absolute percent error (MAPE) and mean absolute scaled error (MASE) were calculated for each forecast in order to gain insight into the changing performance over time of the seven time series methods used in this study. A total of 2,940 forecasts were estimated; 12 sets of forecasts were estimated using the pre-COVID time period, and nine sets of forecasts were estimated using both the full series and post-COVID time periods. The results of the pre-COVID forecasts are shown first in order to establish a baseline of performance for the time series forecasting methods. Next, the results of the full series forecasts are shown, followed by the post-COVID forecasts.

Results of the Pre-COVID Analysis

For the pre-COVID period, 12 sets of forecasts were estimated in order to establish a baseline performance of time series forecasting for US heavy rail ridership. By estimating 12 consecutive forecasts using a moving window, the effect of a full year of seasonal changes in transit ridership on the forecasting performance could be investigated. The forecasting windows were selected by setting the last window to use the last 12 months of observations prior to the COVID-19 pandemic; therefore, the last set of models used testing data from March 2019 to February 2020, and the first set of models used testing data from April 2018 to March 2019 (see Figure 4-1).

Each forecast estimated ridership for the following 12 months, and the estimates were compared to actual ridership in order to evaluate the forecasting performance using the MAPE and MASE

12-month moving window of testing data / forecasting horizon

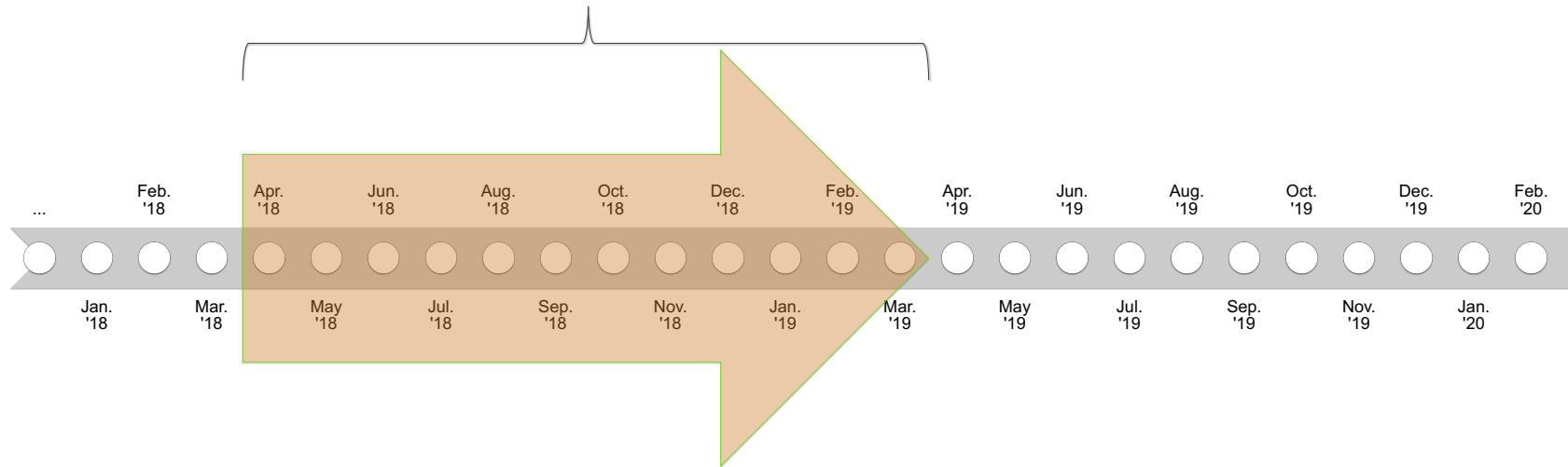


Figure 4-1 Visualization of the Moving Window for a Consecutive Series of 12-Month Pre-COVID Forecasts

(also referred to simply as “errors” in this thesis). In this study, a forecast with a MAPE below 5% was considered to have good performance, and a forecast with a MAPE below 10% was considered to have acceptable performance. The MASE is a measure of the forecast’s performance compared to the (seasonal) naïve method, where a MASE less than 1.00 means the forecast outperformed the naïve method. For all 1,176 forecasts performed for the pre-COVID period, the errors were recorded; in Figure 4-2 and Figure 4-3, the MAPE and MASE, respectively, for each forecasting method at the Chicago Transit Authority were plotted alongside the time series of ridership. In Figure 4-4 and Figure 4-5, the same errors for the Greater Cleveland Regional Transit Authority were similarly plotted; these two agencies were selected as examples of the results found at each of the 14 agencies in this study. The plots of the pre-COVID results by agency for the rest of the agencies were included in Appendix Part A, and Table 4-1 shows the overall performance, aggregated by method. For Figure 4-2 through Figure 4-5, the change in errors is shown on the y-axis of the upper plot, and the x-axis represents which testing/forecasting window was used, using the first month of the testing data as the identifier. The lower plot shows the time series of monthly ridership in unlinked passenger trips from January 2010 to March 2019; although the models were trained on data beginning in January 2002, only the time series from January 2010 to the onset of the pandemic were included, so that the trend and seasonal patterns that were typical of pre-COVID ridership would be clearly visible.

Figure 4-2 shows that for pre-COVID ridership at the Chicago Transit Authority, the seven time series methods generally performed well. With the exception of one of the neural network models, all forecasts produced a MAPE equal to or less than 5% for all forecasting windows. Figure 4-2 also shows that the ETS and ARIMA methods consistently outperformed the other methods, although the hybrid and STL methods outperformed them for the last two forecasting windows. The neural network consistently underperformed compared to the rest of the methods. Figure 4-3 shows that the neural network models struggled to produce forecasts that outperformed the naïve method, and that all models struggled to outperform the naïve method for the forecasting windows starting in November and December. Examining the ridership plot revealed an apparent increase in peak ridership over the previous year in late 2018, followed by a deeper valley in early 2019. This larger-than-previous fluctuation in ridership likely contributed to the slight decrease in forecasting performance for the November and December windows; however, thanks to Chicago Transit Authority’s obvious strong seasonal patterns, the time series methods generally produced good forecasts.

Figure 4-4 shows that for pre-COVID ridership at the Greater Cleveland Regional Transit Authority, the time series methods tended to produce acceptable results until the testing window moved to begin in September 2018. The models’ performance appeared to improve over the course of the first three testing windows, with the ETS and TBATS methods even producing good forecasts with a MAPE less than 5%. However, beginning with the fourth testing window, the performance steadily decreased. Examining the ridership plot revealed discontinuities in relative seasonality in the data, especially in 2019. Also in 2019, ridership decreases were more steep than in previous years, likely due to closures on the heavy rail line for maintenance over the summer in 2019 (*Greater Cleveland RTA 2019*). Overall, there appeared to be fewer and weaker seasonal patterns in Cleveland compared to Chicago, which may have made forecasting more challenging in that region.

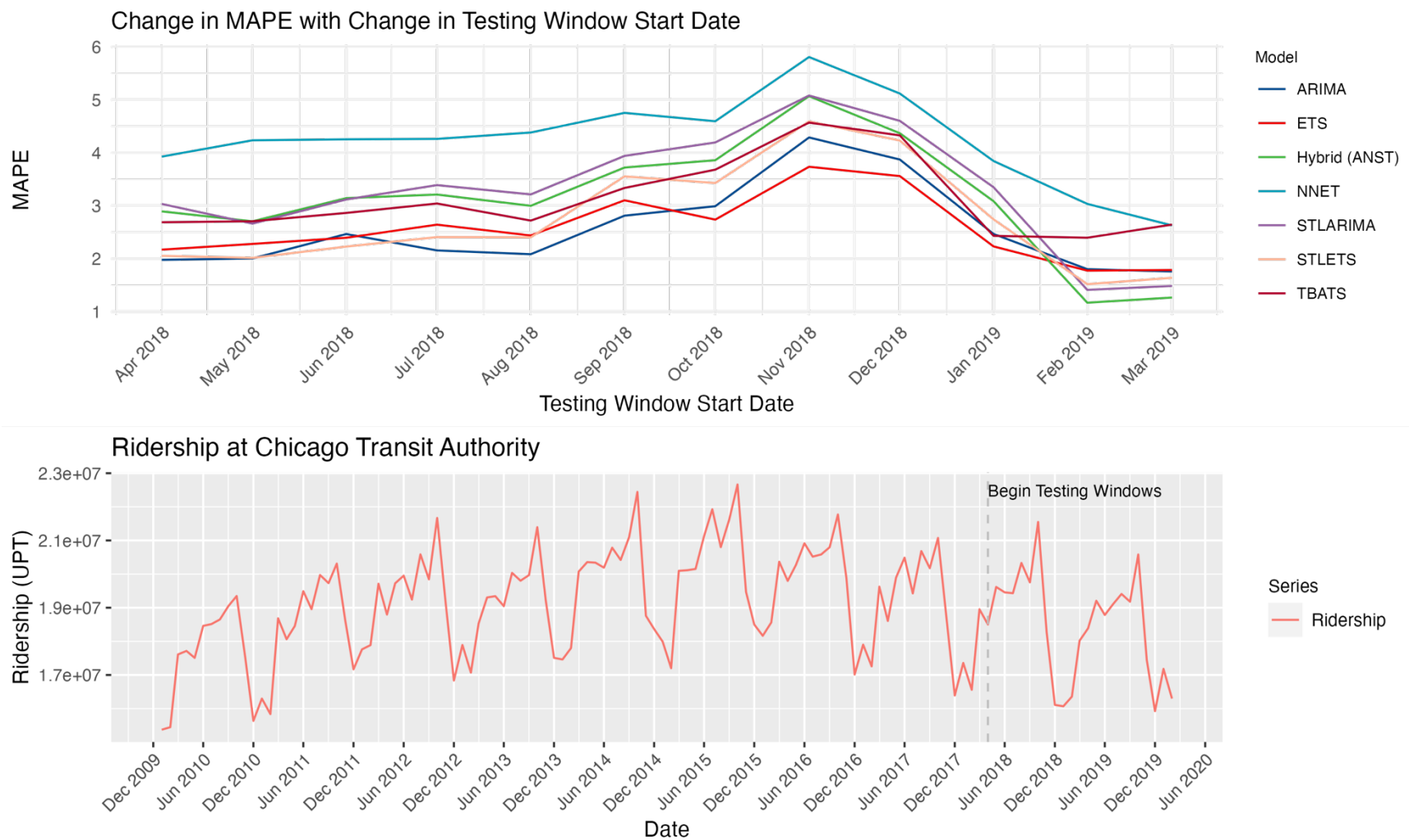


Figure 4-2 Pre-COVID Change in MAPE at the Chicago Transit Authority Using the Moving Window

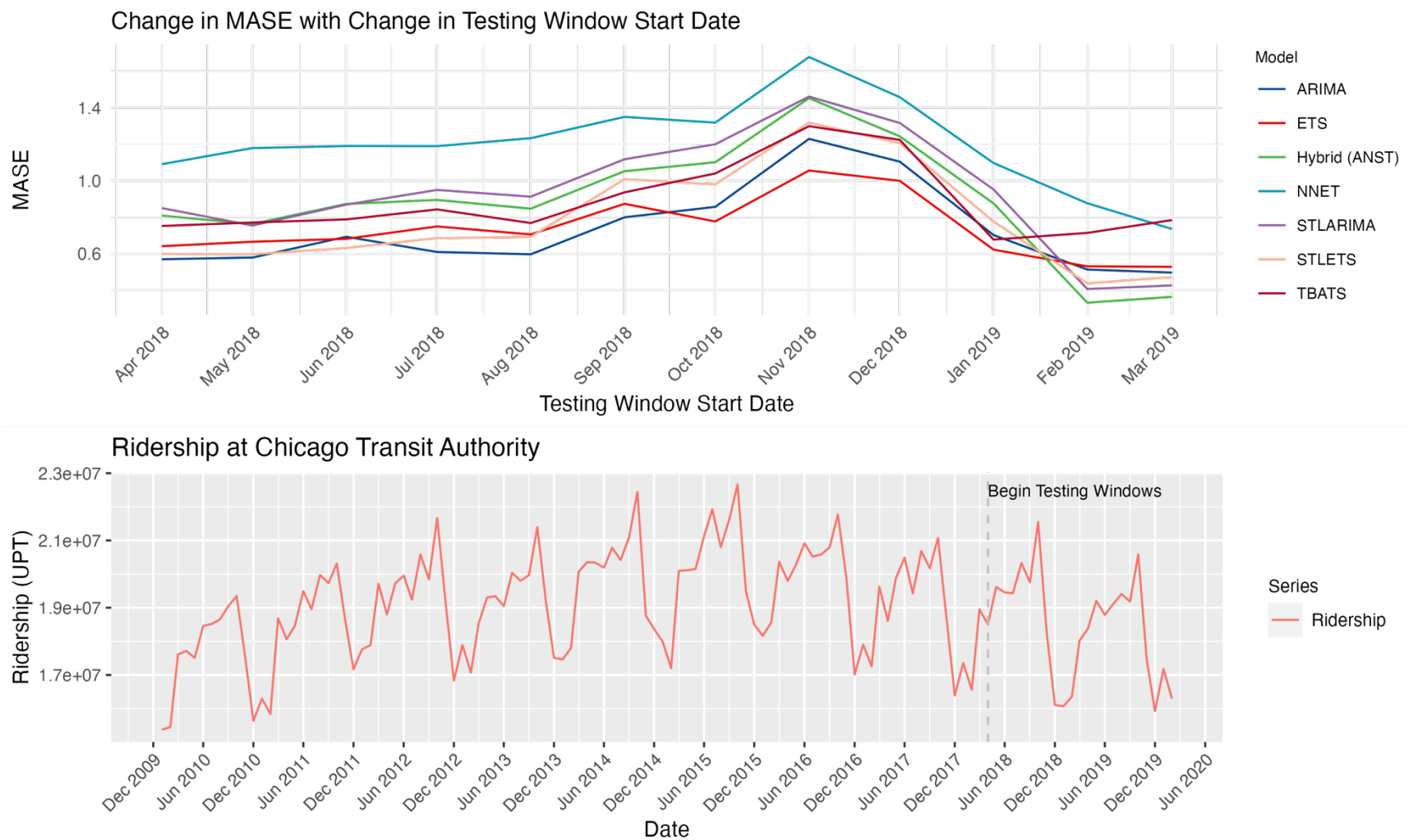


Figure 4-3 Pre-COVID Change in MASE at the Chicago Transit Authority Using the Moving Window

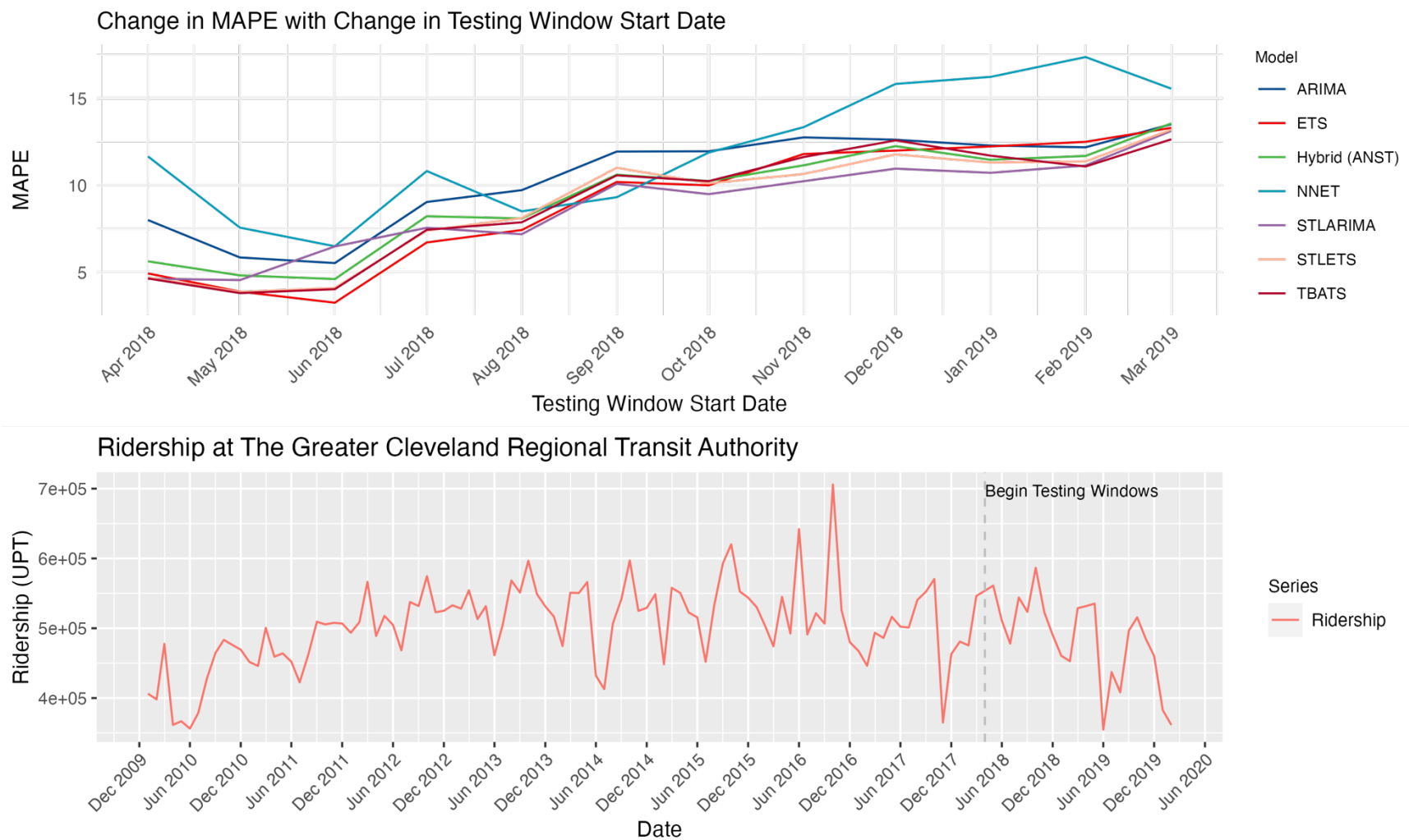


Figure 4-4 Pre-COVID Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

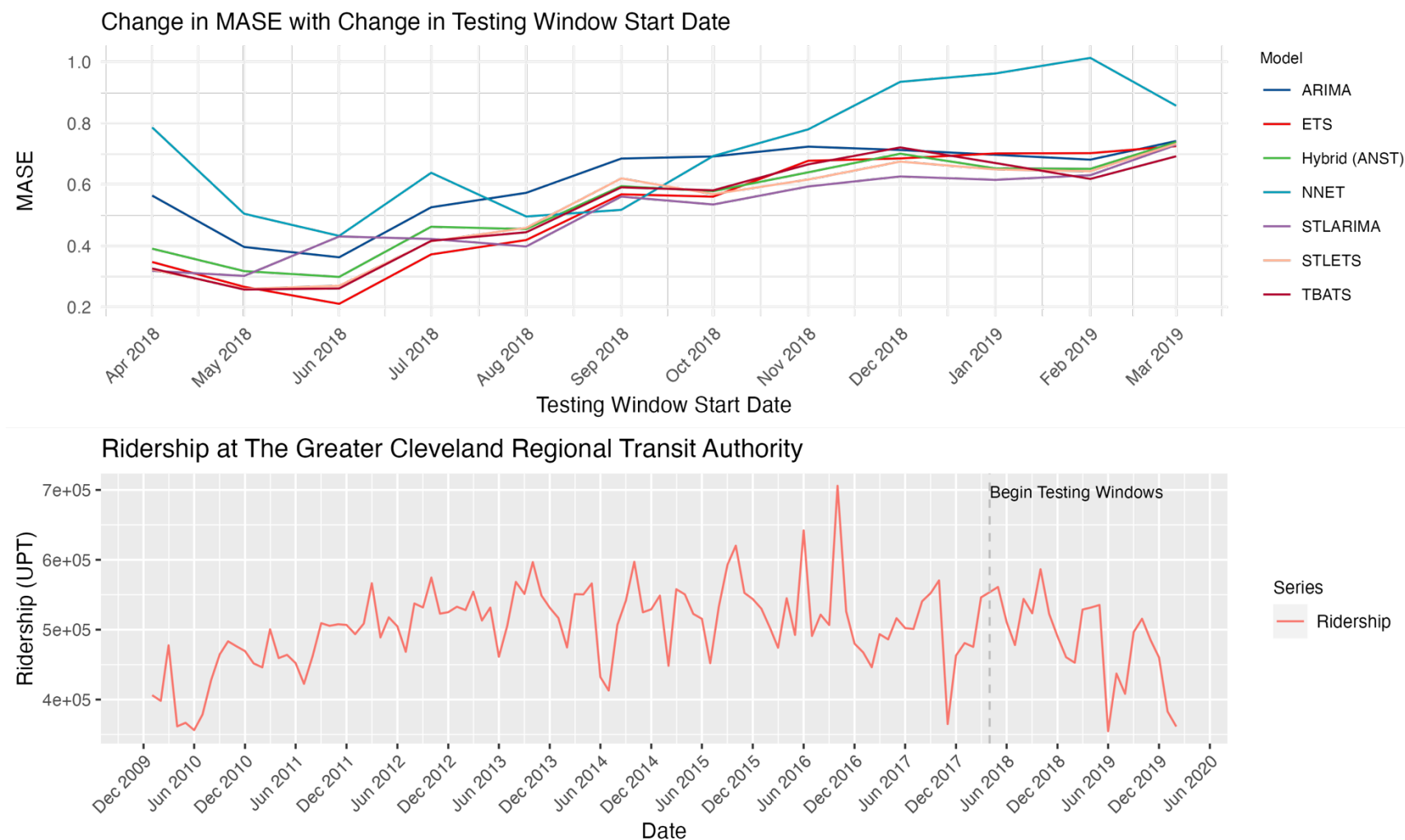


Figure 4-5 Pre-COVID Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

Table 4-1 Percent of Pre-COVID Models that were Good (MAPE < 5%) or Acceptable (MAPE < 10%) by Method and Time Period

Time Period	Performance	ETS	ARIMA	STLETS	STLARIMA	TBATS	NNET	Hybrid (ANST)
Pre-COVID	MAPE < 10%	89.9%	91.1%	90.5%	91.1%	89.9%	87.5%	92.9%
	MAPE < 5%	63.1%	56.5%	67.3%	67.3%	58.9%	42.9%	67.3%

Figures that show the performance of each forecast by method were included in Appendix Part A, and a summary of the same information is shown in Table 4-1. In general, at many agencies, there was a decrease in forecasting performance that emerged with the testing window beginning mid to late 2018. For many agencies, the forecasts then improved, creating a concave shape on the plots. For the agencies whose forecasts improved, the changes in MAPE could be an arbitrary byproduct of measuring performance using an averaged percent error, i.e., the MAPE could be sensitive to unexpectedly high/low seasonal peaks/lulls in ridership, especially when the ridership has been overestimated, producing negative percent errors (*Hyndman and Athanasopoulos 2018d*). But for agencies with steadily worsening forecast performance, in many cases, the decline in forecast performance could be related to the trend in the data in 2019, i.e., higher increases or decreases in ridership compared to previous years. Nevertheless, the majority of the models produced good or acceptable forecasts for all agencies and all testing windows. Generally, about 90% of the models for each forecasting method had an acceptable MAPE, and more or less 60% of the models had a good MAPE; the one exception was the neural network, for which method only 43% of the models produced a good MAPE. Despite the overall acceptable results, there were some agencies for which ridership was consistently more difficult to forecast, e.g., the agencies in Cleveland and Baltimore. This may be due to the limited heavy rail service in those two cities, which each have only one heavy rail line. No one method stands out as having particularly better performance compared to all the rest for pre-COVID heavy rail ridership, although at individual agencies, some methods did seem to outperform the others.

Results of the Full Series Analysis

Nine sets of forecasts were estimated for post-COVID ridership using the full data series (data from January 2002 to December 2023). The forecasting window for the full series period was selected to match the post-COVID period. The STL methods require at least 25 observations in order to produce forecasts. Therefore, the post-COVID series' forecasts needed, at a minimum, to train on the data from April 2020 to April 2022. In order to compare between the forecasts from the full series and post-COVID series, both periods' first testing/forecasting window began with May 2022. The last available observation at the time of this analysis was December 2023, allowing for only nine sets of 12-month forecasts to be estimated (see Figure 4-6).

Similar to the previous section, each of the 882 models produced for the full series period were used to forecast ridership for the following 12 months, and the errors (MAPE and MASE) were recorded. The MAPE and MASE for the Chicago Transit Authority are once again shown in Figure 4-7 and Figure 4-8, respectively. The same errors are shown for the Greater Cleveland Regional Transit Authority in Figure 4-9 and Figure 4-10; these two agencies were selected as examples of the results found at each of the 14 agencies in this study. For each of the four figures, the upper plot is the change in error according to which testing/forecasting window was used, and the lower plot is the ridership in unlinked passenger trips. Only the post-COVID ridership is shown in order to show the trends and patterns more clearly. The plots of the full series for the rest of the agencies are shown in Appendix Part B, but Table 4-2 shows the overall performance aggregated by method.

Figure 4-7 shows that for the full series period, most of the models for the Chicago Transit Authority produced acceptable forecasts, with the exception of the neural network models.

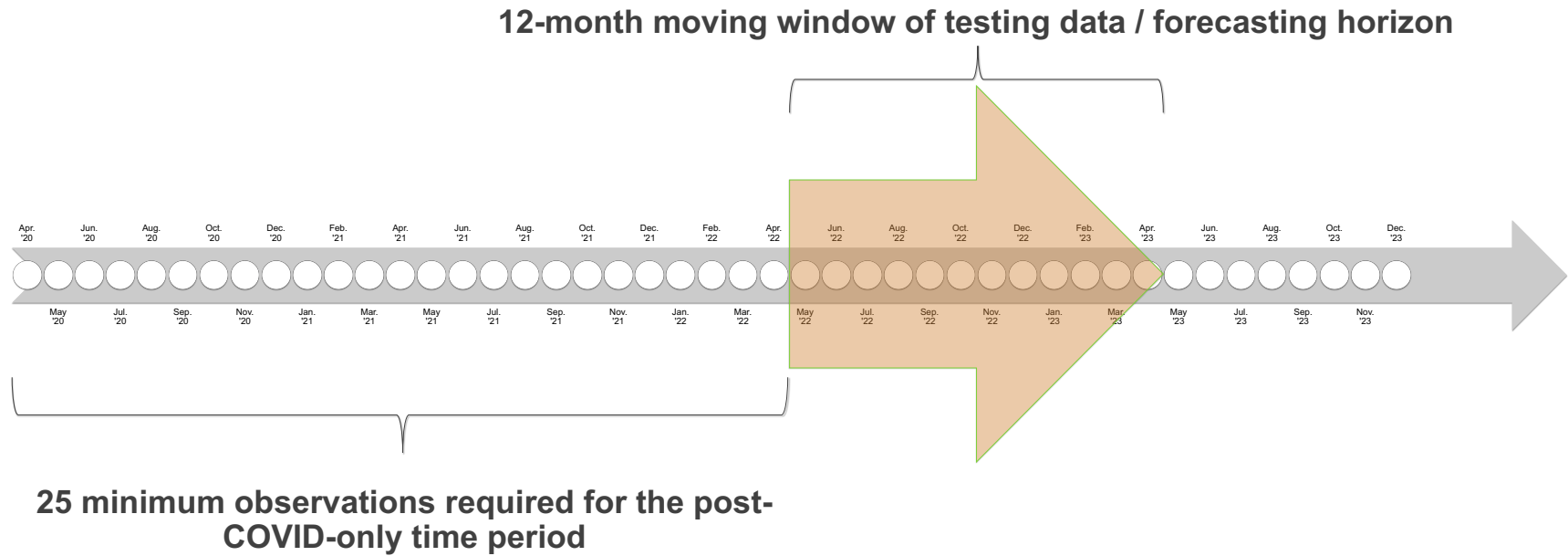


Figure 4-6 Visualization of the Moving Window for a Consecutive Series of 12-Month Post-COVID Forecasts Using the Full Series and Post-COVID Time Periods

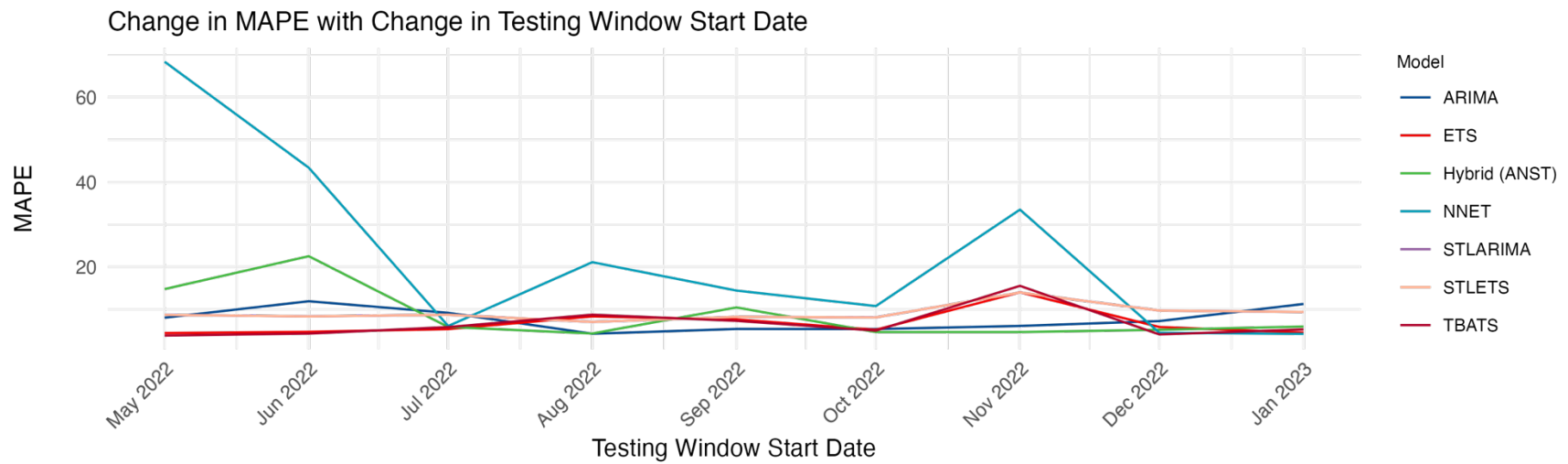
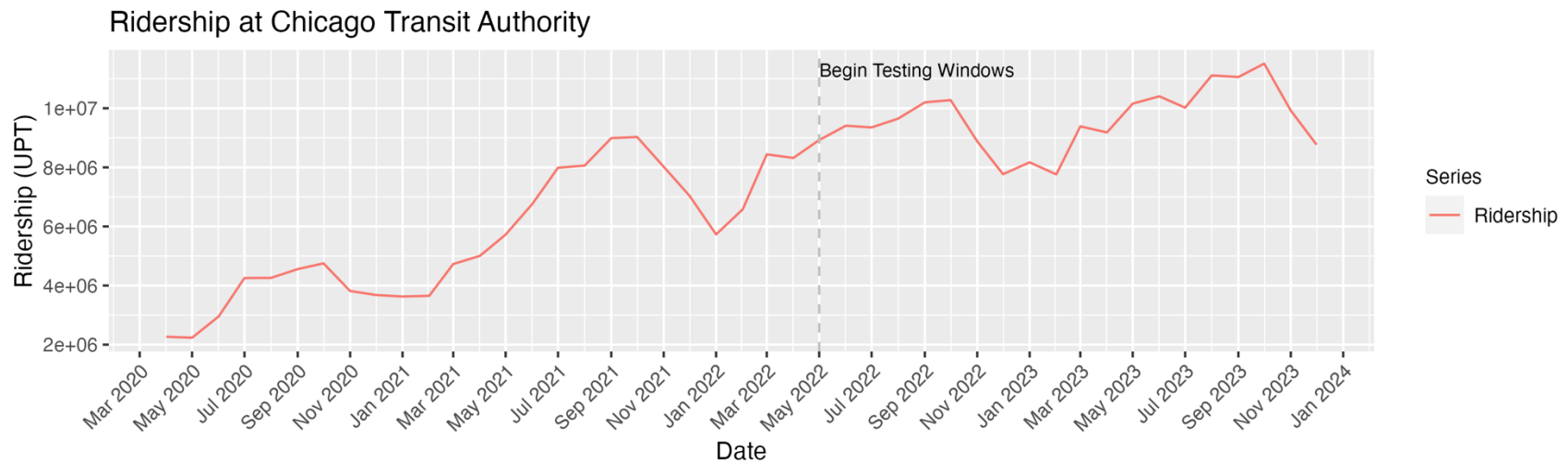


Figure 4-7 Full Series Change in MAPE at the Chicago Transit Authority Using the Moving Window

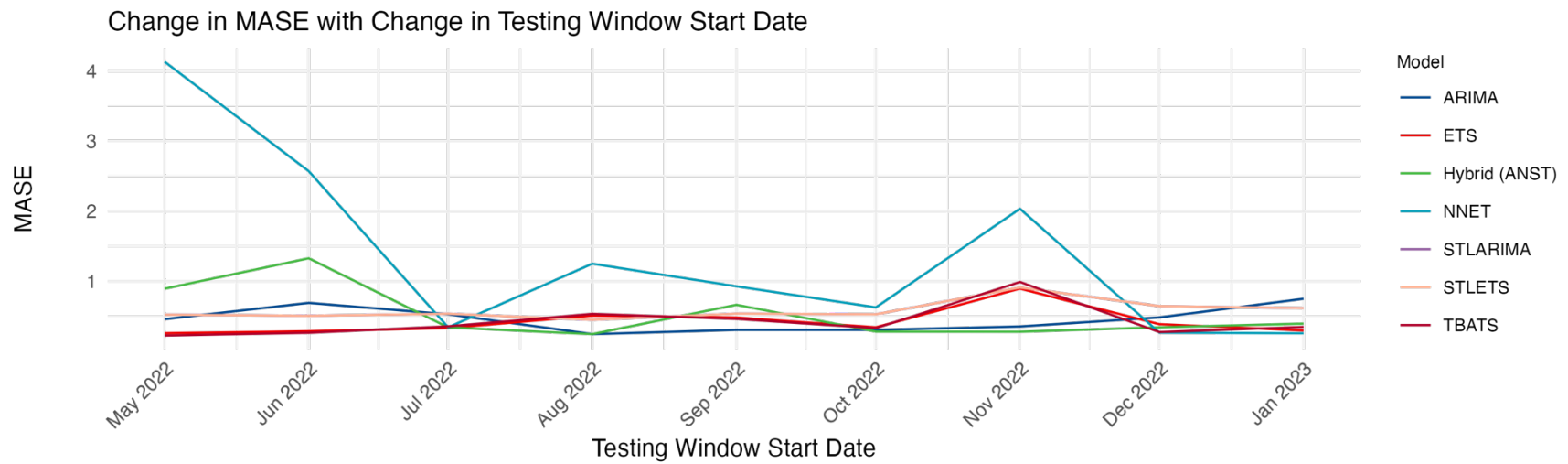
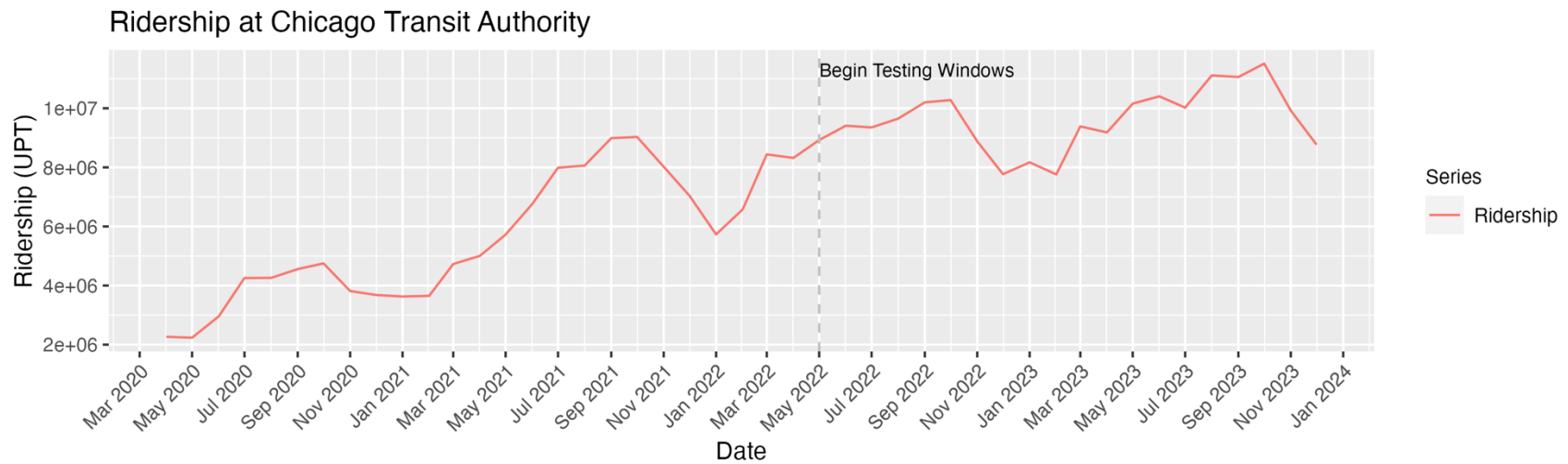


Figure 4-8 Full Series Change in MASE at the Chicago Transit Authority Using the Moving Window

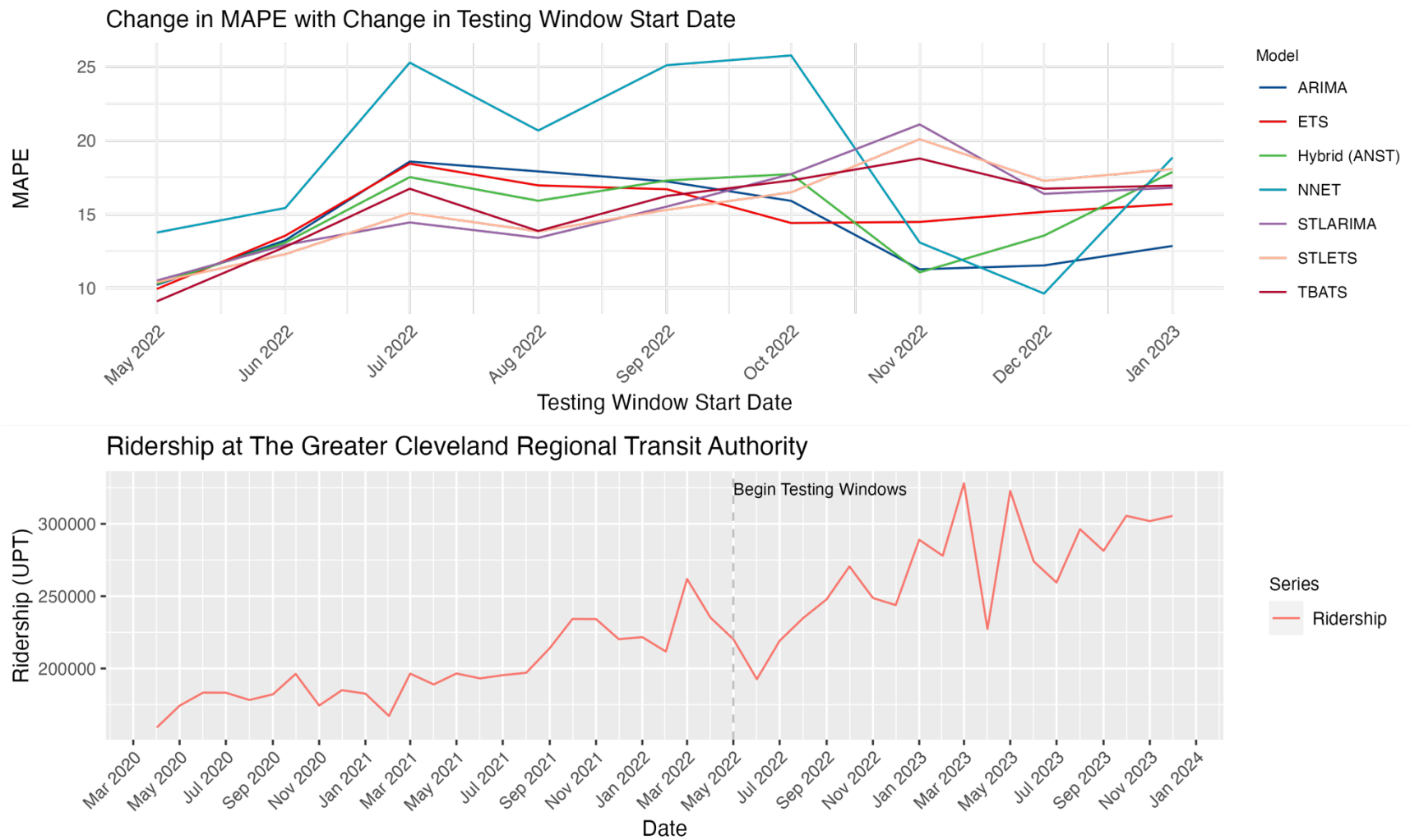


Figure 4-9 Full Series Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

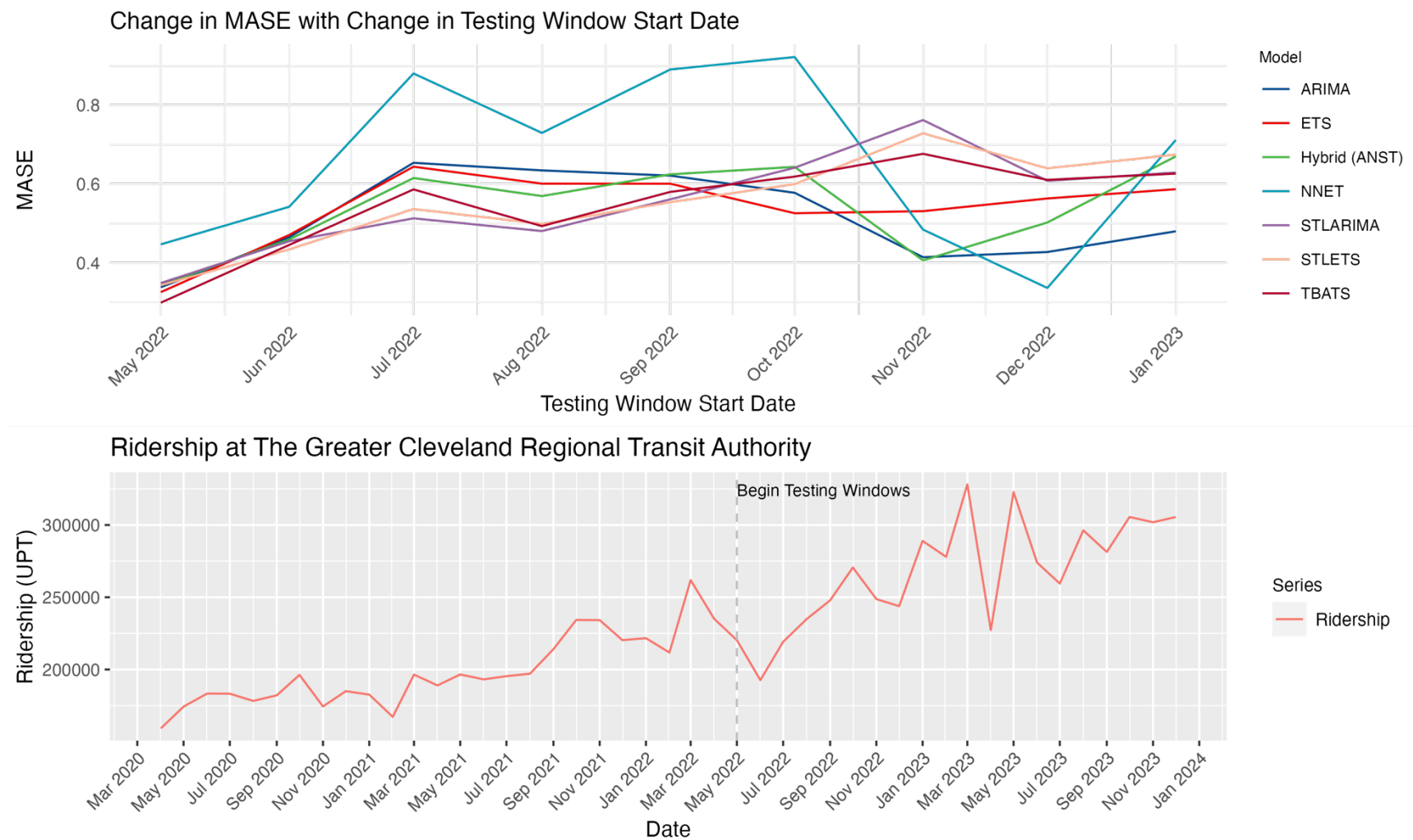


Figure 4-10 Full Series Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

Table 4-2 Percent of Full Series Models that were Good (MAPE < 5%) or Acceptable (MAPE < 10%) by Method and Time Period

Time Period	Performance	ETS	ARIMA	STLETS	STLARIMA	TBATS	NNET	Hybrid (ANST)
Full Series	MAPE < 10%	54%	64.3%	52.4%	52.4%	52.4%	24.6%	49.2%
	MAPE < 5%	9.5%	24.6%	4.8%	4%	10.3%	6.3%	25.4%

Similarly, Figure 4-8 shows that most of the models also outperformed the naïve method, with the exception of a few of the neural network models. No one method stood out as having particularly better performance than all the other methods, although the ETS and TBATS methods produced good forecasts (MAPE below 5%) for the forecasts earlier in the post-COVID period with testing windows beginning in May and June 2022, and the hybrid method produced good forecasts for the testing windows beginning in August, October, and November 2022. Figure 4-8 shows that almost all of the models outperformed the naïve method. The time series plot of ridership shows clear seasonal patterns and a steady, positive trend, which likely contributed to the ability of the time series methods to produce acceptable forecasts.

Figure 4-9 shows that, for the Greater Cleveland Regional Transit Authority, few of the models produced acceptable results; however, as shown in Figure 4-10, all of the models outperformed the naïve method. No one method stood out as having particularly better performance than all the rest, but the neural network method again underperformed. The time series plot of ridership shows a positive trend, but only vague seasonal patterns.

Figures that show the performance of each forecast by method were included in Appendix Part B, and a summary of the same information is given in Table 4-2. The ARIMA and hybrid methods outperformed the rest of the methods for overall performance of time series forecasting for post-COVID heavy rail ridership using the full data series. Roughly 50-55% of the models for all methods produced acceptable forecasts (MAPE < 10%), but for the ARIMA method, 64% of the models produced acceptable forecasts. Roughly 5-10% of the models for all methods produced good forecasts (MAPE < 5%), but roughly 25% of the models using the ARIMA or hybrid methods produced good forecasts. In contrast, the neural network underperformed, with less than 25% of the neural network models producing an acceptable forecast. The neural network also struggled to outperform the naïve method.

Results of the Post-COVID Analysis

Similar to the previous section, nine sets of forecasts were estimated for post-COVID ridership, but now using only post-COVID data (data from May 2020 to December 2023). As described in the previous section, because of the short time span between the onset of the pandemic and the time of this writing, there were only 45 monthly observations for the post-COVID period, 25 of which were required to train the models. Therefore, the training/forecasting window was applied to the final 20 observations, producing 882 post-COVID models, which was the maximum number of forecasting models that could be produced from such a small data set.

Similar to the previous section, each of the 882 models produced for the post-COVID period were used to forecast ridership for the following 12 months, and the errors (MAPE and MASE) were recorded. The MAPE and MASE for the Chicago Transit Authority are once again shown in Figure 4-11 and Figure 4-12, respectively. The same errors are shown for the Greater Cleveland Regional Transit Authority in Figure 4-13 and Figure 4-14; these two agencies were selected as examples of the results found at each of the 14 agencies in this study. The plots of the post-COVID results by agency for the rest of the agencies are shown in Appendix Part C, but Table 4-3 shows the overall performance aggregated by method. For Figure 4-11 through Figure 4-14, the upper plot

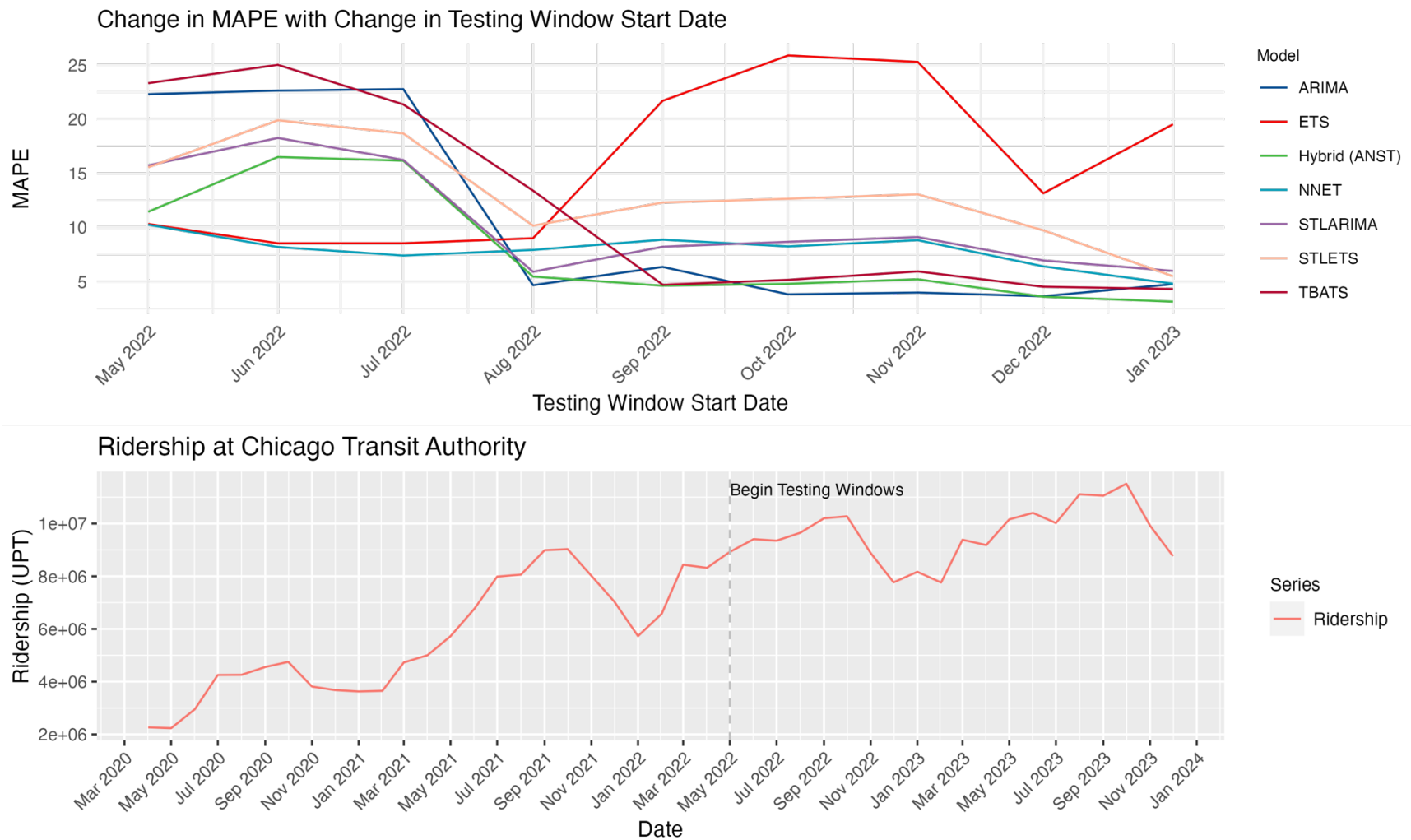


Figure 4-11 Post-COVID Change in MAPE at the Chicago Transit Authority Using the Moving Window

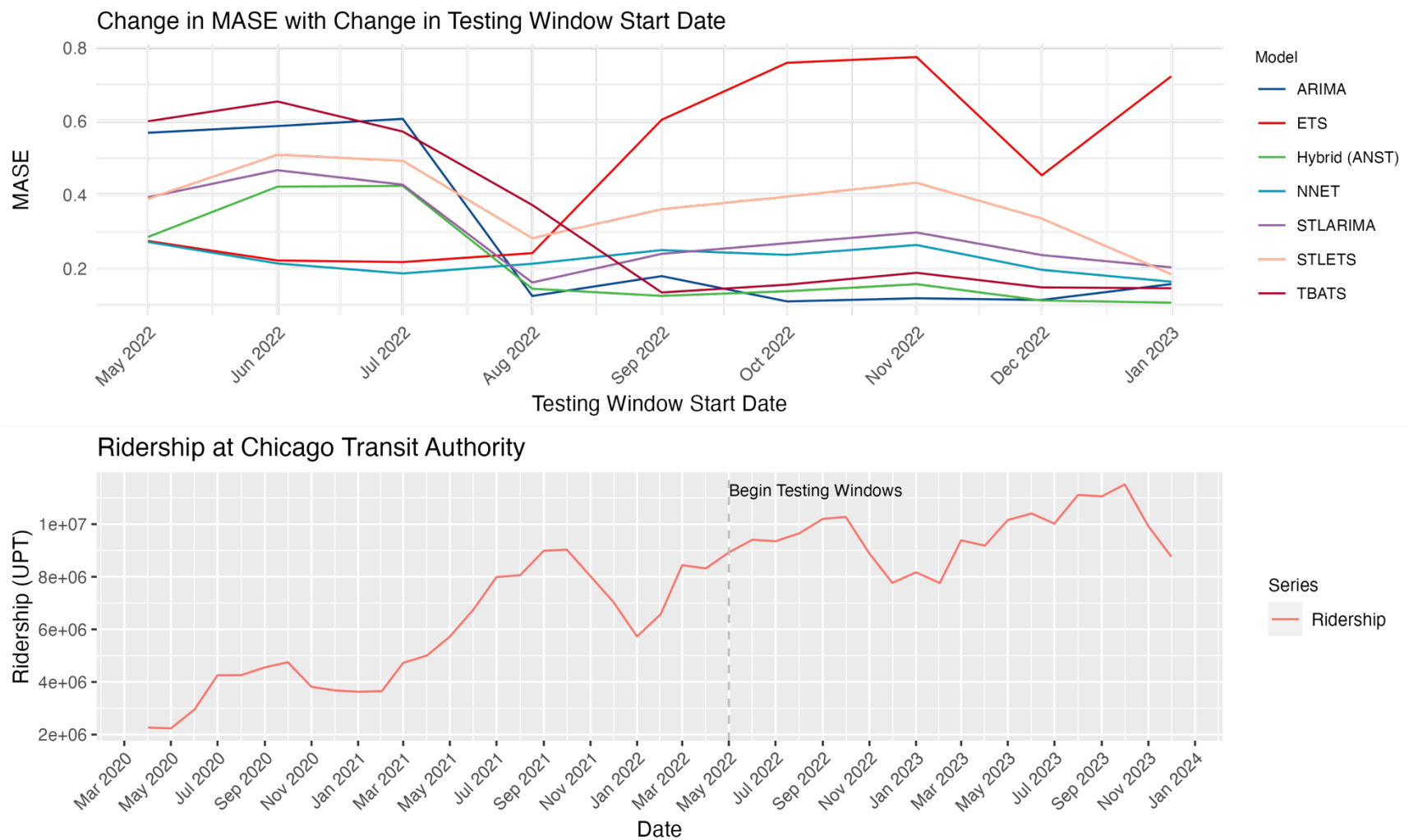


Figure 4-12 Post-COVID Change in MASE at the Chicago Transit Authority Using the Moving Window

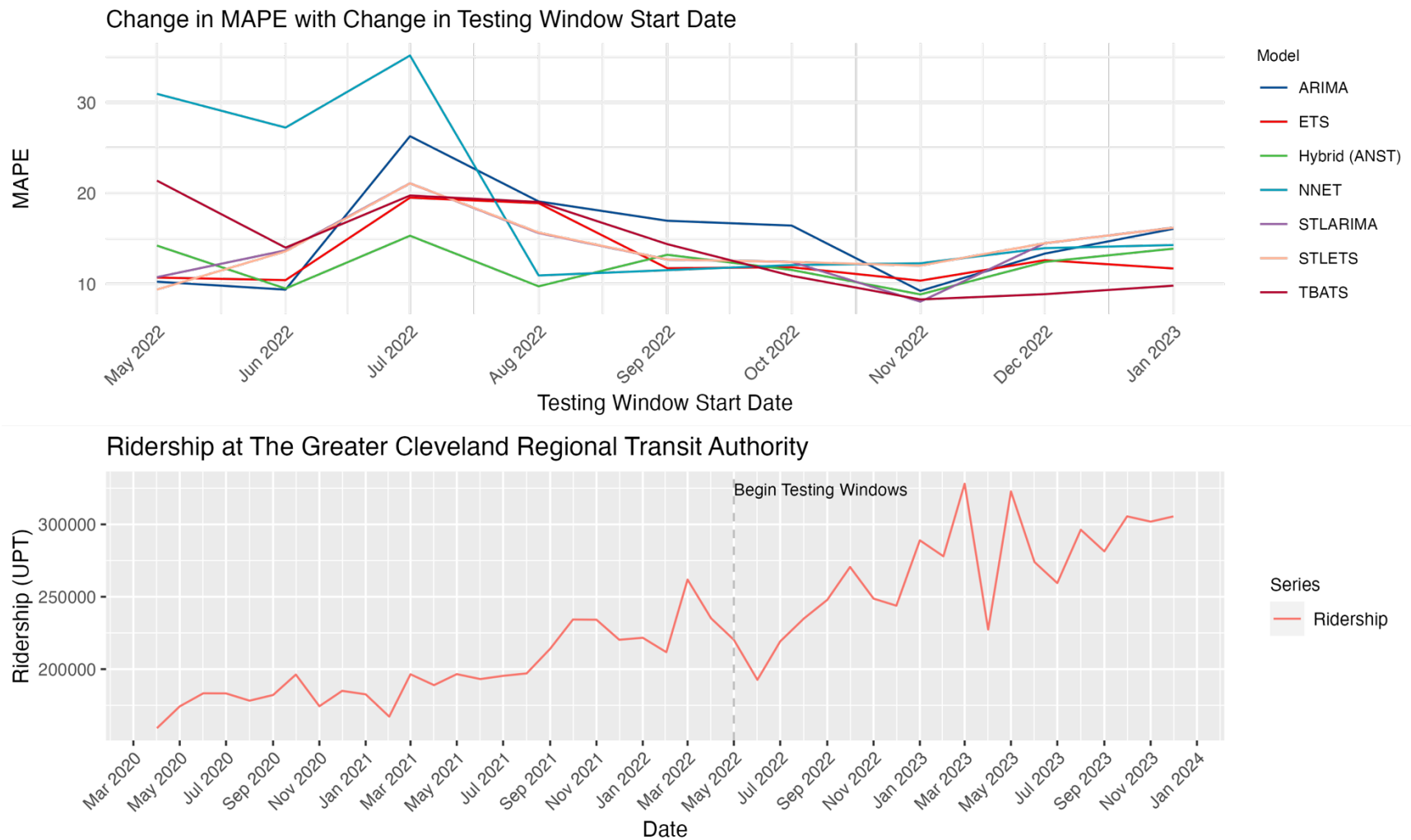


Figure 4-13 Post-COVID Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

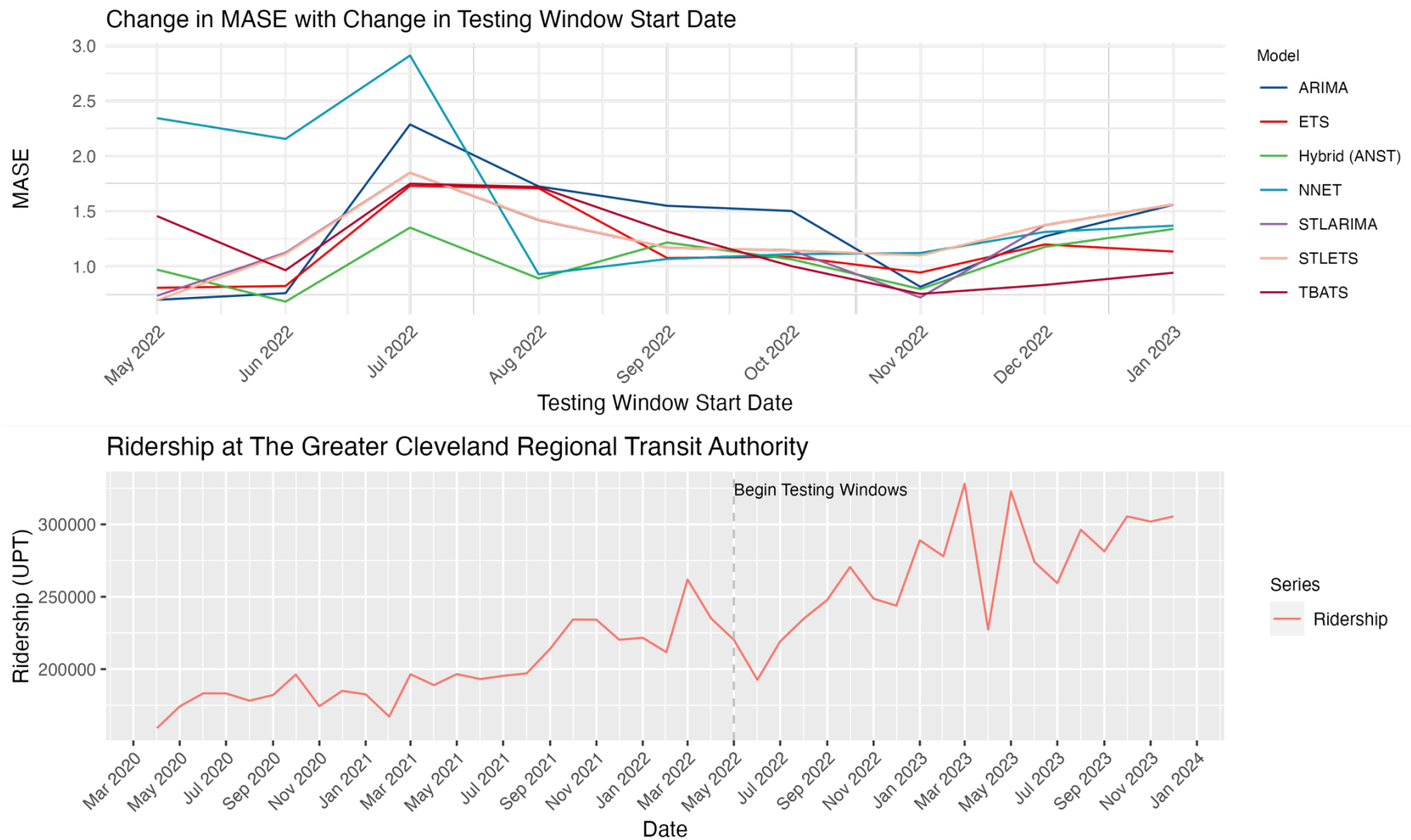


Figure 4-14 Post-COVID Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

Table 4-3 Percent of Post-COVID Models that were Good (MAPE < 5%) or Acceptable (MAPE < 10%) by Method and Time Period

Time Period	Performance	ETS	ARIMA	STLETS	STLARIMA	TBATS	NNET	Hybrid (ANST)
Post-COVID	MAPE < 10%	28.6%	44.4%	46%	35.7%	47.6%	51.6%	50%
	MAPE < 5%	2.4%	7.9%	11.1%	1.6%	7.9%	15.1%	12.7%

is the change in error according to which testing/forecasting window was used, and the lower plot is the ridership in unlinked passenger trips.

Figure 4-11 shows that for the post-COVID period, most of the models for the Chicago Transit Authority produced acceptable forecasts when the training data included observations at least through July 2022. However, for the models without training data including observations at least through July 2022, the forecasts did not produce acceptable MAPEs. The ETS and STL-ETS methods were the exception; opposite to the rest of the methods, the ETS method produced acceptable forecasts when the training data did not include observations beyond July 2022. The STL-ETS method never produced an acceptable forecast. Notably, the neural network method vastly outperformed the rest of the methods, with all but one forecast producing acceptable MAPEs. Figure 4-12 shows that all post-COVID models outperformed the naïve method at the Chicago Transit Authority. As discussed in the prior section, the time series plot of ridership shows clear seasonal patterns and a steady, positive trend, which likely contributed to the ability of the time series methods to produce acceptable forecasts.

Figure 4-13 and Figure 4-14 show that, for the Greater Cleveland Regional Transit Authority, almost none of the models produced acceptable results, nor did many of them outperform the naïve method. Interestingly, about half of the models with forecasts starting on November 2022 produced an acceptable MAPE and outperformed the naïve method; all but the STL-ARIMA and neural network models improved when moving the testing/forecast window from October to November 2022. This result contrasted with the full series forecast for the November 2022 forecasting window; in Figure 4-9, the ETS, STL, and TBATS models worsened or stayed the same, while the ARIMA, neural network, and hybrid models improved. Also, none of the full forecast models for this forecasting period produced acceptable forecasts, whereas four of the methods produced acceptable forecasts using only the post-COVID data. Nevertheless, still no one method stood out as having the best performance at the Greater Cleveland Regional Transit Authority. As discussed in the prior sections, this may be partially due to the positive trend, but only vague seasonal patterns shown in the time series plot of ridership, as well as Cleveland's relatively limited heavy rail service, which is comprised of only one line.

Figures that show the performance of each forecast by method were included in Appendix Part C, and a summary of the same information is given in Table 4-3. Overall, the forecasts for post-COVID ridership using only post-COVID data underperformed compared to the same forecasts using the full data series. Most methods generally produced acceptable forecasts for around 45-50% of the models; the exceptions were the ETS method, which only produced acceptable forecasts for about 29% of the models, and the STL-ARIMA method, which only produced acceptable forecasts for about 35% of the models. The neural network produced good forecasts for at least 15% of the models; the hybrid and STL-ETS methods also produced good forecasts for about 13% and 11% of the models, respectively. The ETS and STL-ARIMA methods underperformed, producing good forecasts for just over 1% of the models.

In summary, the time series methods used in this study generally produced good or acceptable forecasts for most heavy rail agencies before the onset of the COVID-19 pandemic. After COVID, ridership forecasting for heavy rail agencies became less straightforward. In all cases, the good

and acceptable forecasts tended to be concentrated at specific agencies, suggesting that the performance of the time series forecasts may be dependent on the characteristics of the transit agency and its ridership. For example, for all forecasting periods, the forecasts for the Greater Cleveland Regional Transit Authority and the Maryland Transit Administration tended to be poor, with a MAPE greater than 10%. In contrast, forecasting was more straightforward at some agencies such as the Chicago Transit Authority, the County of Miami-Dade, and the Los Angeles County Metropolitan Transportation Authority.

The period used to train the models had a clear impact on the overall performance of the forecasts. Table 4-4 shows a summary of the percent of good and acceptable forecasts produced by method and for each time period, which were described in the previous sections. As shown in Table 4-4, the time series forecasts performed better when the training series was longer; however, the performance of the forecasts appeared to be sensitive to either the last training or testing observation (i.e., misleading training observations or increasingly unexpected ridership observations). For example, many of the forecasts in the full series period had a decrease in performance when the testing/forecasting window began with the observation from October or November 2022. Similarly, several of the forecasts in the post-COVID period had a decrease in performance when the testing/forecasting window began with the observation from September 2022. In most cases, there did not appear to be anything particularly significant about the windows that had particularly better or worse performance than other months; rather, the changing performance appeared to be random. However, one explanation for the changing performance could be competing trends in the time series data, e.g., seasonal fluctuations in ridership being masked by smaller increases in ridership recovery in late 2022.

Additionally, as previously discussed, some methods performed better for certain time periods. As shown in Table 4-4, the neural network method underperformed for the pre-COVID and full series time periods, but slightly outperformed the other methods for the post-COVID time period. One potential reason for the neural network's mixed performance could be that its "P" parameter for the number of seasonal lags defaults to one; for monthly data, 12 seasonal lags is more appropriate and may improve the forecasting performance. However, for the post-COVID data, setting the number of seasonal lags to 12 caused the models to extremely overfit the data and did not improve the forecasting performance, so for the sake of uniformity, all the neural network models in this study used only one seasonal lag. This parameter could be responsible for the neural network's relative underperformance using the pre-COVID and full data series, as well as its relative outperformance using the post-COVID period. In the post-COVID data, there may have been a loss of seasonal patterns at many agencies, so using only one seasonal lag could have given the neural network models an advantage if the previous month's ridership were a better predictor of future ridership than that of the previous year.

Table 4-4 also shows that the ARIMA and hybrid methods exhibited strong performance for the full series time period. In fact, the hybrid method performed fairly well for all time periods, relative to the other methods. The hybrid method used in this study relied on equal weights of the ARIMA, STL-ARIMA, TBATS, and neural network methods to estimate forecasts. It appeared as though the hybrid method may have been able to reinforce the good performance of each individual contributing method, while minimizing the effects of any one method's poor estimates. The good performance of the hybrid method may imply that no one forecasting method was able to

Table 4-4 Percent of All Models that were Good (MAPE < 5%) or Acceptable (MAPE < 10%) by Method and Time Period

Time Period	Performance	ETS	ARIMA	STLETS	STLARIMA	TBATS	NNET	Hybrid (ANST)
Pre-COVID	MAPE < 10%	89.9%	91.1%	90.5%	91.1%	89.9%	87.5%	92.9%
	MAPE < 5%	63.1%	56.5%	67.3%	67.3%	58.9%	42.9%	67.3%
Full Series	MAPE < 10%	54%	64.3%	52.4%	52.4%	52.4%	24.6%	49.2%
	MAPE < 5%	9.5%	24.6%	4.8%	4%	10.3%	6.3%	25.4%
Post-COVID	MAPE < 10%	28.6%	44.4%	46%	35.7%	47.6%	51.6%	50%
	MAPE < 5%	2.4%	7.9%	11.1%	1.6%	7.9%	15.1%	12.7%

adequately capture all patterns in the time series data, but by combining the methods, the errors of the individual models may have been canceled out (*Makridakis, Spiliotis and Assimakopoulos 2020*).

These findings are consistent with previous studies of time series forecasting performance, both for transit ridership as well as more generally. Some pre-COVID studies that compared the performance of time series forecasting methods for transit ridership likewise found that combined methods of ridership forecasting, like the hybrid method, tended to outperform the other methods (*Chen, Zhang and Jiang 2020; Chiang, Russell and Urban 2011*). The performance of time series methods has been evaluated more generally on a large scale through the Makridakis Competitions, which are a series of open forecasting competitions designed to empirically evaluate and compare the performance of time series forecasting methods (*Makridakis Open Forecasting Center N.D.*). Collectively, the competitions have required participants to forecast over 100,000 diverse time series datasets using every major time series forecasting method available (*Makridakis, Spiliotis and Assimakopoulos 2020*). These competitions have consistently found that the more complex forecasting methods such as machine learning methods generally do not outperform simpler methods (*Hyndman 2020; Makridakis, Spiliotis and Assimakopoulos 2020*). One of the reasons behind the underperformance of pure machine learning methods may be their tendency to overfit the data. Additionally, pure statistical and machine learning methods were found to both underperform compared to combined (hybrid) methods, especially when the combined method used both statistical and machine learning methods (*Makridakis, Spiliotis and Assimakopoulos 2020*). Other relevant findings included that the ranking of the forecasting performance changed according to which accuracy measure was used, and the performance of the forecasts depended on the length of the forecasting horizon (*Hyndman 2020*).

CHAPTER FIVE

RESULTS AND DISCUSSION OF THE LATEST FORECASTS

In this chapter, the results of the latest 12-month forecasts from the previous chapter are shown in more detail. The results discussed in this chapter are the pre-COVID forecasts of ridership during the year immediately preceding COVID (March 2019 to February 2020), the full series forecasts of 2023 ridership, and the post-COVID forecasts of 2023 ridership. Plots for each time period are shown, which provide more insight into the forecasts' performance and ability to identify trends and patterns. The exact values for the errors are also shown and discussed.

To assess the fit of the models, the Ljung-Box test was used to assess the white noise of the residuals for each model, and histograms of the residuals were examined to check for normality and influential outliers. The residuals were checked using the “checkresiduals()” function from the “forecast” package (Hyndman *et al.* 2021; Hyndman and Khandakar 2008). For the majority of the pre-COVID models, the histograms were normally distributed with the means close to zero, meaning the models were unbiased. The Ljung-Box test showed that for many of the models, some autocorrelation patterns remained that the models were not able to capture; this means that while the forecasts could be quite good, the prediction intervals may have been inaccurate (Hyndman and Athanasopoulos 2018d). For the full series forecasts, the histograms were normally distributed with the means close to zero, and most of the results from the Ljung-Box test showed that the residuals were white noise; however, some of the models, especially the ETS and neural network methods, were not able to capture all the patterns in the data, meaning that while these forecasts could be quite good, the prediction intervals may have been inaccurate (Hyndman and Athanasopoulos 2018d). For the post-COVID series, the histograms were approximately normally distributed with the means close to zero, and the Ljung-Box test showed that almost all models captured all available patterns in the data, leaving the residuals with only white noise. The residuals therefore showed that the models generally produced unbiased results and captured most of the patterns in the data for each time period (Hyndman and Athanasopoulos 2018d). Even though the pre-COVID residuals showed some remaining patterns, the results below show that the overwhelming majority of the models still produced good or acceptable forecasts.

Results of the Pre-COVID Analysis

For the pre-COVID analysis, the training dataset was from January 2002 through February 2019. The testing dataset was from March 2019 through February 2020. Visualizations of the forecasts for the Chicago Transit Authority and the Greater Cleveland Regional Transit Authority are shown in Figure 5-1 and Figure 5-2 to show examples of the outputs that were created for each of the 14 agencies. Plots for the rest of the agencies are available to view in Appendix Part D, but the numerical results for all agencies are shown in Table 5-1. In the figures, the x-axis is the date, and the y-axis is ridership (UPT). The blue line is the forecasted ridership, and the red line is the actual ridership (testing data). The light purple shaded area is the 95% prediction interval, and the dark purple shaded area is the 80% prediction interval. Although the data was trained from 2002 to 2019, only the training data after 2010 is shown so that both the forecasts and the trends are shown more clearly. At many agencies, for example at the Chicago Transit Authority, the graphs showed clear seasonal patterns and a downward trend prior to the pandemic. Other agencies, such as the

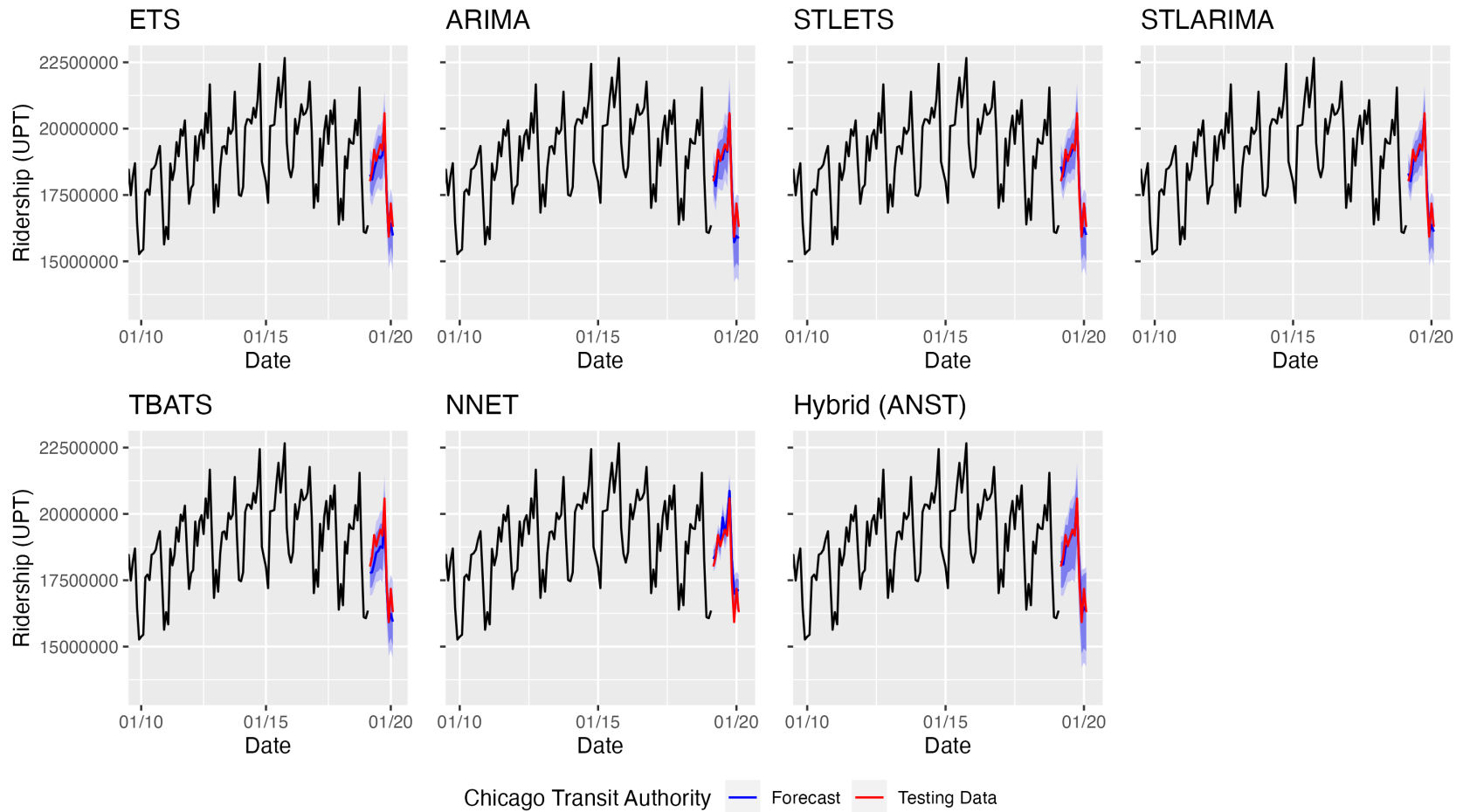


Figure 5-1 Pre-COVID Forecasts of Ridership at the Chicago Transit Authority from March 2019 to February 2020

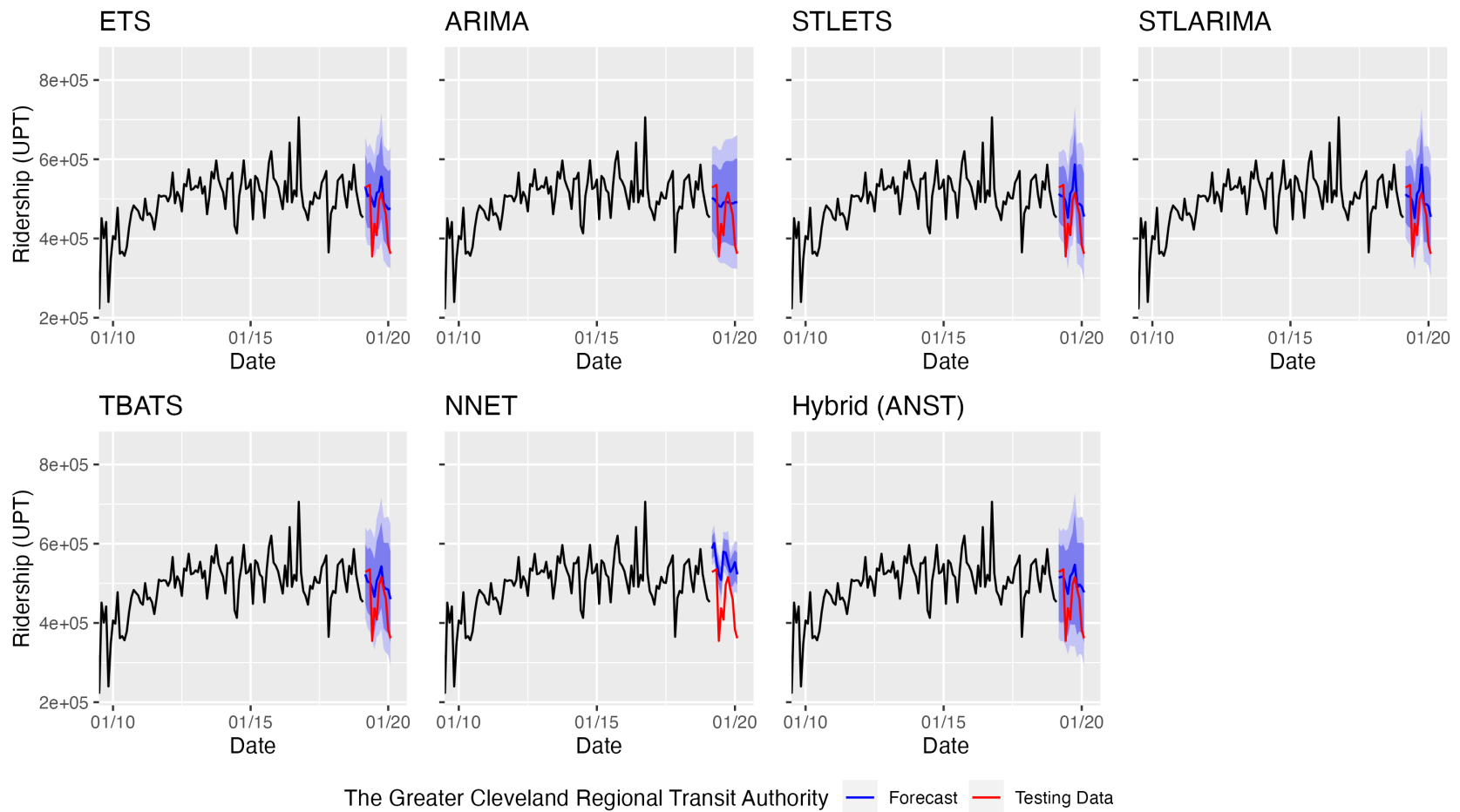


Figure 5-2 Pre-COVID Forecasts of Ridership at the Greater Cleveland Regional Transit Authority from March 2019 to February 2020

Table 5-1 Performance of the Pre-COVID Forecasts for Ridership in the Year Preceding COVID

Agency	Measure	ETS	ARIMA	STL-ETS	STL-ARIMA	TBATS	NNET	Hybrid (ANST)	Minimum	Maximum
Chicago Transit Authority	MAPE	1.79	1.76	1.64	1.49	2.65	2.40	1.33	Hybrid (ANST)	TBATS
	MASE	0.53	0.50	0.47	0.42	0.78	0.67	0.38		
County of Miami-Dade	MAPE	7.99	5.52	7.25	6.78	7.67	8.03	7.64	ARIMA	NNET
	MASE	1.22	0.84	1.12	1.04	1.17	1.22	1.17		
Los Angeles County Metropolitan Transportation Authority	MAPE	6.53	3.53	5.52	5.25	6.10	9.46	5.76	ARIMA	NNET
	MASE	0.94	0.50	0.79	0.75	0.87	1.35	0.82		
Maryland Transit Administration	MAPE	7.42	10.46	7.60	9.69	7.41	24.76	11.94	TBATS	NNET
	MASE	0.49	0.70	0.49	0.63	0.50	1.64	0.80		
Massachusetts Bay Transportation Authority	MAPE	2.92	5.07	3.39	3.39	3.09	4.48	2.96	ETS	ARIMA
	MASE	0.49	0.85	0.57	0.57	0.52	0.74	0.49		
Metropolitan Atlanta Rapid Transit Authority	MAPE	12.75	16.10	12.99	13.25	12.99	10.98	11.81	NNET	ARIMA
	MASE	1.71	2.16	1.74	1.78	1.75	1.45	1.58		
MTA New York City Transit	MAPE	7.71	7.87	7.44	8.09	8.05	10.25	8.65	STL-ETS	NNET
	MASE	1.99	2.03	1.92	2.08	2.08	2.64	2.23		
Port Authority Trans-Hudson Corporation	MAPE	2.82	3.36	2.03	1.96	2.27	3.01	1.90	Hybrid (ANST)	ARIMA
	MASE	0.49	0.57	0.35	0.33	0.40	0.52	0.33		
Port Authority Transit Corporation	MAPE	2.45	3.06	2.14	2.63	3.05	7.44	3.47	STL-ETS	NNET
	MASE	0.69	0.86	0.60	0.74	0.86	2.08	0.98		
San Francisco Bay Area Rapid Transit District	MAPE	2.81	2.40	2.55	1.78	2.11	3.11	2.05	STL-ARIMA	NNET
	MASE	0.65	0.53	0.59	0.41	0.48	0.68	0.46		
Southeastern Pennsylvania Transportation Authority	MAPE	3.35	3.19	2.87	2.87	6.09	5.93	4.29	STL-ETS	TBATS
	MASE	0.60	0.57	0.52	0.52	1.12	1.07	0.78		
Staten Island Rapid Transit Operating Authority	MAPE	4.88	7.07	5.23	4.60	4.66	5.60	5.16	STL-ARIMA	ARIMA
	MASE	0.63	0.89	0.67	0.59	0.60	0.72	0.66		
The Greater Cleveland Regional Transit Authority	MAPE	13.30	13.51	13.20	13.12	12.64	22.65	13.77	TBATS	NNET
	MASE	0.73	0.74	0.73	0.73	0.69	1.28	0.75		
Washington Metropolitan Area Transit Authority	MAPE	10.00	8.62	7.33	7.72	7.93	6.19	7.29	NNET	ETS
	MASE	2.04	1.73	1.49	1.57	1.62	1.25	1.48		
Green - MAPE below 5%, Yellow - MAPE below 10%, Red - MASE above 1.00										

Greater Cleveland Regional Transit Authority, had weaker seasonal patterns and a less dramatic downward ridership trend.

Table 5-1 presents the results of the pre-COVID model performance for each agency. The lowest/highest MAPE and MASE for the testing data (also referred to simply as errors) are shown, with the highest error indicating the poorest performance and the lowest error indicating the best performance. In this study, models with a MAPE less than 5% were considered to have good performance, and models with a MAPE less than 10% were considered to have acceptable performance (*Hyndman and Athanasopoulos 2018d*). In the table, a MAPE below 5% (good performance) is highlighted green, a MAPE below 10% (acceptable performance) is highlighted yellow, and a MASE over 1.00 (did not outperform the naïve method) is highlighted red.

For 81.6% (80 out of 98) of the models, the MAPEs were acceptable (below 10%), and for 42.9% (42 out of 98) of the models the MAPEs were good (below 5%). These results show that, using R software to automatically select model parameters, the seven time series forecasting methods were capable of producing acceptable pre-COVID ridership forecasts at most of the selected agencies.

Despite generally good performance, at four of the agencies no model produced a MAPE below 5% (the County of Miami-Dade, Maryland Transit Administration, MTA New York City Transit, and Washington Metropolitan Area Transit Authority). At those four agencies, the MASEs were generally over 1.00, indicating that the models did not outperform the naïve method. At the Metropolitan Atlanta Rapid Transit Agency and Greater Cleveland Regional Transit Authority, none of the models produced a MAPE below 10%. None of the Metropolitan Atlanta Rapid Transit Agency models outperformed the naïve method, while almost all of the Greater Cleveland Regional Transit Authority models did. The difficulty in forecasting at these agencies appeared to be related to changes in ridership trend in 2019; in New York City, ridership rose much higher than in prior years, whereas in the rest of the cities, ridership decreased more than in prior years. In the case of Cleveland, ridership was over estimated due to closures for maintenance on their one and only heavy rail line over the summer of 2019.

Among the seven methods, no one method stood out as having the best performance, as they all performed well for most agencies. The neural network underperformed compared to the other methods. In general, the pre-COVID results suggest that these seven methods of time series forecasting perform well when the ridership data have steady seasonal patterns and trends. However, for agencies whose ridership data do not exhibit these features, univariate forecasts of ridership using time series methods may be more challenging.

Results of the Full Series Analysis

For the full series analysis, the training dataset was from January 2002 through December 2022, and the testing dataset was from January 2023 through December 2023. Similar to the pre-COVID results, visualizations of the forecasts for the transit agencies in Chicago and Cleveland are provided in Figure 5-3 and Figure 5-4 to show examples of the outputs that were created for each of the 14 agencies. The figures for the other agencies are available to view in Appendix Part E, but the numerical results for all agencies are shown in Table 5-2. Although the data was trained from

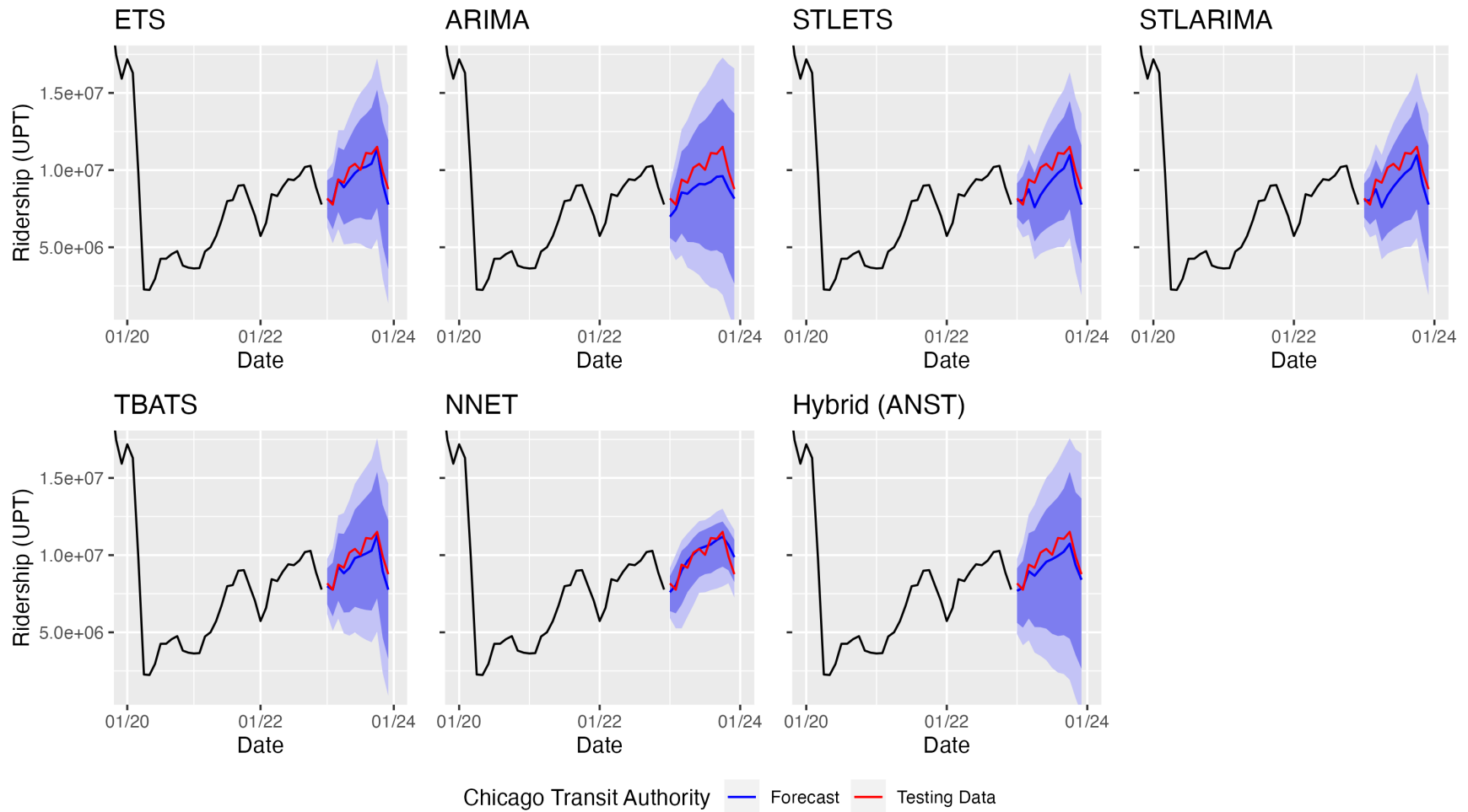


Figure 5-3 Full Series Forecasts of 2023 Ridership at the Chicago Transit Authority

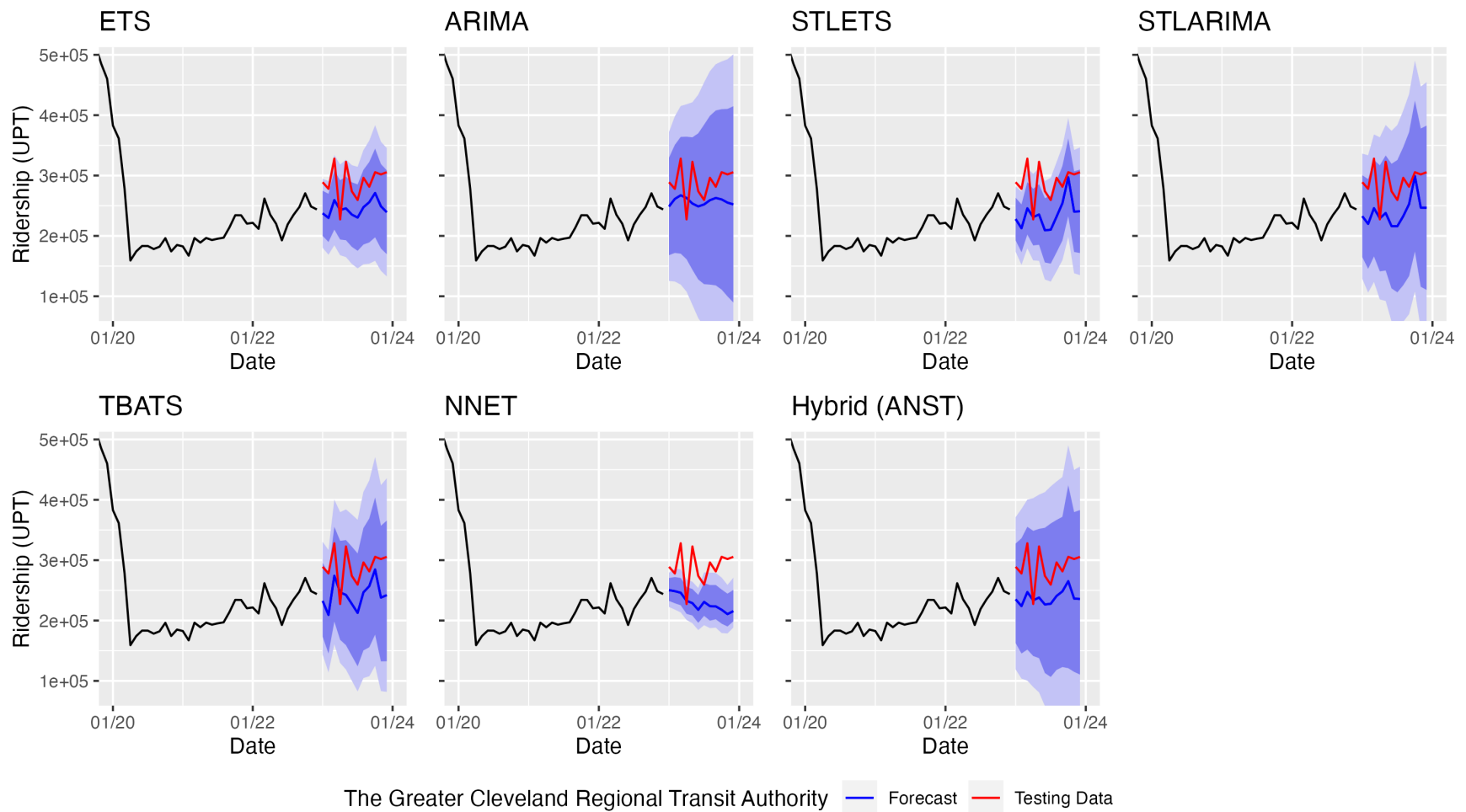


Figure 5-4 Full Series Forecasts of 2023 Ridership at the Greater Cleveland Regional Transit Authority

Table 5-2 Performance of the Full Series Forecasts for 2023 Ridership

Agency	Measure	ETS	ARIMA	STL-ETS	STL-ARIMA	TBATS	NNET	Hybrid (ANST)	Minimum	Maximum
Chicago Transit Authority	MAPE	4.49	11.25	9.37	9.37	5.25	4.43	6.09	NNET	ARIMA
	MASE	0.30	0.75	0.62	0.62	0.35	0.27	0.41		
County of Miami-Dade	MAPE	5.14	6.89	9.38	9.48	5.59	5.94	5.09	Hybrid (ANST)	STL-ARIMA
	MASE	0.40	0.51	0.73	0.74	0.44	0.44	0.39		
Los Angeles County Metropolitan Transportation Authority	MAPE	9.58	13.23	14.27	14.16	10.42	13.35	12.18	ETS	STL-ETS
	MASE	0.60	0.81	0.94	0.92	0.66	0.76	0.74		
Maryland Transit Administration	MAPE	41.39	49.25	38.31	50.46	34.28	40.33	38.19	TBATS	STL-ARIMA
	MASE	1.03	1.36	1.01	1.30	0.90	1.08	1.09		
Massachusetts Bay Transportation Authority	MAPE	5.01	5.20	4.79	4.79	4.41	8.05	4.18	Hybrid (ANST)	NNET
	MASE	0.27	0.27	0.26	0.26	0.23	0.43	0.22		
Metropolitan Atlanta Rapid Transit Authority	MAPE	5.92	4.25	5.81	10.27	5.47	31.12	11.53	ARIMA	NNET
	MASE	0.28	0.20	0.28	0.49	0.26	1.49	0.55		
MTA New York City Transit	MAPE	5.25	6.97	6.94	6.94	9.31	3.66	4.18	NNET	TBATS
	MASE	0.44	0.55	0.58	0.58	0.78	0.30	0.35		
Port Authority Trans-Hudson Corporation	MAPE	8.49	5.71	11.67	12.80	9.64	4.79	6.65	NNET	STL-ARIMA
	MASE	0.50	0.34	0.69	0.75	0.57	0.28	0.40		
Port Authority Transit Corporation	MAPE	3.57	4.98	7.83	7.86	3.26	17.20	5.83	TBATS	NNET
	MASE	0.21	0.30	0.46	0.47	0.19	1.02	0.35		
San Francisco Bay Area Rapid Transit District	MAPE	9.46	15.50	12.44	14.11	9.14	50.03	18.23	TBATS	NNET
	MASE	0.43	0.72	0.57	0.65	0.41	2.31	0.84		
Southeastern Pennsylvania Transportation Authority ¹	MAPE	14.20	26.98	11.55	11.23	18.46	16.98	18.72	STL-ARIMA	ARIMA
	MASE	0.75	1.43	0.62	0.60	1.03	0.89	1.00		
Staten Island Rapid Transit Operating Authority	MAPE	24.03	22.82	28.41	29.32	24.76	32.76	27.56	ARIMA	NNET
	MASE	1.35	1.32	1.60	1.66	1.40	1.86	1.57		
The Greater Cleveland Regional Transit Authority	MAPE	15.69	12.85	18.07	16.80	16.94	20.44	17.45	ARIMA	NNET
	MASE	0.59	0.48	0.67	0.63	0.63	0.77	0.66		
Washington Metropolitan Area Transit Authority	MAPE	8.36	11.11	15.92	16.85	12.20	15.92	7.12	Hybrid (ANST)	STL-ARIMA
	MASE	0.49	0.66	0.95	1.01	0.72	0.91	0.42		
Green - MAPE below 5%, Yellow - MAPE below 10%, Red - MASE above 1.00, Gray – Quality Control Issue										
¹ Southeastern Pennsylvania Transportation Authority's ridership data appear to have a quality control issue which has negatively impacted the performance of the models										

2002 to 2022, only the training data after 2020 is shown so that the post-COVID forecasts can be seen clearly. Once again, most of the forecasts, like those for the Chicago Transit Authority, appear to have captured fairly well the patterns in the data and have forecasted approximately the correct scale of ridership. However, for a small number of agencies, such as the Greater Cleveland Regional Transit Authority and the Maryland Transit Administration, the forecasts over- or underestimated ridership and failed to capture much of a pattern at all.

Table 5-2 presents the results of the full series model performance for each agency. The lowest/highest errors were again used to measure the performance of each method. For 52% (47 out of 91) of the models, the MAPEs were below 10%, and for 14% (13 out of 91) of the models the MAPEs were below 5%. It should be noted that the data from the Southeastern Pennsylvania Transportation Authority had a quality control issue that impacted the performance of the forecasts; therefore, the results for the Southeastern Pennsylvania Transportation Authority were omitted from the discussion.

Most of the methods produced acceptable MAPEs at around half the agencies using the full series. The neural network and STL-ARIMA methods underperformed for this set of forecasts. There was once again a division of model performance between transit agencies; at three of the smaller agencies, the Maryland Transit Authority, Greater Cleveland Regional Transit Authority, and Staten Island Rapid Transit Operating Authority, none of the models produced acceptable forecasts; with the exception of the models for the Greater Cleveland Regional Transit Authority, almost none of the forecasts for these three agencies outperformed the naïve method. For the agencies in Los Angeles, San Francisco, and Washington D.C., only the ETS method was consistently able to produce an acceptable forecast.

The results for the pre-COVID period showed that none of the MTA New York City Transit models produced a MAPE below 5%; the pre-COVID results from the previous chapter reveal that the forecasting performance for MTA was consistently good prior to the testing window beginning with December 2018, after which point, the forecasting performance worsened month-over-month, not even outperforming the naïve method. For the full series forecasts for 2023 ridership, the neural network and hybrid models have now produced good forecasts, and the rest of the forecasts for MTA were acceptable. Similarly, for the Metropolitan Atlanta Rapid Transit Authority, none of the pre-COVID forecasts in the previous section were acceptable or outperformed the naïve method, but half of the forecasts were acceptable for the full-series forecasts in this section. For these two agencies, most of the full series forecasts that trained through the onset of the pandemic actually outperformed the last set of forecasts that trained off of only pre-COVID data. A possible explanation for the improved performance using the full series compared to the pre-COVID series could be that in New York, there was an unexpected period of higher ridership before the pandemic; the opposite situation is true in Atlanta.

The residual tests showed that most of the full series models captured all patterns that were present in the data, leaving only white noise. However, for many of the pre-COVID models, the residuals still contained some patterns. These findings may reflect a continued interruption in the stable seasonal and periodic transit ridership trends that were present at most agencies pre-COVID, which has made it more difficult to extract patterns from the post-COVID data. As a result, the full series forecast results are mixed, reflecting much more uncertainty; for some agencies, the methods were

able to predict the general periodic trend and produce good or acceptable forecasts, but for other agencies, the methods were not able to capture much of a pattern at all, and the forecasts underperformed. Nevertheless, the methods were able to produce good or acceptable forecasts at about half of the agencies, and for some agencies (e.g., MTA New York City Transit and the Metropolitan Atlanta Rapid Transit Authority) the models produced better forecasts than were produced using the last forecasting window of the pre-COVID series. In the next section, the post-COVID observations are isolated in order to try to better understand the present trends and patterns that may exist in post-COVID ridership.

Results of the Post-COVID Analysis

For the post-COVID period, the training dataset was from April 2020 through December 2022, and the testing dataset was from January 2023 through December 2023. A visualization of the forecasts for Chicago Transit Authority and the Greater Cleveland Regional Transit Authority are provided in Figure 5-5 and Figure 5-6, as examples of the outputs that were created for each of the 14 heavy rail agencies. The plots for the rest of the agencies are available to view in Appendix Part F, but the numerical results for all agencies are shown in Table 5-3. Despite having used only the post-COVID data, the forecast results are overall similar to the forecasts produced using the full data series. The major differences between the full series plots and the post-COVID plots are that the post-COVID forecasts tend to be smoother and have more of an upward trend compared to the full series forecasts. In particular, the ETS models struggled to identify much trend or pattern at all, reflecting their relative computational simplicity and lack of robustness. The prediction intervals for the two STL methods, the TBATS method, and the neural network also tended to be much smaller for the post-COVID forecasts, indicating that the models struggled with overfitting the data (*Halloway 2021*).

Table 5-3 presents the results of the post-COVID forecasting performance at each agency. The errors were again used to measure the performance of each method. For 55% (50 out of 91) of the models, the MAPEs were acceptable (below 10%), and for 13% (12 out of 91) of the models the MAPEs were good (below 5%). The results for Southeastern Pennsylvania Transportation Authority were again omitted from the discussion due to a quality control issue in the data.

The overall performance of the models is similar to that of the full series; 47 of the full series models and 50 of the post-COVID models had at least an acceptable MAPE. Also, 13 of the full series models and 12 of the post-COVID models had a good MAPE. Despite potentially overfitting the data, the TBATS and neural network methods performed rather well relative to the other methods, having produced the most acceptable and good MAPEs, respectively. The STL-ETS and hybrid methods also performed fairly well, each producing good/acceptable MAPEs at eight of the agencies. The STL-ARIMA method underperformed, having produced the worst MAPE at just under half the agencies. The ETS method also underperformed, having produced an acceptable MAPE at only four agencies.

Generally, all models outperformed the naïve method, with the exception of two of the three smallest agencies, the Greater Cleveland Regional Transit Authority and the Maryland Transit Administration. As discussed in the previous chapter, ridership at these two agencies may be more

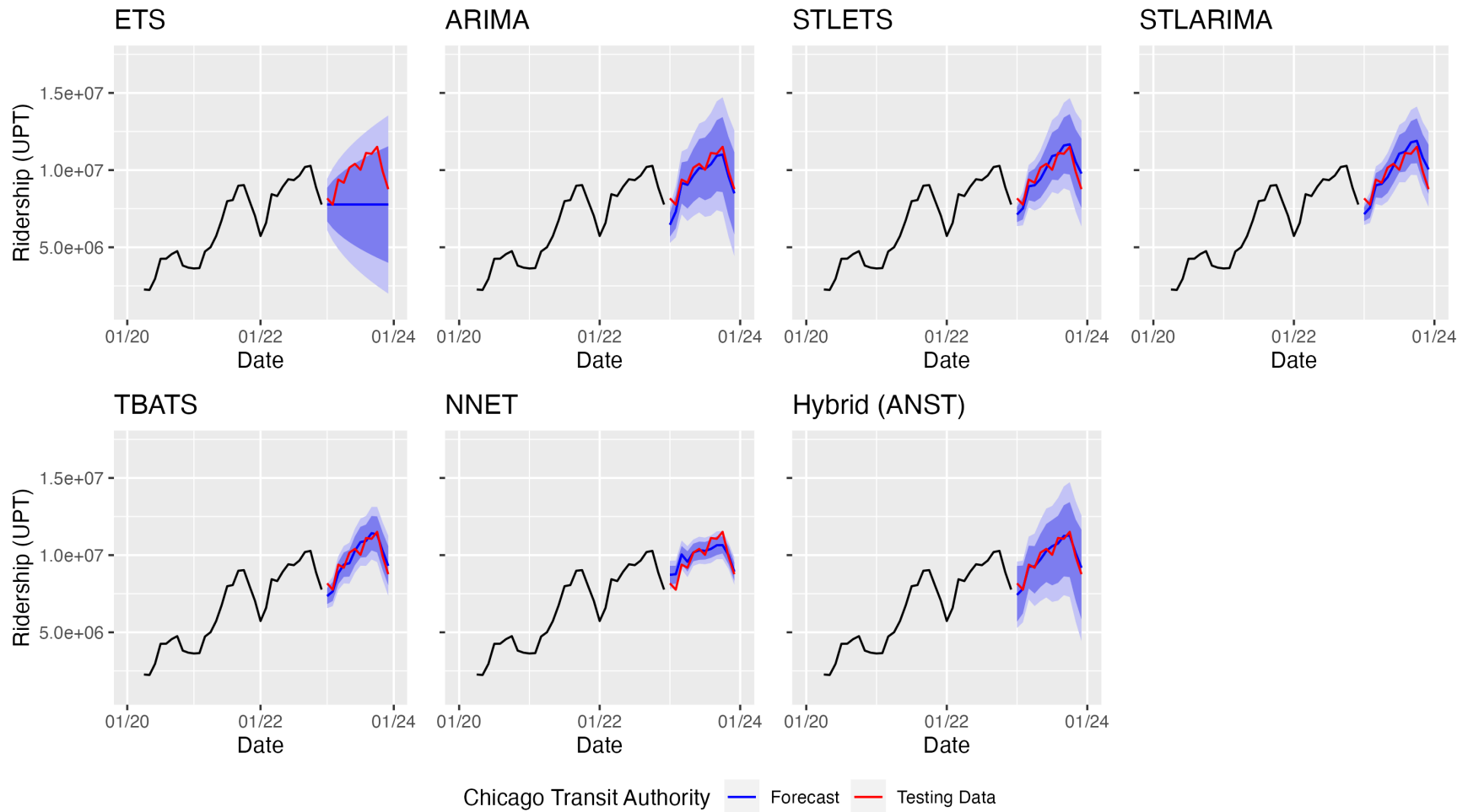


Figure 5-5 Post-COVID Forecasts for 2023 Ridership at the Chicago Transit Authority

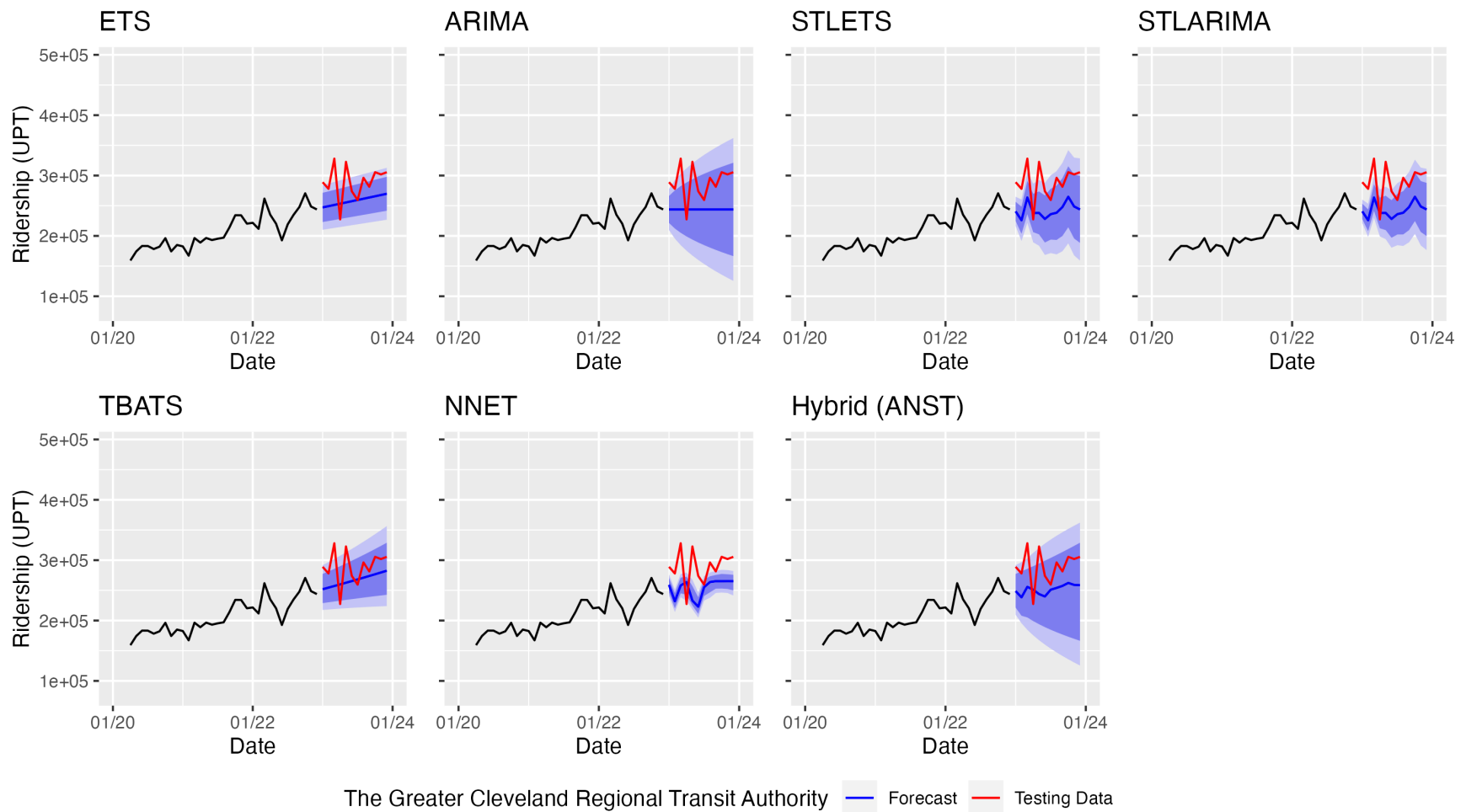


Figure 5-6 Post-COVID Forecasts for 2023 Ridership at the Greater Cleveland Regional Transit Authority

Table 5-3 Performance of the Post-COVID Forecasts for 2023 Ridership

Agency	Measure	ETS	ARIMA	STL-ETS	STL-ARIMA	TBATS	NNET	Hybrid (ANST)	Minimum	Maximum
Chicago Transit Authority	MAPE	19.53	4.76	5.49	5.98	4.31	4.58	3.11	Hybrid (ANST)	ETS
	MASE	0.72	0.16	0.18	0.20	0.15	0.16	0.11		
County of Miami-Dade	MAPE	6.68	11.68	5.63	9.49	8.29	7.19	5.81	STL-ETS	ARIMA
	MASE	0.37	0.62	0.31	0.50	0.47	0.41	0.31		
Los Angeles County Metropolitan Transportation Authority	MAPE	10.79	10.99	14.11	14.11	14.13	10.62	12.47	NNET	TBATS
	MASE	0.59	0.61	0.79	0.79	0.77	0.58	0.69		
Maryland Transit Administration	MAPE	42.00	42.00	45.53	45.53	43.15	33.73	36.75	NNET	STL-ARIMA
	MASE	2.50	2.50	2.54	2.54	2.56	1.64	2.19		
Massachusetts Bay Transportation Authority	MAPE	14.32	8.50	14.52	14.86	8.58	6.18	7.31	NNET	STL-ARIMA
	MASE	0.43	0.26	0.45	0.46	0.26	0.19	0.22		
Metropolitan Atlanta Rapid Transit Authority	MAPE	6.23	4.99	4.92	7.37	4.57	5.85	4.62	TBATS	STL-ARIMA
	MASE	0.28	0.23	0.22	0.34	0.21	0.27	0.21		
MTA New York City Transit	MAPE	16.98	7.83	6.40	12.59	6.22	3.73	7.67	NNET	ETS
	MASE	0.58	0.27	0.22	0.44	0.22	0.13	0.26		
Port Authority Trans-Hudson Corporation	MAPE	8.78	5.11	6.78	8.87	7.80	3.63	4.77	NNET	STL-ARIMA
	MASE	0.29	0.16	0.22	0.29	0.26	0.12	0.15		
Port Authority Transit Corporation	MAPE	12.07	6.04	7.38	12.80	9.17	3.10	6.97	NNET	STL-ARIMA
	MASE	0.43	0.21	0.26	0.46	0.33	0.11	0.25		
San Francisco Bay Area Rapid Transit District	MAPE	7.68	13.51	8.36	7.53	8.11	26.08	10.99	STL-ARIMA	NNET
	MASE	0.24	0.41	0.25	0.22	0.24	0.79	0.33		
Southeastern Pennsylvania Transportation Authority ¹	MAPE	36.27	24.79	34.88	32.36	25.43	14.42	23.98	NNET	ETS
	MASE	1.01	0.67	0.96	0.89	0.70	0.38	0.65		
Staten Island Rapid Transit Operating Authority	MAPE	12.75	10.53	20.00	16.29	10.53	21.02	12.66	TBATS	NNET
	MASE	0.57	0.45	0.85	0.69	0.46	0.90	0.56		
The Greater Cleveland Regional Transit Authority	MAPE	11.72	16.08	16.20	16.20	9.82	13.96	13.94	TBATS	STL-ARIMA
	MASE	1.13	1.56	1.56	1.56	0.94	1.33	1.34		
Washington Metropolitan Area Transit Authority	MAPE	14.36	8.37	8.02	7.77	8.66	12.02	7.59	Hybrid (ANST)	ETS
	MASE	0.54	0.28	0.28	0.27	0.30	0.44	0.26		
Green - MAPE below 5%, Yellow - MAPE below 10%, Red - MASE above 1.00, Gray – Quality Control Issue										
¹ Southeastern Pennsylvania Transportation Authority's ridership data appear to have a quality control issue which has negatively impacted the performance of the models										

difficult to forecast due to the limited heavy rail service provided in Cleveland and Baltimore, which each have only one heavy rail line. Different methods of forecasting or additional variables may be necessary to overcome the challenges associated with identifying patterns to predict ridership at these agencies.

In summary, the results found in this chapter are consistent with the findings of Chapter 4. Pre-COVID, forecasting transit ridership with time series methods was straightforward, and each method performed fairly well, with the models collectively producing acceptable results for about 80% of the forecasts. Forecasting in the post-COVID era was more challenging, with the models that trained on either the full series or post-COVID datasets producing acceptable results for about half the forecasts. Generally, the classical methods outperformed the other methods when trained on the full data series, but the more complex methods outperformed the other methods when trained only on the post-COVID data. For the models with training data starting from January 2002 (the pre-COVID and full series periods), the neural network method notably underperformed; however, the neural network outperformed the other methods when it trained only off of post-COVID data, perhaps because it used only one seasonal lag as opposed to 12. The hybrid method tended to perform relatively well for all time periods. The performance of each method varied by agency; for some agencies like the Chicago Transit Authority and the Port Authority Trans-Hudson Corporation, forecasting with time series methods was relatively straightforward regardless of the period used to train the models. For a few agencies, like those in New York City and Washington D.C., the methods actually performed better when forecasting post-COVID ridership compared to forecasting pre-COVID ridership. At a couple of agencies, like those in Cleveland and Baltimore, time series forecasting was challenging for all time periods and using all methods; those agencies generally had limited heavy rail service, e.g., only a single heavy rail line.

These findings are also consistent with the findings of some recent studies. Prior studies found substantial decreases in forecasting performance in situations with dynamic conditions relative to stable conditions, such as before and after the onset of the COVID-19 pandemic and a major national protest (*Azimian and Jiao 2021; Caicedo, González and Walker 2023*). The performance measures of the forecasts in prior studies, when comparing pre- and post-COVID conditions, were found to decrease in performance by anywhere from about 200% to about 600%, depending on the method used to forecast. In one prior study, at least around 45 new observations were required for the models to learn a new demand pattern (*Caicedo, González and Walker 2023*). In this thesis, the maximum number of observations used to train the models on the new demand pattern was 33, which could partially explain the full series and post-COVID models' overall poor performance relative to the pre-COVID condition. Other prior studies have found that the performance of a time series method varied by transit agency, with ridership being more challenging to predict at agencies that have more limited or low-quality service (*Gao et al. 2023*). Prior studies have also found better performance of classical time series methods relative to machine learning methods given more uncertain conditions (*Azimian and Jiao 2021*).

CHAPTER SIX

CONCLUSIONS AND FUTURE RESEARCH

This study compared the performance of seven time series forecasting methods for pre-COVID and post-COVID transit ridership at the 14 heavy rail agencies in the continental United States. Three forecasting time periods were examined, which consisted of pre-COVID (prior to March 2020), full series (January 2002 to December 2023) and post-COVID data (after March 2020). More than 3,000 forecasts were estimated over the course of this thesis in order to understand the changing performance of time series forecasting methods for transit ridership over time. Several key findings have emerged from this research.

In Chapter 4, moving 12-month forecasting windows were used to evaluate the changing performance of time series forecasts over time. The analysis revealed four major findings. First, in the pre-COVID era, forecasting transit ridership using univariate time series methods was relatively straightforward. At many agencies, the forecasting performance changed over the course of the last two years prior to the onset of the COVID-19 pandemic, usually by 1) worsening when the 12-month testing window began with observations in mid/late 2018 and then improving again afterwards, or 2) becoming worse as the 12-month testing window approached the onset of COVID. Nevertheless, 90% of the models produced good or acceptable pre-COVID forecasts.

Second, forecasting for the post-COVID forecasts was more challenging, and the performance of the time series methods decreased in the post-COVID era. The models that trained off the full data series (i.e., pre- and post-COVID data) overall produced slightly better forecasts compared to the models that trained only off post-COVID data. Using the full data series, most of the methods produced acceptable forecasts about 50-55% of the time, compared to only 45-50% of the time for most of the models that trained only off post-COVID data.

Third, each individual method had changing performance according to which time period was used as training data. In the pre-COVID period, no one method particularly outperformed all the rest, but the neural network slightly underperformed. Using the full series, the ARIMA and hybrid methods outperformed the rest of the models, and the neural network notably underperformed. However, using only post-COVID data to train the models, the neural network and hybrid methods outperformed all the other methods. The neural network may have outperformed the other methods when trained only on the post-COVID data because it was set to use only one seasonal lag. This implies that, in the post-COVID era, at some agencies, the previous month's ridership may be a better predictor of future ridership compared to the previous year's ridership. The hybrid method consistently performed relatively well for all time periods, perhaps due to its ability to minimize the effect of the errors from any one forecasting method. These findings are consistent with prior studies that compared time series forecasting methods and showed that 1) combined methods of forecasting outperform pure statistical and pure machine learning methods, and

2) pure machine learning methods underperform compared to pure statistical methods (*Chen, Zhang and Jiang 2020; Gao et al. 2023; Makridakis, Spiliotis and Assimakopoulos 2020*).

Fourth, there were differences in overall performance of time series forecasting methods according to the agency for which the forecasts were being done. At some agencies, like the Chicago Transit Authority, County of Miami-Dade, or the Los Angeles County Metropolitan Transportation Authority, the time series forecasting methods used in this study tended to produce acceptable results regardless of which time period was used to train the models. In contrast, at some agencies like the Greater Cleveland Regional Transit Authority or the Maryland Transit Administration, for every combination of method or time period, almost none of the models produced an acceptable forecast, and many of the forecasts did not even outperform the simple naïve method, perhaps due to the limited heavy rail service at these agencies.

In Chapter 5, the last set of forecasts for each time period were examined in more detail in order to identify potential influencing factors for the time series methods' performance. The results from Chapter 5 were consistent with the findings from Chapter 4; pre-COVID forecasting using each time series method was overall straightforward, and about 80% of the models produced acceptable forecasts. For the post-COVID forecasts, only about half the models produced acceptable forecasts, regardless of whether the full series or only post-COVID data were used to train the models. Generally, the classical methods tended to perform well for the longer data series that contained pre-COVID ridership (the pre-COVID and full series periods), and the more complex methods tended to perform well for the post-COVID period, which used only post-COVID data to train the models. The hybrid method, which was modeled using equal weights of two of the classical time series methods (ARIMA and STL-ARIMA) and two of the more complex methods (TBATS and neural network), tended to perform well for all time periods.

Similar to Chapter 4, Chapter 5 also showed that the neural network underperformed for the pre-COVID and full series periods, but for the post-COVID period, it outperformed the other methods. One reason for this could be that the neural network was set to only have one seasonal lag, instead of using 12 seasonal lags for monthly data. This may have given the neural network an advantage at some agencies in the post-COVID period due to a continued lack of clear seasonal patterns, which may be caused by competing trends in the ridership data due factors like ever-recovering ridership, especially now that COVID-related restrictions and trends of social isolation have relaxed. Particularly at agencies with more limited heavy rail service (i.e., smaller heavy rail agencies like the Greater Cleveland Regional Transit Authority), there seemed to be a lack of patterns in the heavy rail ridership data, as demonstrated by the white noise test and the performance of the forecasts, which were generally poor.

From the findings, it can be concluded that univariate time series forecasting is a simple, quick, and efficient method to forecast ridership at agencies with strong and regular seasonality, periodicity, and/or trends, which was typical of transit ridership prior to the

COVID-19 pandemic. However, based on the findings of this study, the strong, stable ridership patterns found at many US heavy rail agencies prior to the pandemic have still not returned, perhaps due to external factors such as telework and people relocating. Interestingly, at some agencies in major US cities (e.g., New York City and Washington D.C.), monthly transit ridership has become more predictable or has remained about as predictable post-COVID as compared to just before the pandemic. Additionally, in some cities with more limited heavy rail service (for example, Cleveland and Baltimore), ridership remains about as unpredictable as it was prior to the pandemic. These mixed findings demonstrate a need for agency-specific solutions to ridership forecasting (i.e., picking the most suitable forecasting method based on the features of the dataset).

Several areas for future research have emerged from this study. First, more post-COVID data will become available in the future, allowing for further exploration of post-pandemic trends and patterns. Future research should compare forecasts between cities to understand the differences in trends at some agencies, especially at smaller agencies where the time series methods struggled to produce good forecasts. In particular, looking at the predictability of route-level, post-COVID ridership may shed more light on the challenges to predict ridership in cities with limited heavy rail service, like Baltimore and Cleveland, which each have only one heavy rail line.

Another area for future research is to further examine the changing performance of time series forecasting for transit ridership over time. In this study, only 12 sets of forecasts were estimated for pre-COVID ridership using the moving window, and only nine sets of forecasts were estimated for post-COVID ridership (using both the full series and post-COVID periods). Future studies should produce more moving window forecasts for both pre- and post-COVID ridership. In the pre-COVID period, a minimum of 24 sets of forecasts should be estimated in order to determine if specific and recurring characteristics of the last observation may be impacting the forecasting performance, e.g., if seasonal increases/declines in ridership are consistently causing a decrease in forecast accuracy. Similarly, as more post-COVID data become available, and as post-COVID ridership trends and patterns further stabilize, it may be possible to identify what factors of post-COVID ridership are negatively affecting the forecast performance, e.g., the limited number of post-COVID observations, potential continued lack of strong seasonal patterns and stable trends, or even a potentially permanent shift in rider behavior for which the pre-COVID data is ill-suited to be used to train the forecasting models.

Future studies may use larger datasets, e.g., daily or weekly data with a length of at least 1,000 datapoints, which would make suitable forecasting with more complex time series methods such as deep learning methods (e.g., LSTM). Additional methods outside of time series methods may also be considered, e.g., regression-based methods. Future studies should examine in more detail the differences in forecasting performance using pure statistical, pure machine learning, and combined methods. Prior studies have consistently shown that combined methods outperform the pure statistical and pure machine learning methods, and pure statistical methods outperform pure machine learning methods.

However, machine learning methods become more sophisticated every year, and their potential likely has not yet been fully realized.

Before the pandemic, one prior study found that transit ridership forecasts generally tended to be optimistic and overestimate ridership in practice, although this tendency was improving over time (*Hoque et al. 2023*). Although the forecasting methods were not explicitly stated, the study included over 160 transit projects over five decades, and most likely included methods like the four-step model and activity based models, among others. Future studies should further examine the overall accuracy of transit ridership forecasting, especially since the pandemic has impacted the performance of time series forecasting, and has also almost certainly required adjustments to the assumptions and base parameters required to forecast using the four-step and activity based models. Future studies may also compare the overall accuracy of ridership forecasts using time series methods versus methods like the four-step model.

Last, future research should seek to identify any external factors that have an impact on post-COVID heavy rail ridership and to quantify their impact; for example, a recently published study quantified the impact of external factors on post-COVID bus ridership levels using a multiple mediation analysis and found that unemployment, telework, and people relocating explained 13% to 38% of the ridership declines (*Ziedan, Lima and Brakewood 2023*). Future studies should also investigate the use of exogenous regressors in the models to account for external factors impacting ridership, which could possibly improve the performance of the forecasts.

Based on the findings of this study, time series forecasting is likely to be a promising method of predicting short- and medium-term, system-level transit ridership at many heavy rail agencies, even in the post-COVID era. Univariate time series forecasts like the ones demonstrated in this thesis are likely to be suitable for agencies whose ridership data exhibit stable seasonality, periodicity, and trends. By making the code used in this study publicly available, as well as bringing more visibility to Minneapolis Metro's forecasting app and the code that powers it, transit agencies may find these methods of transit ridership forecasting more accessible, helping them to produce accurate and low-cost ridership forecasts more frequently and with a wider variety of methods. This is critical to practitioners, planners, and policy makers as they attempt to forecast system-wide ridership levels in the post-COVID era to set budget levels, plan schedules, and perform other important real world tasks.

LIST OF REFERENCES

Ayman, A., J. Martinez, P. Pugliese, A. Dubey, and A. Laszka. Neural Architecture and Feature Search for Predicting the Ridership of Public Transportation Routes. Presented at 2022 IEEE International Conference on Smart Computing (SMARTCOMP), Helsinki, Finland. 2022. 10.1109/SMARTCOMP55677.2022.00023. Accessed December 15, 2023.

Azimian, A., and J. Jiao. Prediction of “L” Train’s Daily Ridership in Downtown Chicago During the COVID-19 Pandemic. *Findings*, No. December, 2021. <https://doi.org/10.32866/001c.30181>. Accessed July 15, 2022.

Babcock, M. W., X. Lu, and J. Norton. Time Series Forecasting of Quarterly Railroad Grain Carloadings. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 35, No. 1, 1999, pp. 43-57. Accessed July 15, 2022.

Boyle, D. TCRP Synthesis 66: Fixed-Route Transit Ridership Forecasting and Service Planning Methods. *Transit Cooperative Research Program*, 2006. <https://dx.doi.org/10.17226/14001>. Accessed December 14, 2023.

Bunner, R., and M. Catala. TBEST 4.8 User Guide. Florida Department of Transportation. https://tbest.org/wp-content/files/TBESTUserGuide_48.pdf. Accessed March 18, 2024.

Caicedo, J. D., M. C. González, and J. L. Walker. Public Transit Demand Prediction During Highly Dynamic Conditions: A Meta-Analysis of State-of-the-ART Models and Open-Source Benchmarking Infrastructure. 2023. <https://doi.org/10.48550/arXiv.2306.06194>. Accessed December 15, 2023.

Central Transportation Planning Staff. Appendix A Travel Demand Modeling. Boston Region Metropolitan Planning Organization. https://www.ctps.org/data/pdf/plans/LRTP/needs/2035NA_AppA.pdf. Accessed March 9, 2024.

Cervero, R. Alternative Approaches to Modeling the Travel-Demand Impacts of Smart Growth. *Journal of the American Planning Association*, Vol. 72, 2006, pp. 285-295. <https://doi.org/10.1080/01944360608976751>. Accessed March 9, 2024.

Chen, C.-H. P., and G. A. Naylor. Development of a Mode Choice Model for Bus Rapid Transit in Santa Clara County, California. *Journal of Public Transportation*, Vol. 14, 2011, pp. 41-62. <https://doi.org/10.5038/2375-0901.14.3.3>. Accessed October 23, 2022.

Chen, D., J. Zhang, and S. Jiang. Forecasting the Short-Term Metro Ridership with Seasonal and Trend Decomposition Using Loess and LSTM Neural Networks. *IEEE Access*, Vol. 8, 2020. 10.1109/ACCESS.2020.2995044. Accessed June 30, 2022.

Chiang, W.-C., R. A. Russell, and T. L. Urban. Forecasting ridership for a metropolitan transit authority. *Transportation Research Part A: Policy and Practice*, Vol. 45, No. 7, 2011, pp. 696-705. <https://doi.org/10.1016/j.tra.2011.04.016>. Accessed March 20, 2024.

Chicago Metropolitan Agency for Planning. *Modeling Data*. Chicago Metropolitan Agency for Planning, Chicago, IL. <https://www.cmap.illinois.gov/data/transportation/modeling>. Accessed March 9, 2024.

Connecticut Department of Transportation. *Travel Demand Forecasting*. Connecticut Department of Transportation, Connecticut. https://portal.ct.gov/DOT/PP_SysInfo/Travel-Demand-Forecasting. Accessed March 9, 2024.

Craw, A. R. Time Series Forecasting of Highway Accident Fatalities. National Highway Traffic Safety Administration. Accessed March 10, 2024.

Ding, C., J. Duan, Y. Zhang, and G. Yu. Using an ARIMA-GARCH Modeling Approach to Improve Subway Short-Term Ridership Forecasting Accounting for Dynamic Volatility. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 19, No. 4, 2018, pp. 1054-1064. <http://dx.doi.org/10.1109/TITS.2017.2711046>. Accessed June 30, 2022.

Doi, M., and W. B. Allen. A Time Series Analysis of Monthly Ridership for an Urban Rail Rapid Transit Line. *Transportation*, Vol. 13, 1986, pp. 257-269. <https://doi.org/10.1007/BF00148619>. Accessed July 1, 2022.

Driscoll, R. A., K. R. Lehmann, S. Polzin, and J. Godfrey. The Effect of Demographic Changes on Transit Ridership Trends. *Transportation Research Record*, Vol. 2672, No. 8, 2018. <https://doi.org/10.1177/0361198118777605>. Accessed March 7, 2024.

Egu, O., and P. Bonnel. Medium-term Public Transit Route Ridership Forecasting: What, how and why? A Case Study in Lyon. *Transport Policy*, Vol. 105, 2021, pp. 124-133. <https://doi.org/10.1016/j.tranpol.2021.03.002>. Accessed June 30, 2022.

Erhardt, G. D., J. M. Hoque, V. Goyal, S. Berrebi, C. Brakewood, and K. E. Watkins. Why has public transit ridership declined in the United States? *Transportation Research Part A: Policy and Practice*, Vol. 161, 2022, pp. 68-87. <https://doi.org/10.1016/j.tra.2022.04.006>. Accessed March 7, 2024.

Federal Transit Administration. *STOPS – FTA’s Simplified Trips-on-Project Software*. Federal Transit Administration, Washington, D.C. <https://www.transit.dot.gov/funding/grant-programs/capital-investments/stops>. Accessed March 9, 2024.

Federal Transit Administration. *Monthly Module Adjusted Data Release*. Federal Transit Administration. <https://www.transit.dot.gov/ntd/data-product/monthly-module-adjusted-data-release>. Accessed November 15, 2023.

Gao, Y., J. Li, J. Wang, and Z. Yang. U.S. public transportation ridership analysis and prediction based on COVID-19. *International Society for Optical Engineering*, Vol. 12596, 2023. <https://doi.org/10.1117/12.2672649>. Accessed November 15, 2023.

Ge, S. Y., C. J. Zheng, and M. M. Hou. Forecast of Bus Passenger Traffic Based on Exponential Smoothing and Trend Moving Average Method. *Applied Mechanics and Materials*, Vol. 433-435, 2013, pp. 1374-1378. <http://dx.doi.org/10.4028/www.scientific.net/AMM.433-435.1374>. Accessed July 1, 2022.

Graehler, M., A. Mucci, and G. D. Erhardt. Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes? Presented at Transportation Research Board 98th Annual Meeting, Washington, D.C., 2019. Accessed March 8, 2024.

Greater Cleveland RTA. *RTA to re-open Red Line between Airport and West Blvd. beginning Monday morning*. Greater Cleveland RTA, Cleveland, OH. <https://www.riderta.com/news/rta-re-open-red-line-between-airport-and-west-blvd-beginning-monday-morning>. Accessed March 24, 2024.

Greenwood, C. City of Atlanta 2023 Q3 Update. MARTA.
https://www.itsmarta.com/uploadedFiles/More/About_MARTA/2023%20Q3%20COA%2008.30.2023_presentation-v2.pdf. Accessed March 9, 2024.

Grisby, D., M. Dickens, and M. Hughes-Cromwick. Understanding Recent Ridership Changes. American Public Transportation Association. <https://www.apta.com/wp-content/uploads/Resources/resources/reportsandpublications/Documents/APTA-Understanding-Recent-Ridership-Changes.pdf>. Accessed March 7, 2024.

Halloway, B. S. Understanding Prediction Intervals. Bryan S. Halloway.
<https://www.bryanshalloway.com/2021/03/18/intuition-on-uncertainty-of-predictions-introduction-to-prediction-intervals/#a-few-things-to-know-about-prediction-intervals>. Accessed December 14, 2023.

Hammon, M. The State of Public Transit Ridership Across the US. *Planetizen*.
<https://www.planetizen.com/news/2023/12/126731-state-public-transit-ridership-across-us>. 2023. Accessed March 5, 2024.

Hoque, J. M., I. Zhang, D. Schmitt, and G. D. Erhardt. Are Public Transit Investments Based on Accurate Forecasts? An Analysis of the Improving Trend of Transit Ridership Forecasts in the United States. Published, No. Issue, 2023. SSRN.
<https://dx.doi.org/10.2139/ssrn.4557555>. Accessed Access Date.

Hyndman, R., and G. Athanasopoulos. 8.8 Forecasting. In *Forecasting: principles and practice, 2nd edition*, OTexts, Melbourne, Australia, 2018a. Accessed December 15, 2023.

Hyndman, R., G. Athanasopoulos, C. Bergmeir, G. Caceres, L. Chhay, M. O'Hara-Wild, F. Petropoulos, S. Razbash, E. Wang, and F. Yasmeen. forecast: Forecasting functions for time series and linear models. R package version 8.15. 2021. Accessed July 18, 2022.

Hyndman, R., and Y. Khandakar. Automatic time series forecasting: the forecast package for R. *Journal of Statistical Software*, Vol. 26 (3), 2008, pp. 1-22.
<https://www.jstatsoft.org/article/view/v027i03>. Accessed December 15, 2023.

Hyndman, R. J. Prediction intervals for NNETAR models. Rob J. Hyndman.
<https://robjhyndman.com/hyndsight/nnetar-prediction-intervals/>. Accessed December 15, 2023.

Hyndman, R. J. A brief history of forecasting competitions. *International Journal of Forecasting*, Vol. 36, No. 1, 2020, pp. 7-14. <https://doi.org/10.1016/j.ijforecast.2019.03.015>. Accessed March 20, 2024.

Hyndman, R. J., and G. Athanasopoulos. 6.8 Forecasting with decomposition. In *Forecasting: principles and practice, 2nd edition*, OTexts, Melbourne, Australia, 2018b. Accessed December 15, 2023.

Hyndman, R. J., and G. Athanasopoulos. 11.3 Neural network models. In *Forecasting: principles and practice, 2nd edition*, OTexts, Melbourne, Australia, 2018c. Accessed December 15, 2023.

Hyndman, R. J., and G. Athanasopoulos. *Forecasting: Principles and Practice, 2nd Edition*. Melbourne, Australia. OTexts.com/fpp2. 2018d. Accessed December 15, 2023.

Hyndman, R. J., and G. Athanasopoulos. A taxonomy of exponential smoothing methods. In *Forecasting: principles and practice, 2nd edition*, OTexts, Melbourne, Australia, 2018e. Accessed December 15, 2023.

Jayanthi, G., and P. Jothilakshmi. Traffic Time Series Forecasting on Highways - A Contemporary Survey of Models, Methods and Techniques. *International Journal of Logistics Systems and Management*, Vol. 39, No. 1, 2021, pp. 77-110. <https://doi.org/10.1504/IJLSM.2021.115068>. Accessed July 15, 2022.

Kyte, M., J. Stoner, and J. Cryer. A Time-Series Analysis of Public Transit Ridership in Portland, Oregon, 1971-1982. *Transportation Research Part A: General*, Vol. 22, No. 5, 1988, pp. 345-359. [https://doi.org/10.1016/0191-2607\(88\)90012-X](https://doi.org/10.1016/0191-2607(88)90012-X). Accessed July 1, 2022.

Lee, Y., and B. Lee. What's eating public transit in the United States? Reasons for declining transit ridership in the 2010s. *Transportation Research Part A: Policy and Practice*, Vol. 157, 2022, pp. 126-143. <https://doi.org/10.1016/j.tra.2022.01.002>. Accessed March 8, 2024.

Lind, E., J. Reid, and K. E. Ky. *MetroTransit / Route-Trends, Build Complete Base Function App*. <https://github.com/metrotransit/route-trends/commit/752d7b50fd250d66e334c8dc31487890f8d1b8ab>. Accessed December 14, 2023.

Livera, A. M. D., R. J. Hyndman, and R. D. Snyder. Forecasting Time Series with Complex Seasonal Patterns Using Exponential Smoothing. *Journal of the American Statistical Association*, Vol. 106, No. 496, 2011, pp. 1513-1527. Accessed November 11, 2023.

Makridakis Open Forecasting Center. *Makridakis Competitions*.
<https://mofc.unic.ac.cy/history-of-competitions/>.

Makridakis, S., E. Spiliotis, and A. Assimakopoulos. The M4 Competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting*, Vol. 36, No. 1, 2020, pp. 54-74. <https://doi.org/10.1016/j.ijforecast.2019.04.014>. Accessed March 20, 2024.

McNally, M. G., and C. Rindt. The Activity-Based Approach. In *The Handbook of Transport Modelling, No. 1*, Emerald Group Publishing Limited, Leeds, England, 2008. pp. 55-73. Accessed March 9, 2024.

Metropolitan Washington Council of Governments. *Travel Demand Modeling*. Metropolitan Washington Council of Governments, Washington, D.C.
<https://www.mwcog.org/transportation/data-and-tools/modeling/>. Accessed March 9, 2024.

Miami-Dade Transportation Planning Organization. *ETAP Tools*. Miami-Dade Transportation Planning Organization. Accessed March 9, 2024.

Miller, E. The current state of activity-based travel demand modelling and some possible next steps. *Transport Reviews*, Vol. 43, No. 4, 2023.
<https://doi.org/10.1080/01441647.2023.2198458>. Accessed March 9, 2024.

Minneapolis Metro Transit. *Route Trends and Info*, Minneapolis.
<https://metrotransitm.shinyapps.io/route-trends/>. Accessed July 13, 2022.

Moghim, B., C. Kanga, A. Safikhani, S. Mudigonda, and P. Vicuna. Non-Stationary Time Series Model for Station-Based Subway Ridership During COVID-19 Pandemic: Case Study of New York City. *Transportation Research Record*, Vol. 2677, No. 4, 2022.
<https://doi.org/10.1177/03611981221084698>. Accessed June 21, 2022.

Moreland, A., C. Herlihy, M. A. Tynan, G. Sunshine, R. F. McCord, C. Hilton, J. Poovey, A. K. Werner, C. D. Jones, E. B. Fulmer, A. V. Gundlapalli, H. Strosnider, A. Potvien, M. C. García, S. Honeycutt, G. Baldwin, CDC Public Health Law Program, and CDC COVID-19 Response Team Mitigation Policy Analysis Unit. *Timing of State and Territorial COVID-19 Stay-at-Home Orders and Changes in Population Movement — United States, March 1–May 31, 2020*. CDC. [https://www.cdc.gov/mmwr/volumes/69/wr/mm6935a2.htm#:~:text=During%20March%201–May%2031%2C%2042%20states%20and%20territories%20issued,by%20California%20\(March%2019\)](https://www.cdc.gov/mmwr/volumes/69/wr/mm6935a2.htm#:~:text=During%20March%201–May%2031%2C%2042%20states%20and%20territories%20issued,by%20California%20(March%2019).). Accessed March 22, 2024.

Mucci, A., and G. D. Erhardt. Evaluating the Ability of Transit Direct Ridership Models to Forecast Medium-Term Ridership Changes: Evidence from San Francisco. *Transportation Research Record*, Vol. 2672, No. 46, 2018. <https://doi.org/10.1177/0361198118758632>. Accessed October 23, 2022.

New York Metropolitan Transportation Council. *Data and Modeling*. New York Metropolitan Transportation Council, New York City, NY. <https://www.nymtc.org/en-us/DATA-AND-MODELING>. Accessed March 9, 2024.

Nihan, N. L., and K. O. Holmesland. Use of the Box and Jenkins Time Series Technique in Traffic Forecasting. *Transportation*, Vol. 9, 1980, pp. 125-143. <https://doi.org/10.1007/BF00167127>. Accessed July 15, 2022.

OAG. *COVID-19 Air Travel Recovery: How Did the COVID-19 Pandemic Affect Global Air Travel?* <https://www.oag.com/coronavirus-airline-schedules-data#:~:text=At%20the%20very%20lowest%20point,in%202022%20in%20some%20regions>. Accessed March 6, 2024.

Perry, J. Measuring the Accuracy of Bus Rapid Transit Forecasts. *Journal of Public Transportation*, Vol. 20, 2017, pp. 119-138. <https://doi.org/10.5038/2375-0901.20.1.7>. Accessed October 23, 2022.

Plotch, P. *Transit Ridership: Not Expected to Return to Pre-Pandemic Levels This Decade*. Eno Center for Transportation. <https://www.enotrans.org/article/transit-ridership-not-expected-to-return-to-pre-pandemic-levels-this-decade/>. Accessed July 10, 2022.

Polhemus, N. W. Time series analysis of local fluctuations in traffic parameters. *Transportation Research*, Vol. 10, No. 5, 1976, pp. 311-317. [https://doi.org/10.1016/0041-1647\(76\)90110-6](https://doi.org/10.1016/0041-1647(76)90110-6). Accessed March 10, 2024.

Pougala, J., T. Hillel, and M. Bierlaire. Parameter estimation for activity-based models. Presented at 22nd Swiss Transport Research Conference, Monte Verità, Ascona, Switzerland, 2022. Accessed May 9, 2024.

R Core Team. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <http://www.r-project.org/>. Accessed July 25, 2022.

Razbash, S., and R. J. Hyndman. *tbats: TBATS model (Exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components)*. RDocumentation.org. <https://www.rdocumentation.org/packages/forecast/versions/8.21.1/topics/tbats>. Accessed November 11, 2023.

Rowlands, D., and T. H. Loh. Ensuring the intertwined post-pandemic recoveries of downtowns and transit systems. Brookings Institute, 2023. <https://www.brookings.edu/articles/ensuring-the-intertwined-post-pandemic-recoveries-of-downtowns-and-transit-systems/>. Accessed March 5, 2023.

Shaub, D. *Using the “forecastHybrid” package*. cran.r-project.org. <https://cran.r-project.org/web/packages/forecastHybrid/vignettes/forecastHybrid.html#forecasting>. Accessed November 11, 2023.

Sound Transit. ST3 Regional High-Capacity Transit System Plan: Transit Ridership Forecasting Methodology Report. Sound Transit. https://www.wsdot.wa.gov/partners/erp/background/ST3%20Draft%20RidershipForecastingMethodologyReport_6March2015.pdf. Accessed March 9, 2024.

Twin Cities Metropolitan Council. *Travel Forecasting*. Twin Cities Metropolitan Council, St. Paul, MN. <https://metro council.org/Transportation/Performance/Travel-Forecasting.aspx>. Accessed March 9, 2024.

USAFacts. *Has vehicle traffic returned to pre-pandemic levels?* USAFacts. <https://usafacts.org/articles/has-vehicle-traffic-returned-to-pre-pandemic-levels/>. Accessed March 6, 2024.

Vanderkam, D., J. Allaire, J. Owen, D. Gromer, and B. Thieurmél. dygraphs: Interface to “Dygraphs” Interactive Time Series Charting Library. R package version 1.1.1.6. 2018. Accessed February 2, 2022.

Wang, X., N. Zhang, Y. Chen, and Y. Zhang. Short-Term Forecasting of Urban Rail Transit Ridership Based on ARIMA and Wavelet Decomposition. Presented at 6th International Conference on Computer-Aided Design, Manufacturing, Modeling and Simulation, Busan, South Korea. AIP Conference Proceedings 1967, 2018. doi:10.1063/1.5039099. Accessed June 22, 2022.

Washington, S., M. Karlaftis, F. Mannering, and P. Anastasopoulos. *Statistical and Econometric Methods for Transportation Data Analysis*. CRC Press, New York, NY. 2020. Accessed December 15, 2023.

Watkins, K., S. Berrebi, C. Diffie, B. Kiriazes, D. Ederer, Transit Cooperative Research Program, Transportation Research Board, and E. National Academies of Sciences, and Medicine,. TCRP Report 209: Analysis of Recent Public Transit Ridership Trends. Transit Cooperative Research Program. Accessed March 7, 2024.

Wickham, H. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, New York, 2016. Accessed July 25, 2022.

Wickham, R. R. Evaluation of Forecasting Techniques for Short-Term Demand of Air Transportation. Boston, MA, 1995. Massachusetts Institute of Technology. <http://hdl.handle.net/1721.1/11584>. Accessed July 15, 2022.

Yule, G. U. On the Time-Correlation Problem, with Especial Reference to the Variate-Difference Correlation Method. *Journal of the Royal Statistical Society*, Vol. 84, 1921, pp. 497-537. <https://doi.org/10.2307/2341101>. Accessed March 10, 2024.

Yule, G. U. On a Method of Investigating Periodicities in Disturbed Series, with Special Reference to Wolfer's Sunspot Numbers. *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character*, Vol. 226, 1927, pp. 267-298. <https://www.jstor.org/stable/91170>. Accessed March 10, 2024.

Zheng, X., and P. Wei. Air Transportation Direct Share Time Series Forecasting: A Hybrid Model. *Journal of Advanced Transportation*, Vol. 3, 2020, pp. 1-13. <http://dx.doi.org/10.1155/2020/8924095>. Accessed July 15, 2022.

Ziedan, A., C. Brakewood, and K. Watkins. Will transit recover? A retrospective study of nationwide ridership in the United States during the COVID-19 pandemic. *Journal of Public Transportation*, Vol. 25, 2023. <https://doi.org/10.1016/j.jpubtr.2023.100046>. Accessed March 5, 2024.

Ziedan, A., L. Lima, and C. Brakewood. A multiple mediation analysis to untangle the impacts of COVID-19 on nationwide bus ridership in the United States. *Transportation Research Part A: Policy and Practice*, Vol. 173, 2023. <https://doi.org/10.1016/j.tra.2023.103718>. Accessed December 15, 2023.

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Part A: Pre-COVID Moving Window Forecasts

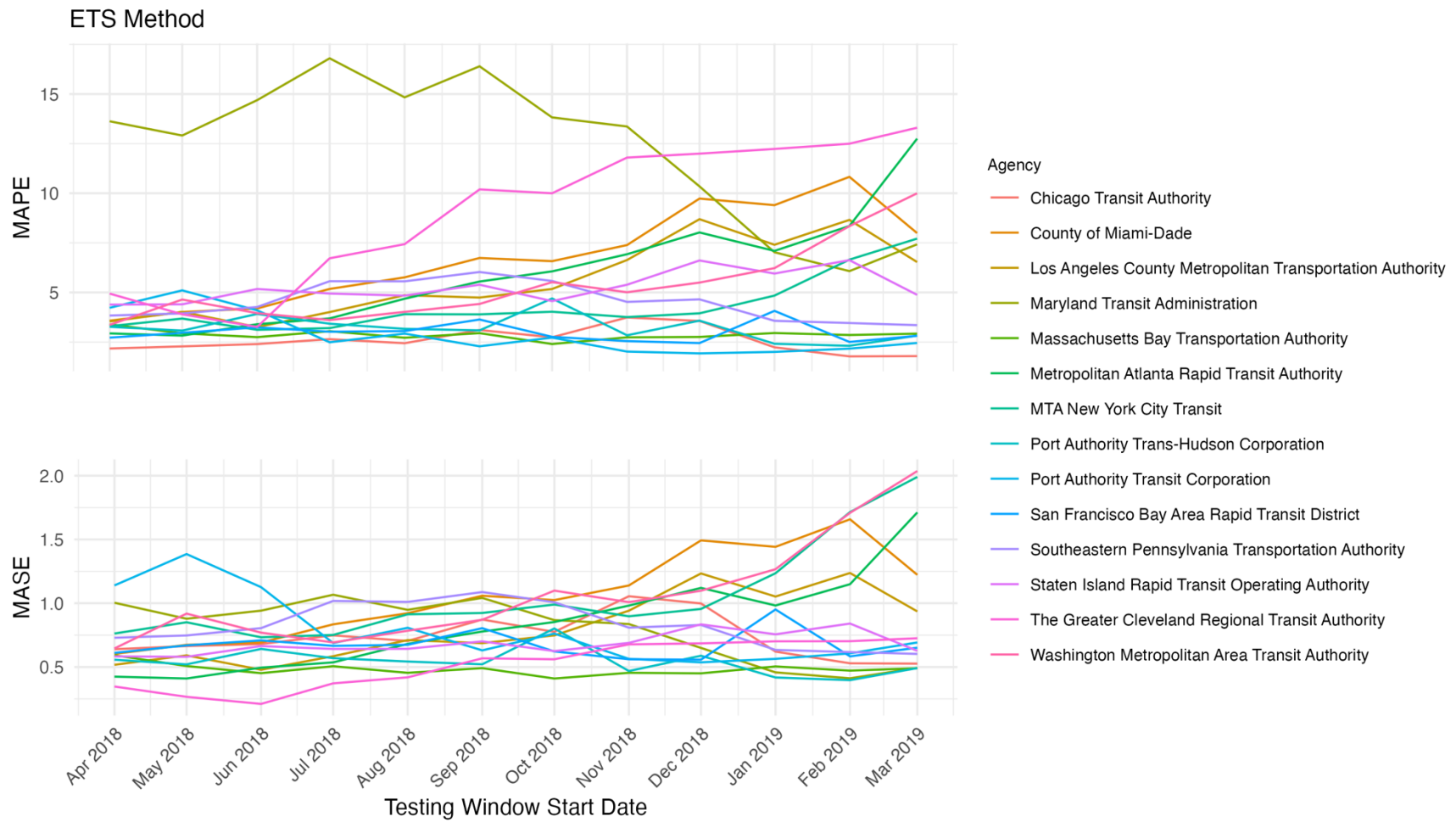


Figure A-1 Pre-COVID Performance of the ETS Method

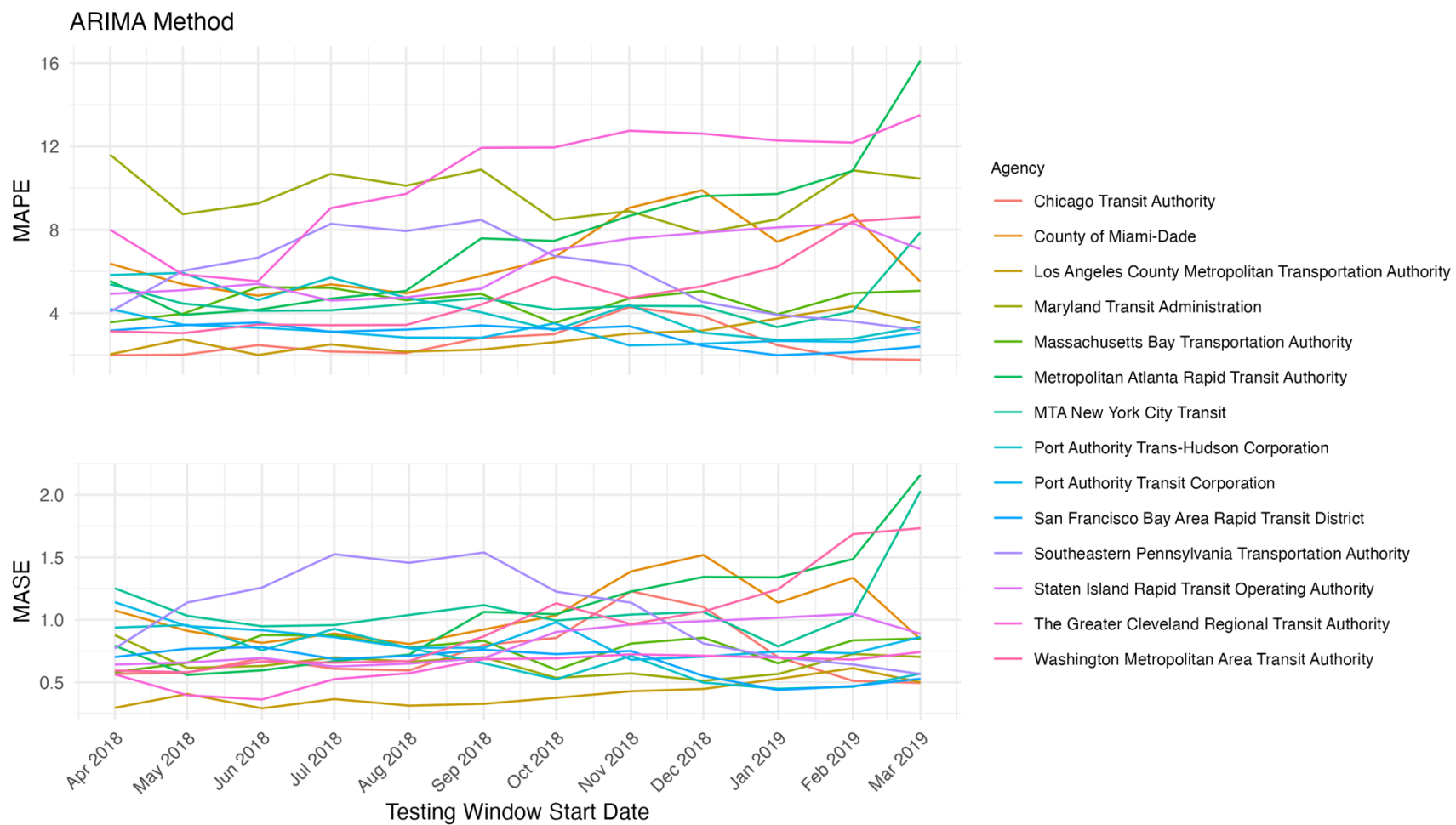


Figure A-2 Pre-COVID Performance of the ARIMA Method

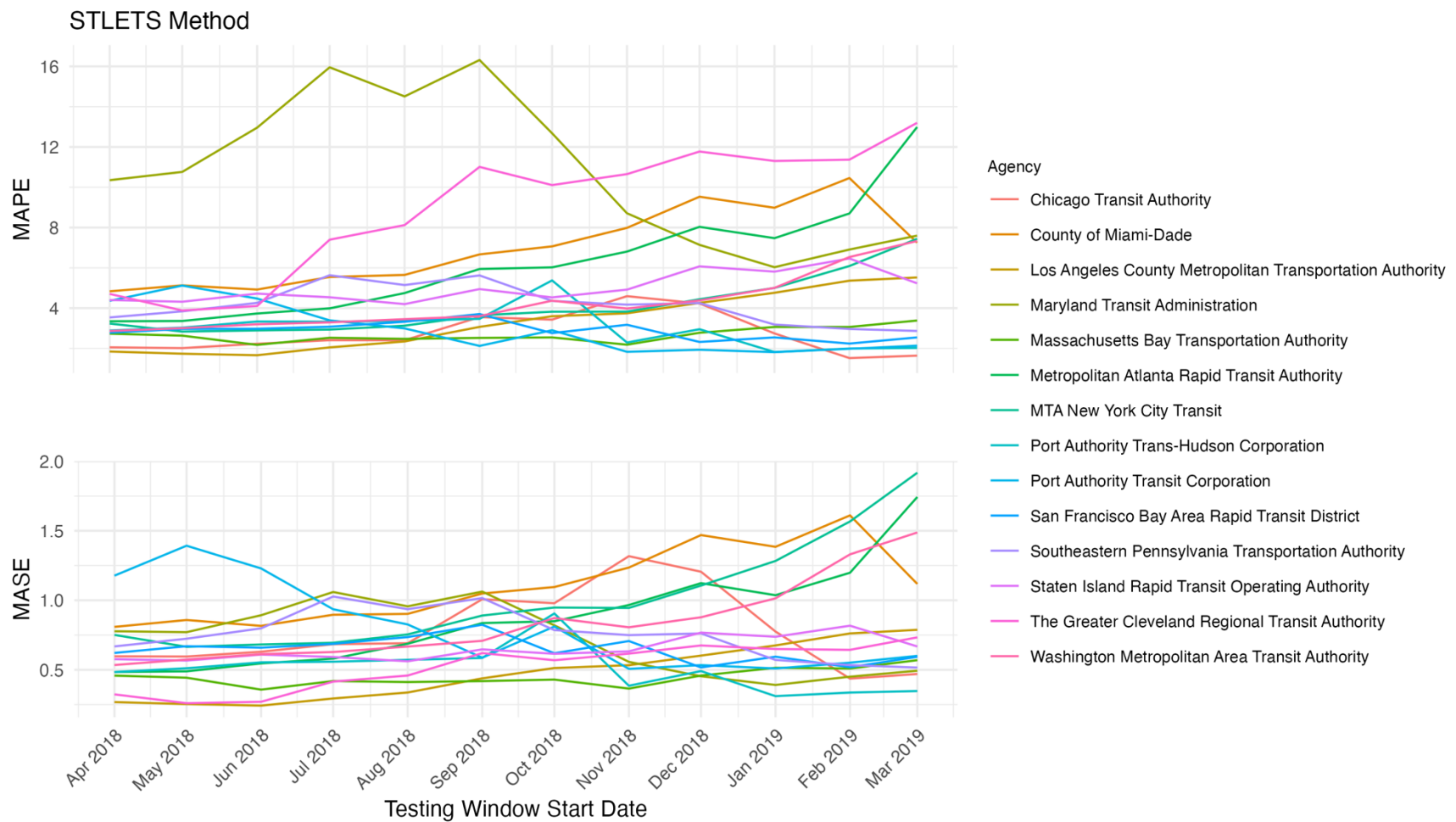


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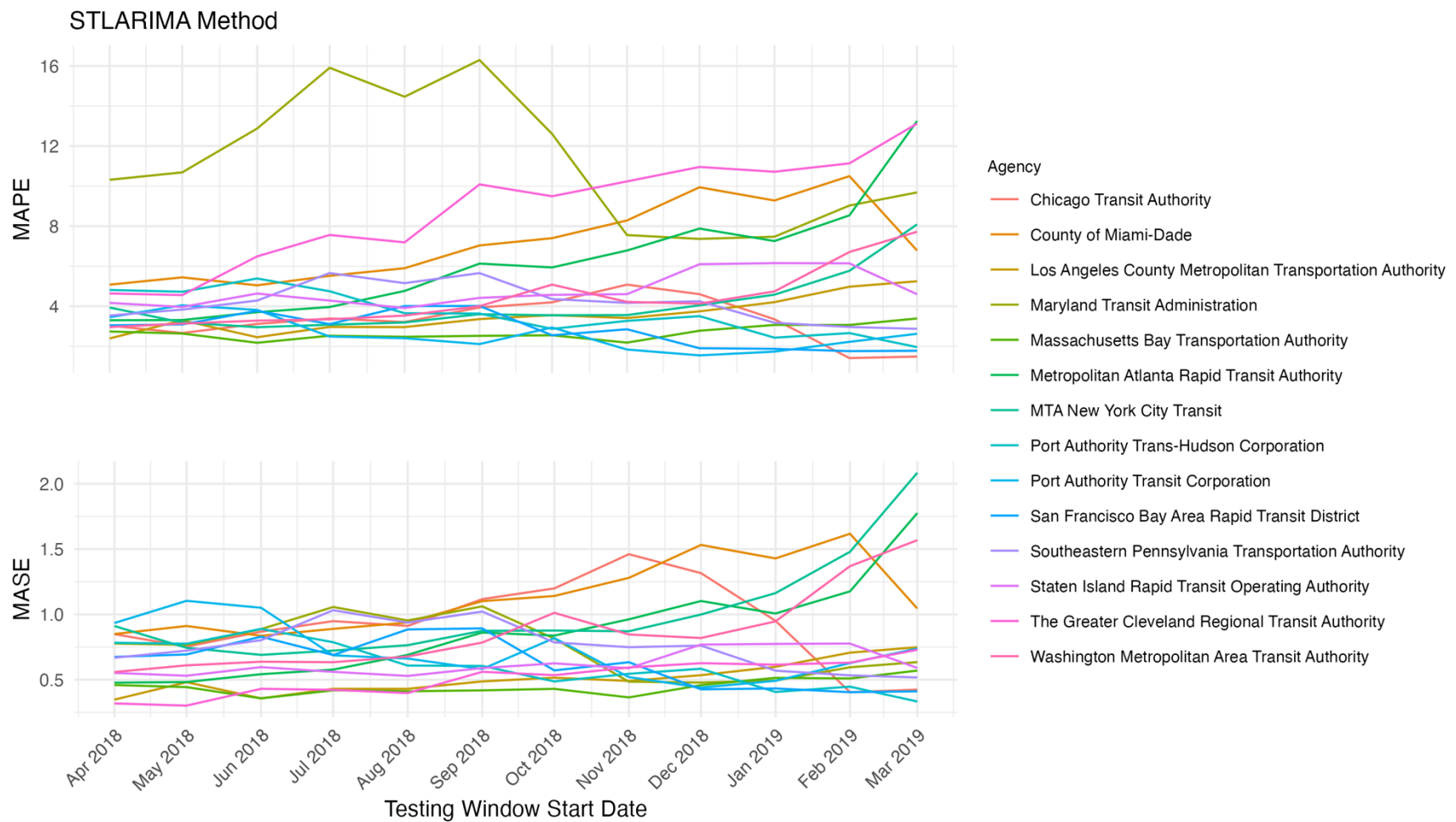


Figure A-4 Pre-COVID Performance of the STL-ARIMA Method

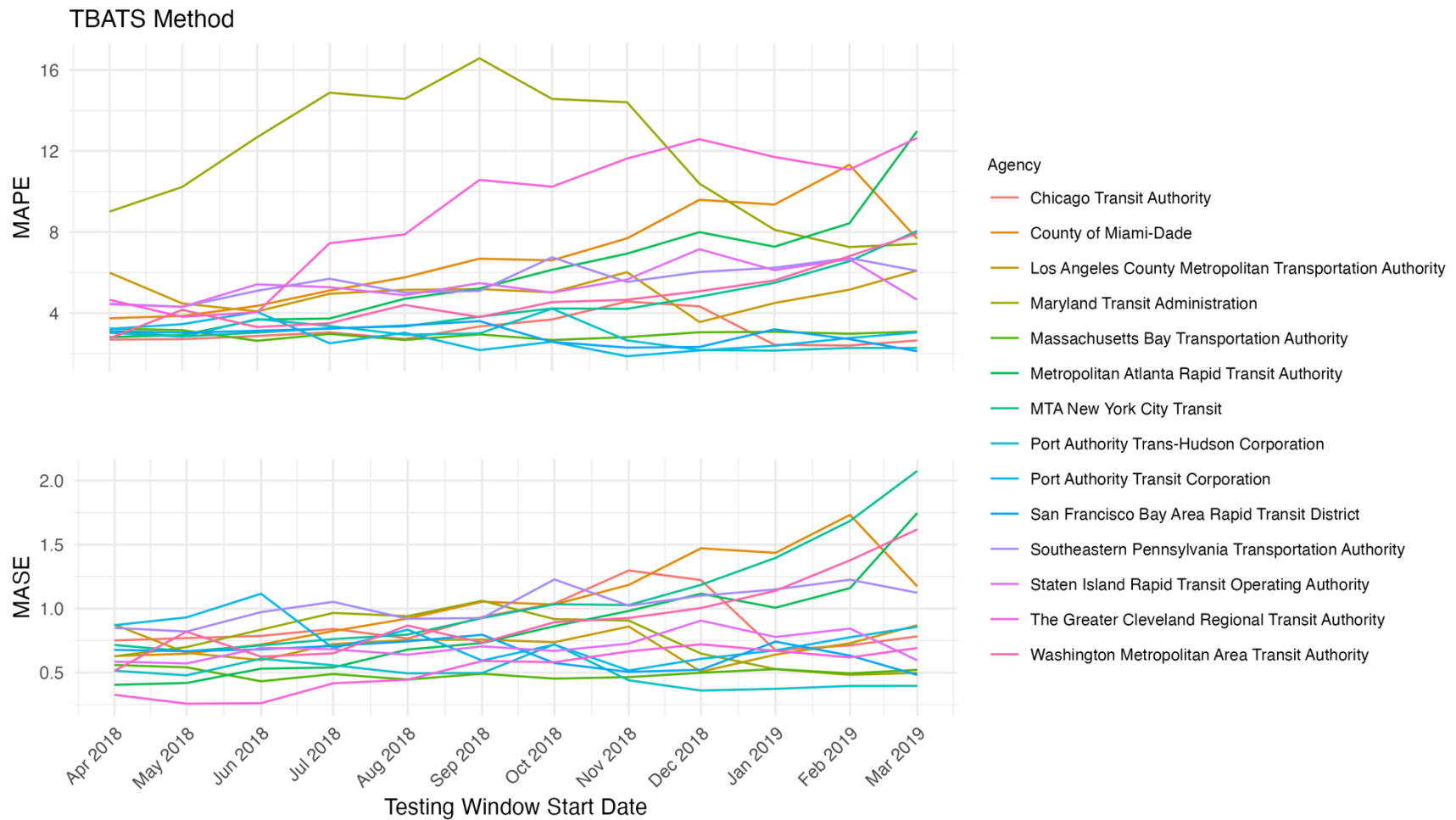


Figure A-5 Pre-COVID Performance of the TBATS Method

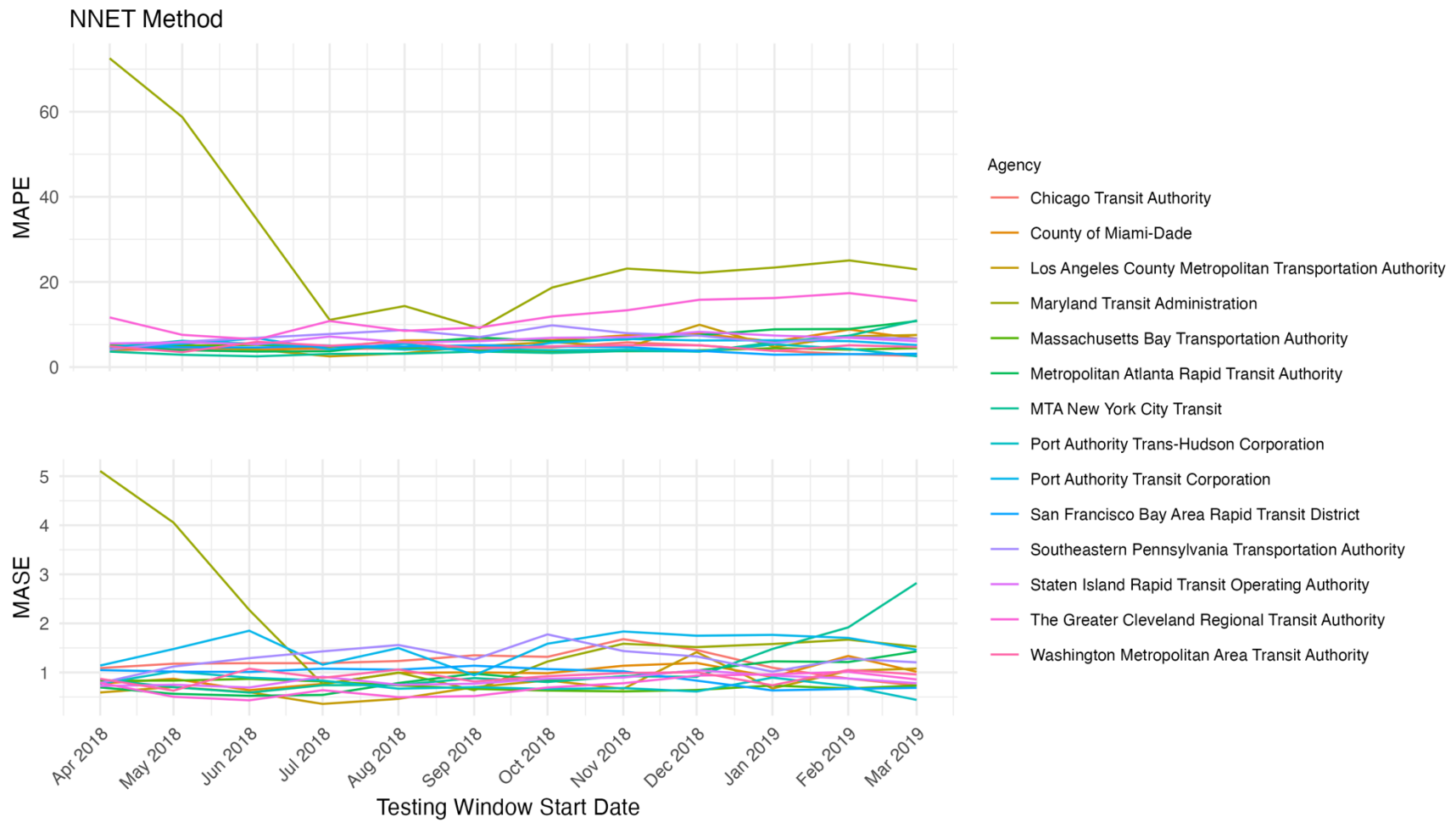


Figure A-6 Pre-COVID Performance of the NNET Method

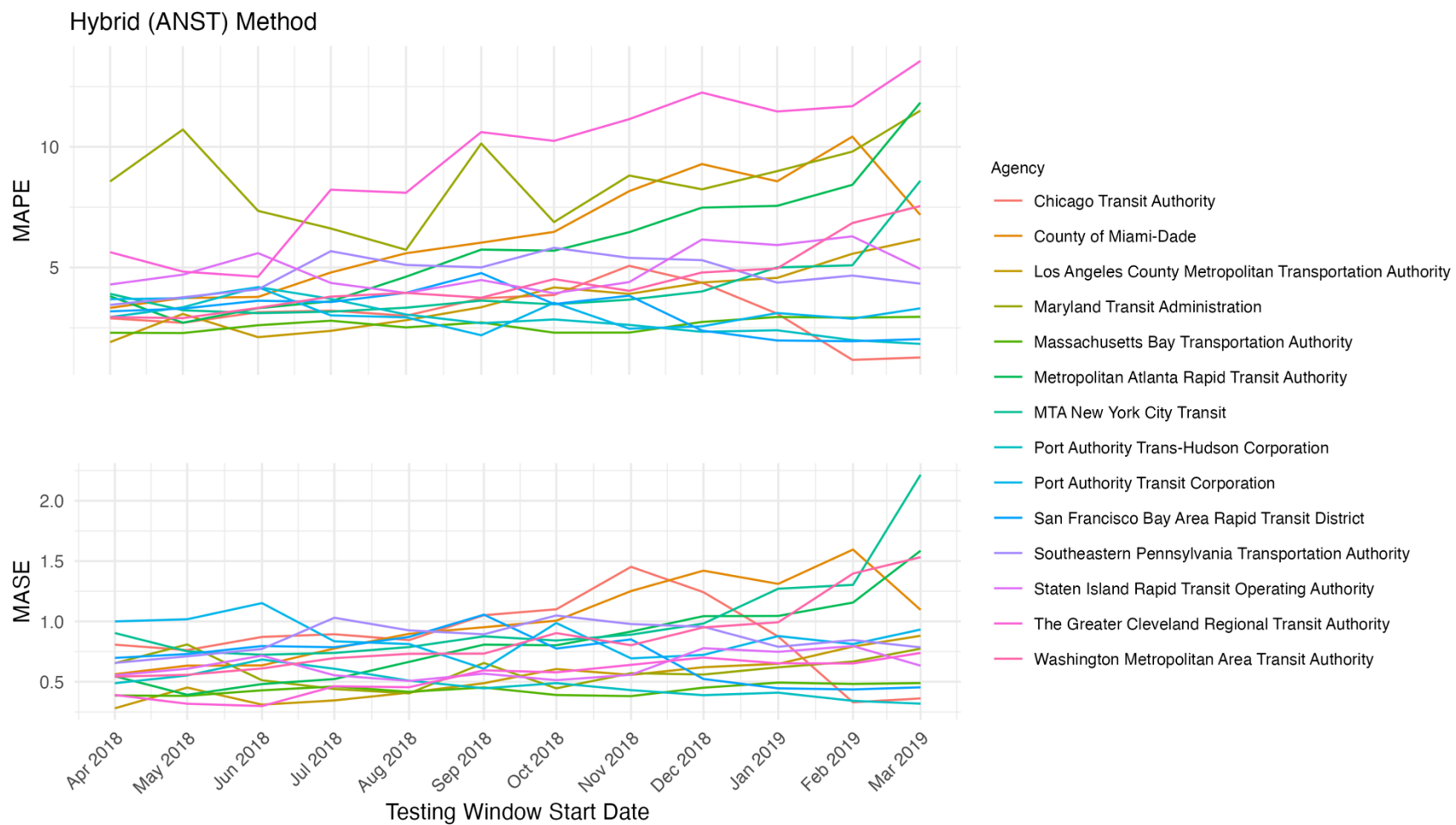


Figure A-7 Pre-COVID Performance of the Hybrid Method

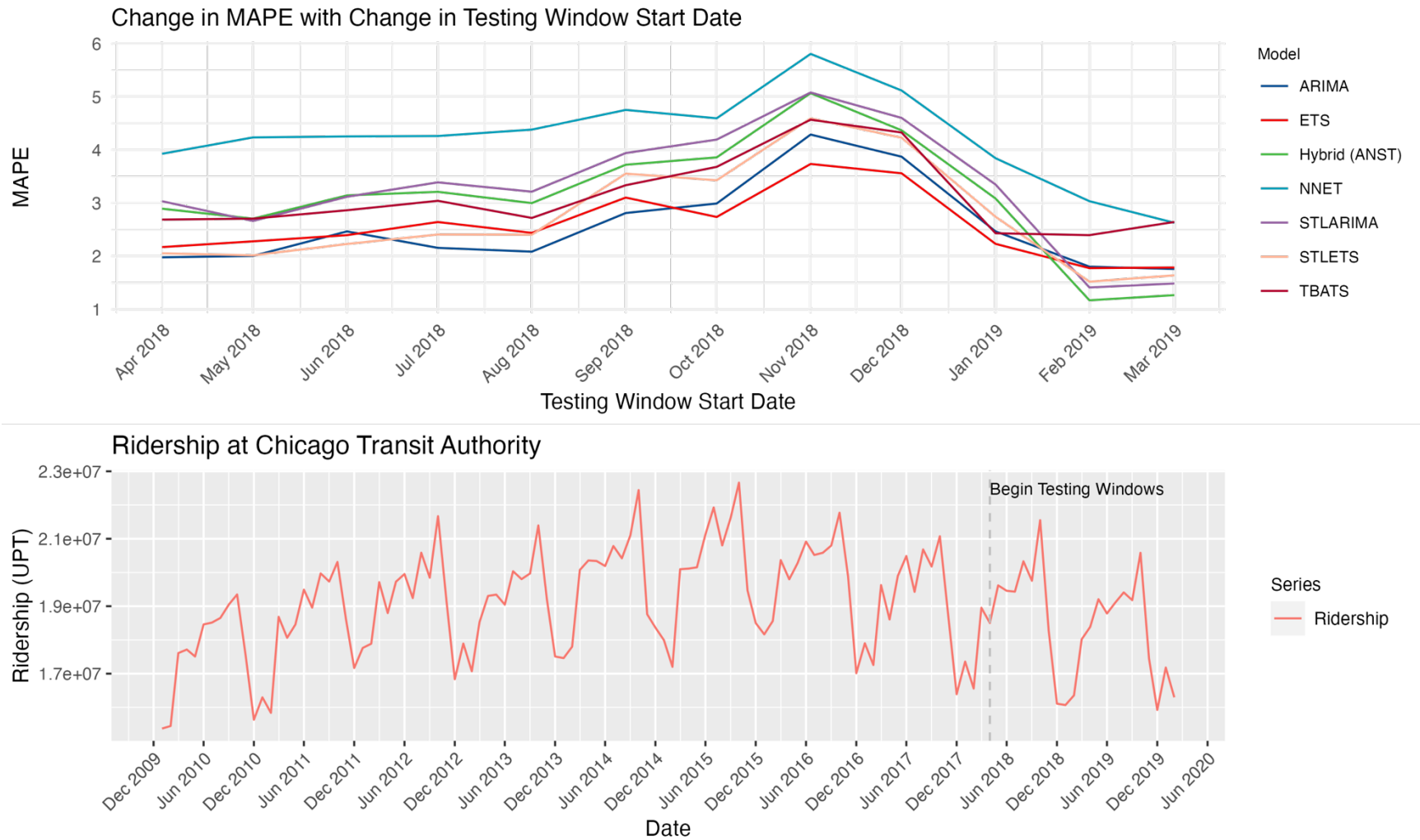


Figure A-8 Pre-COVID Change in MAPE at the Chicago Transit Authority Using the Moving Window

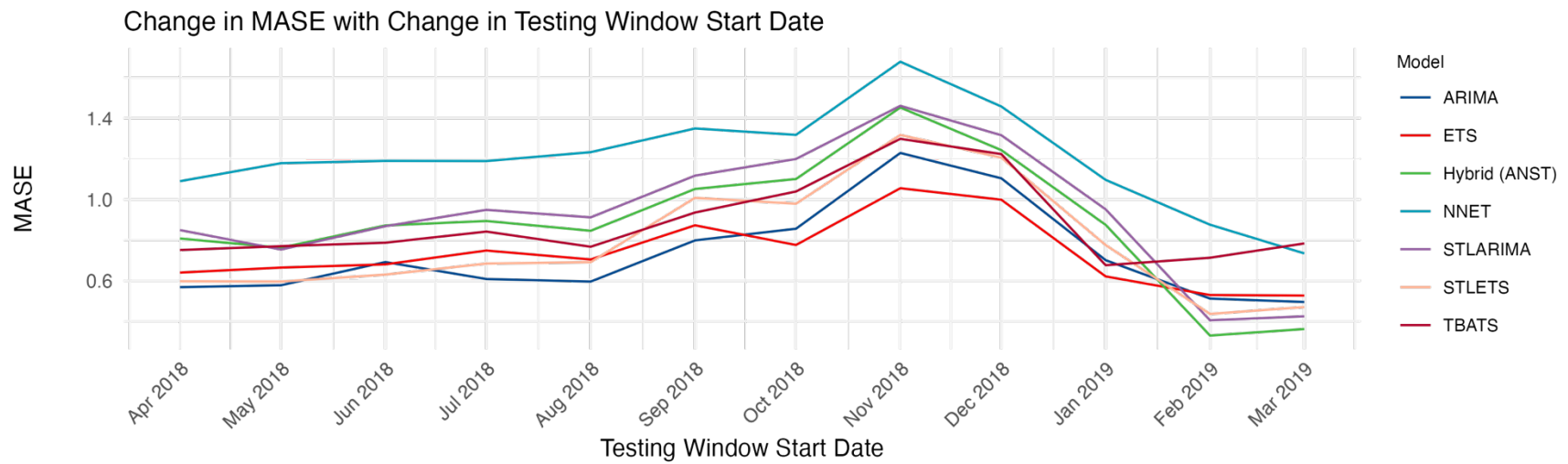
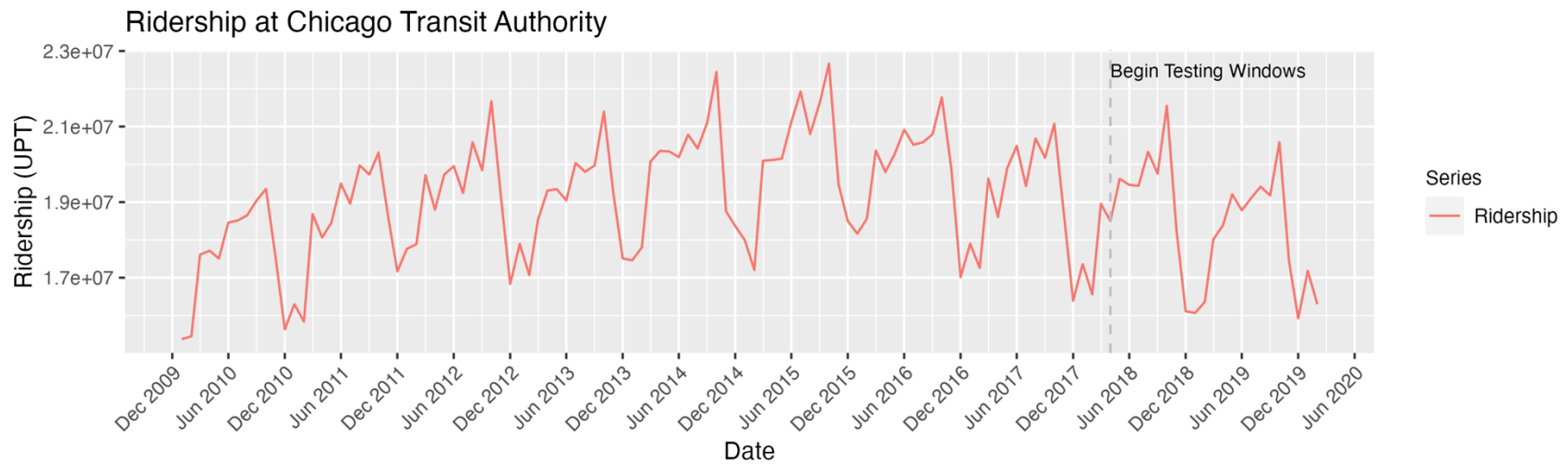


Figure A-9 Pre-COVID Change in MASE at the Chicago Transit Authority Using the Moving Window

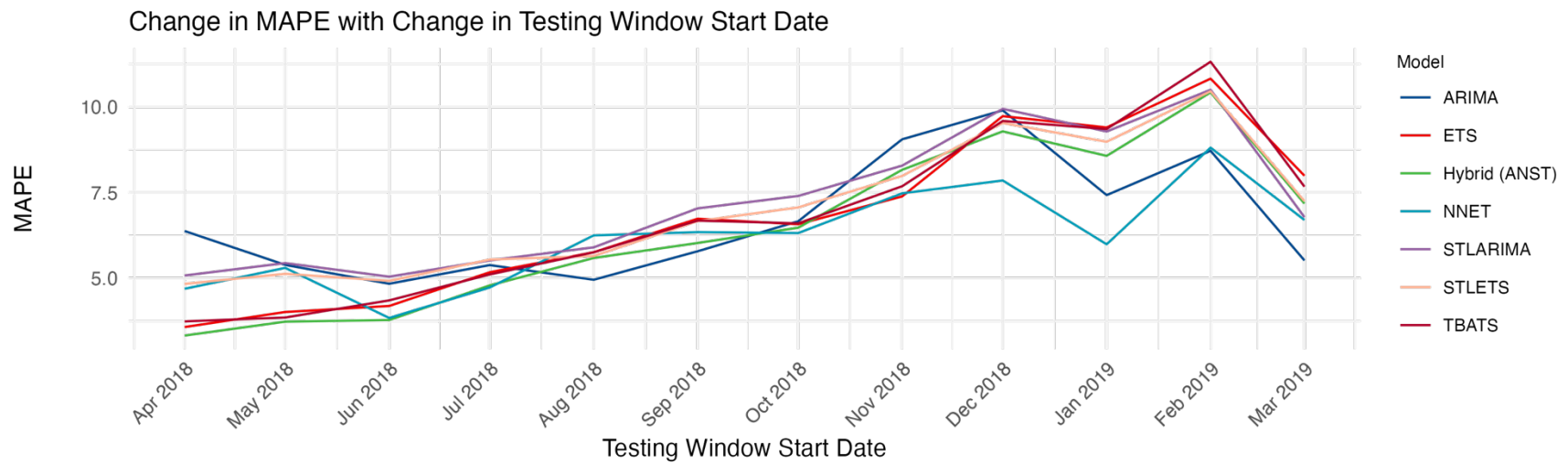
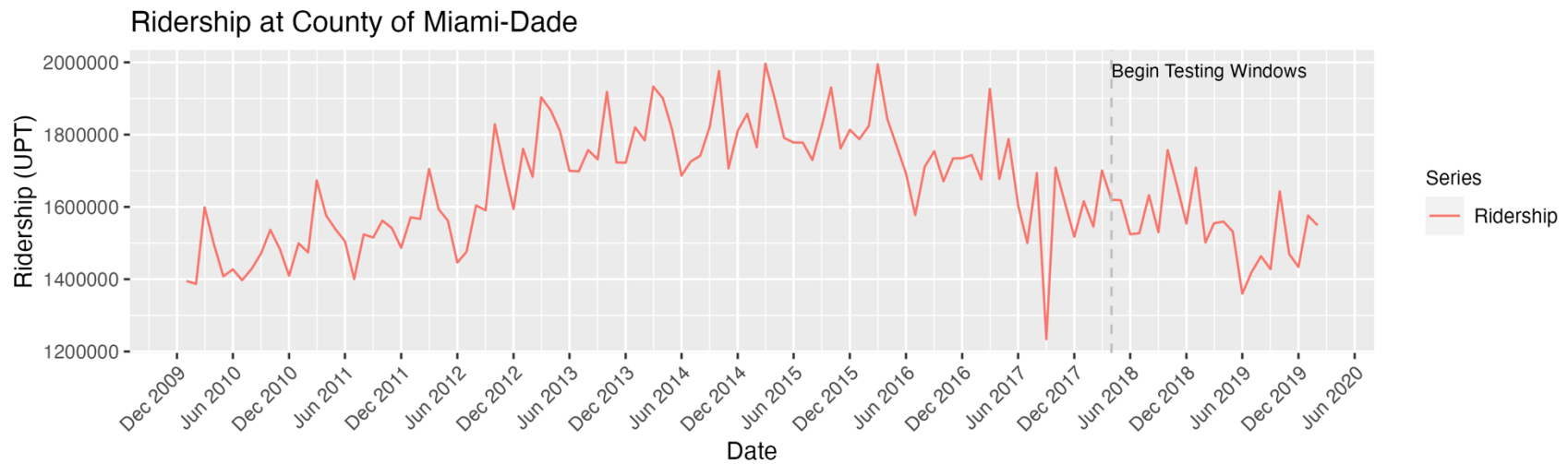


Figure A-10 Pre-COVID Change in MAPE at the County of Miami-Dade Using the Moving Window

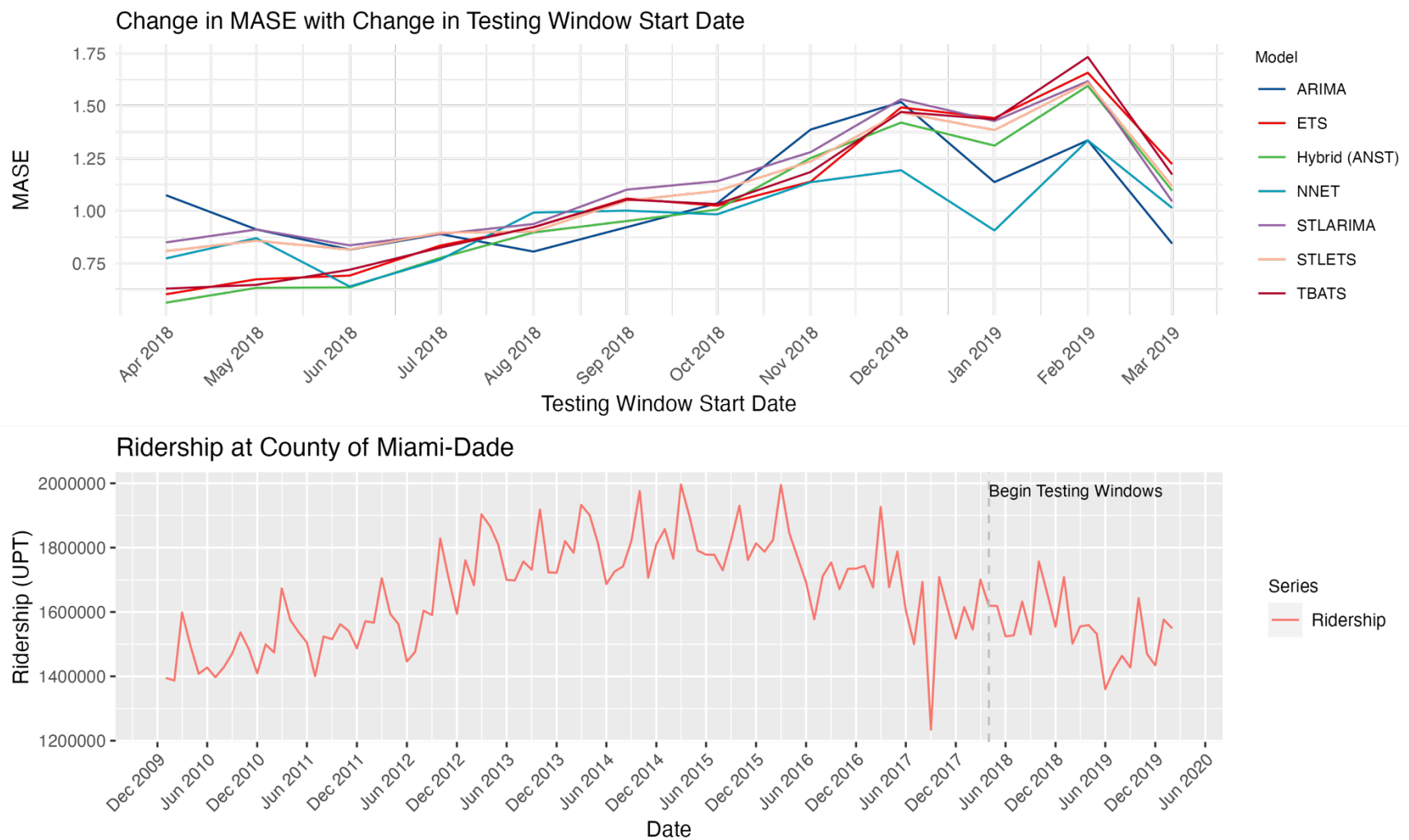


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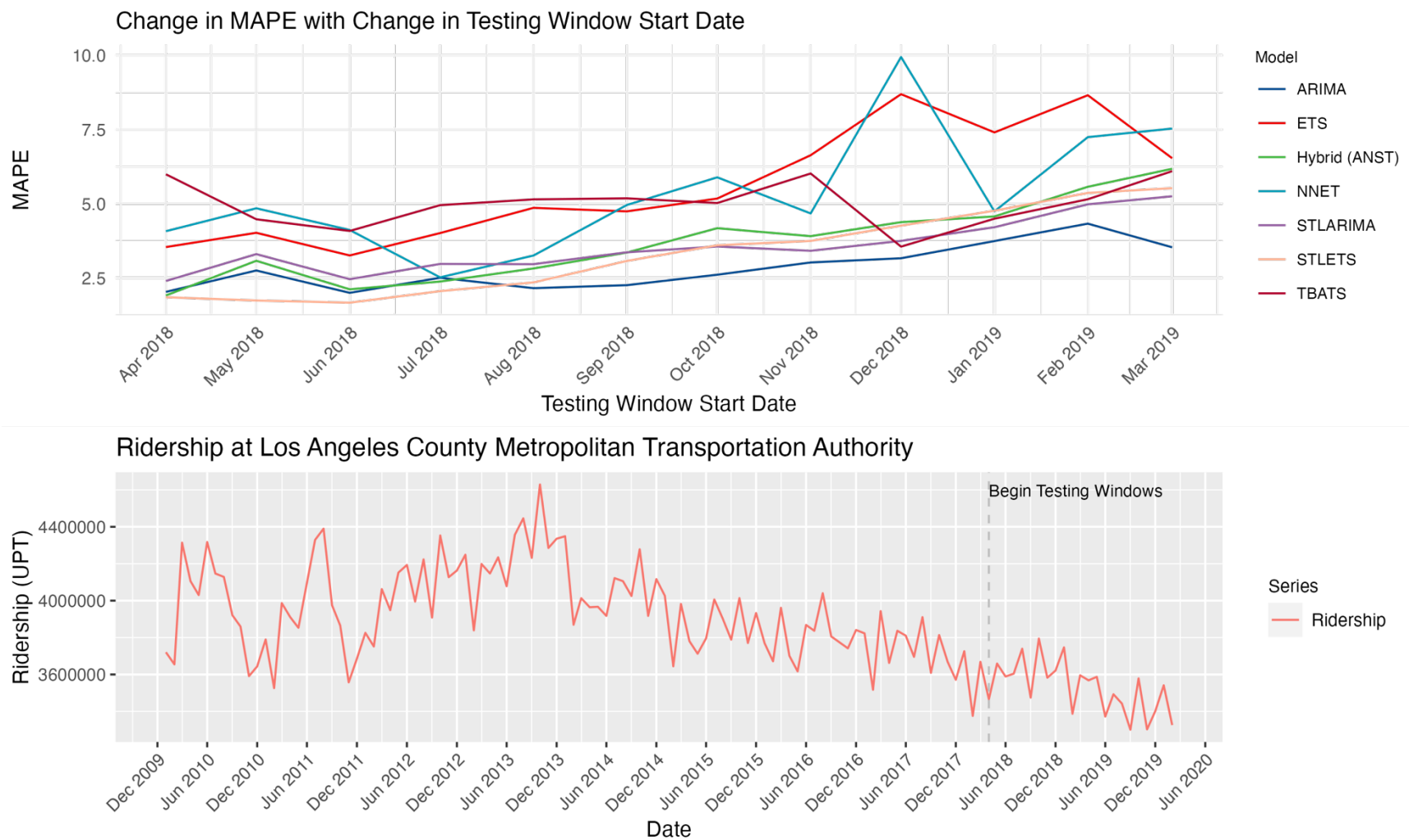


Figure A-12 Pre-COVID Change in MAPE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

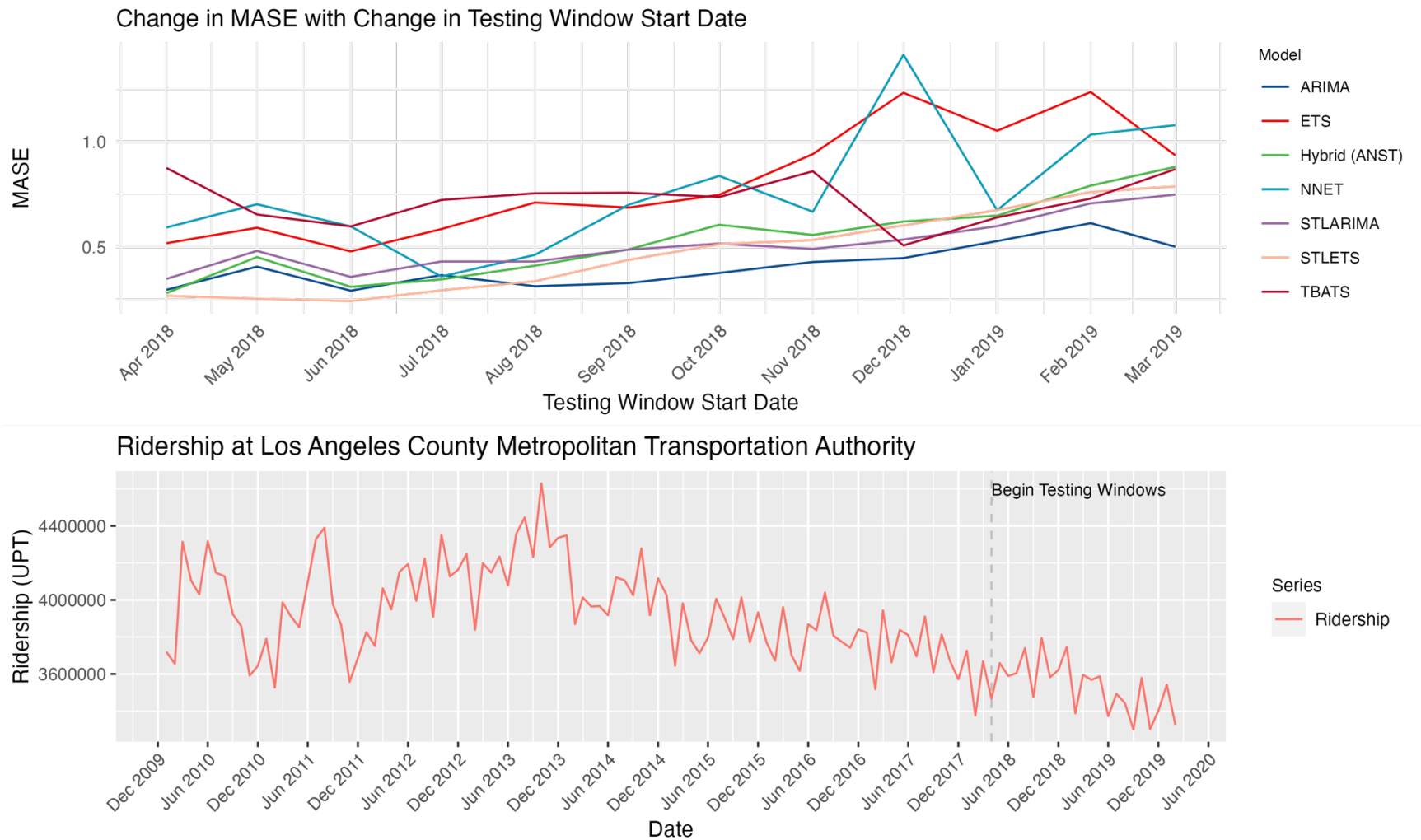


Figure A-13 Pre-COVID Change in MASE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

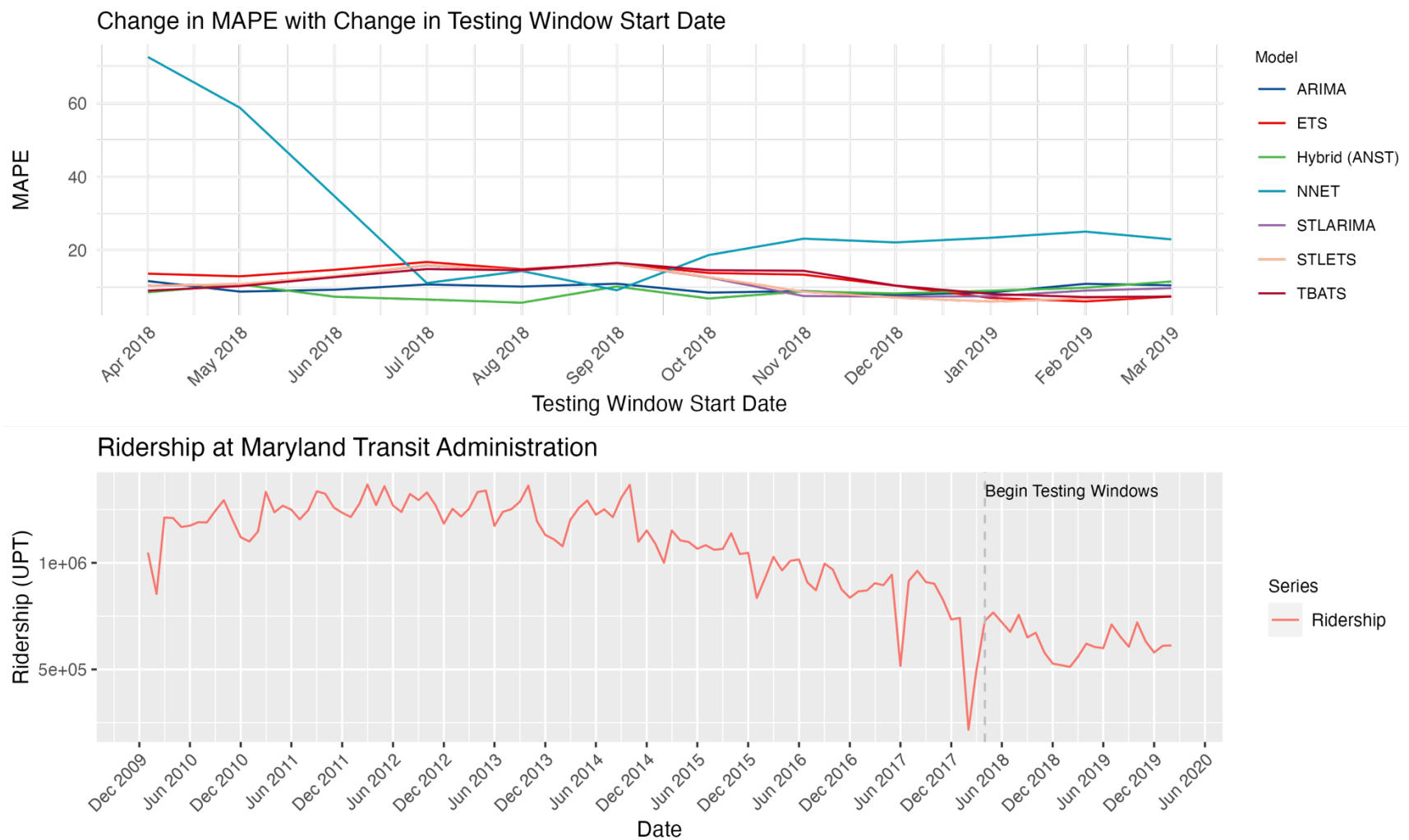


Figure A-14 Pre-COVID Change in MAPE at the Maryland Transit Administration Using the Moving Window

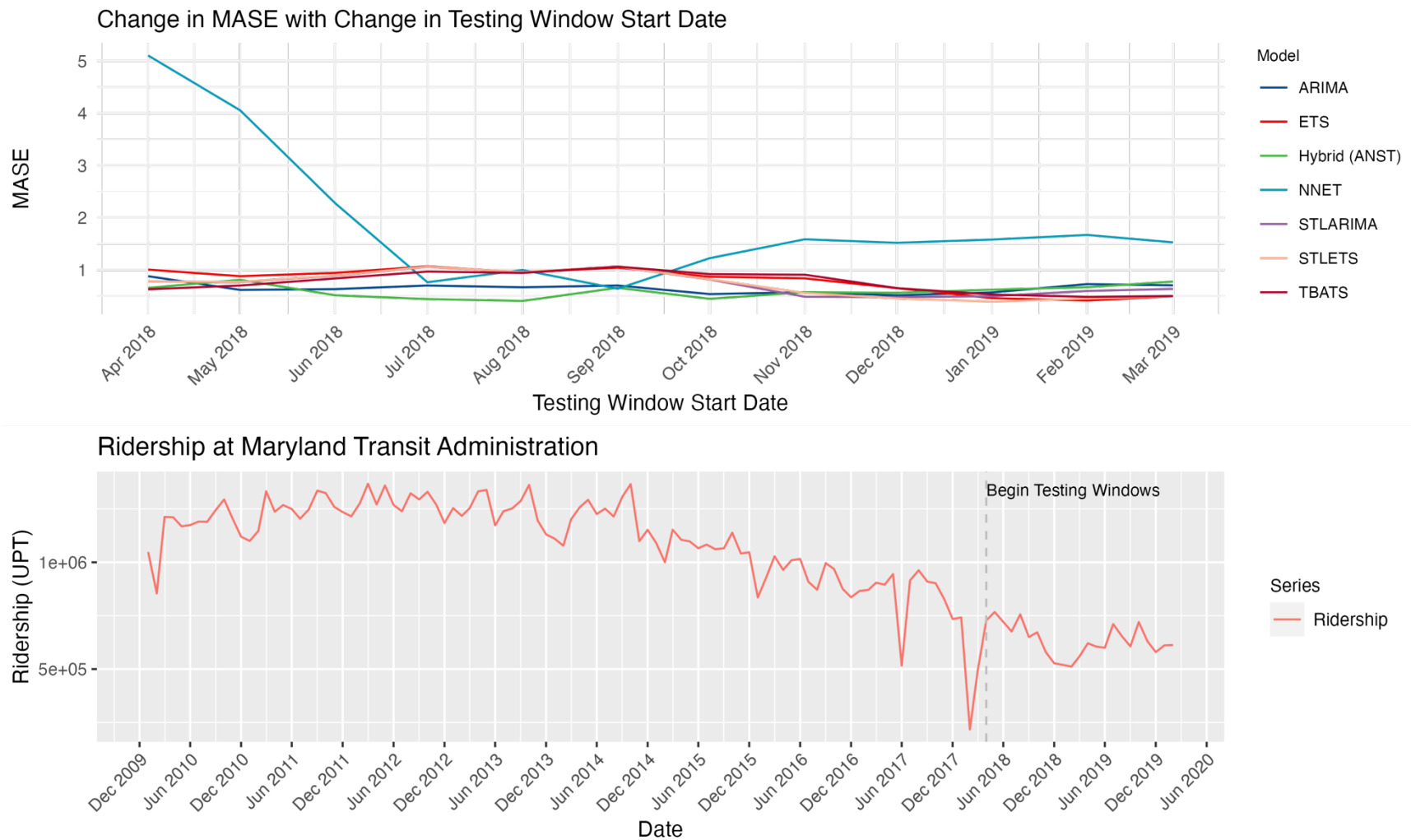


Figure A-15 Pre-COVID Change in MASE at the Maryland Transit Administration Using the Moving Window

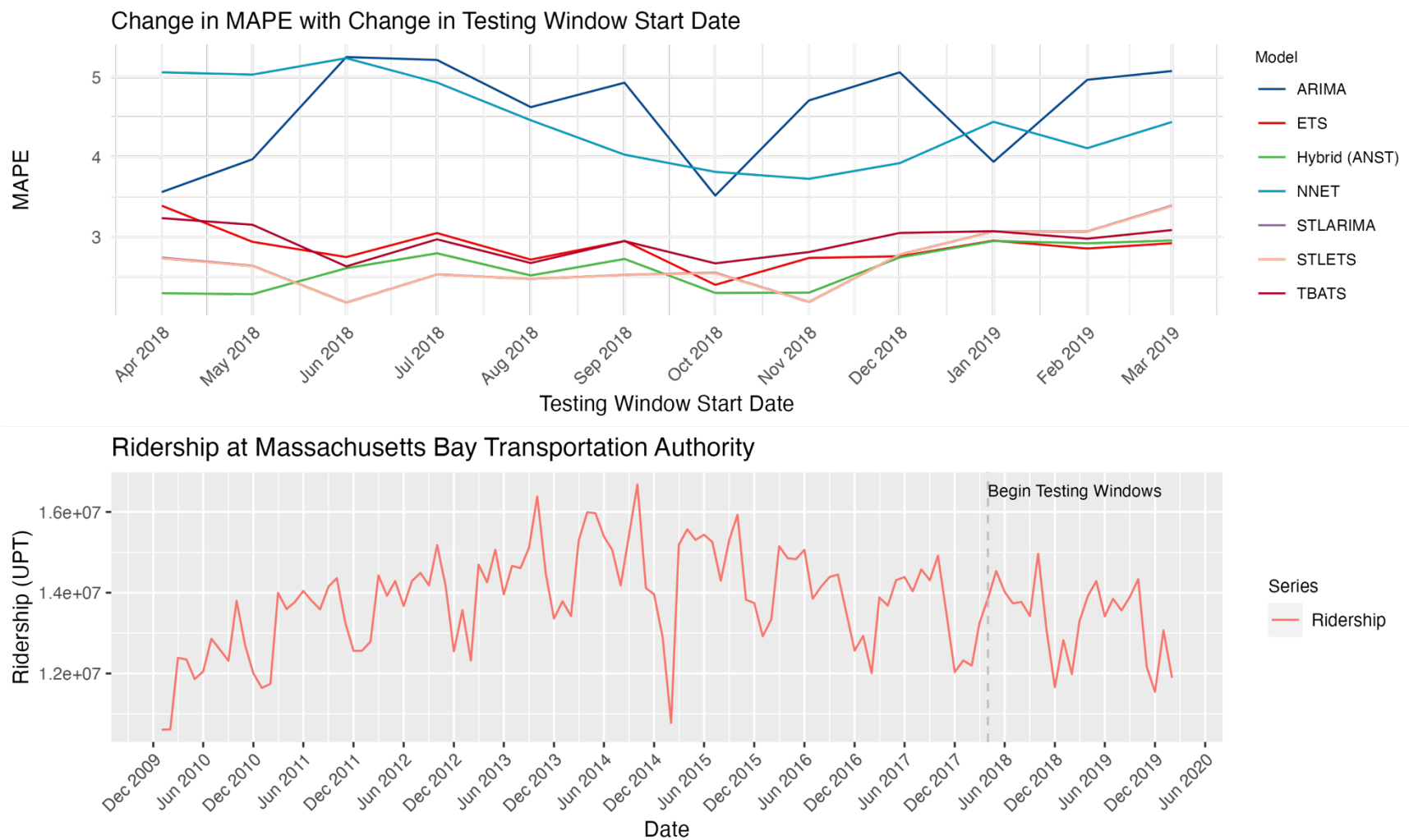


Figure A-16 Pre-COVID Change in MAPE at the Massachusetts Bay Transportation Authority Using the Moving Window

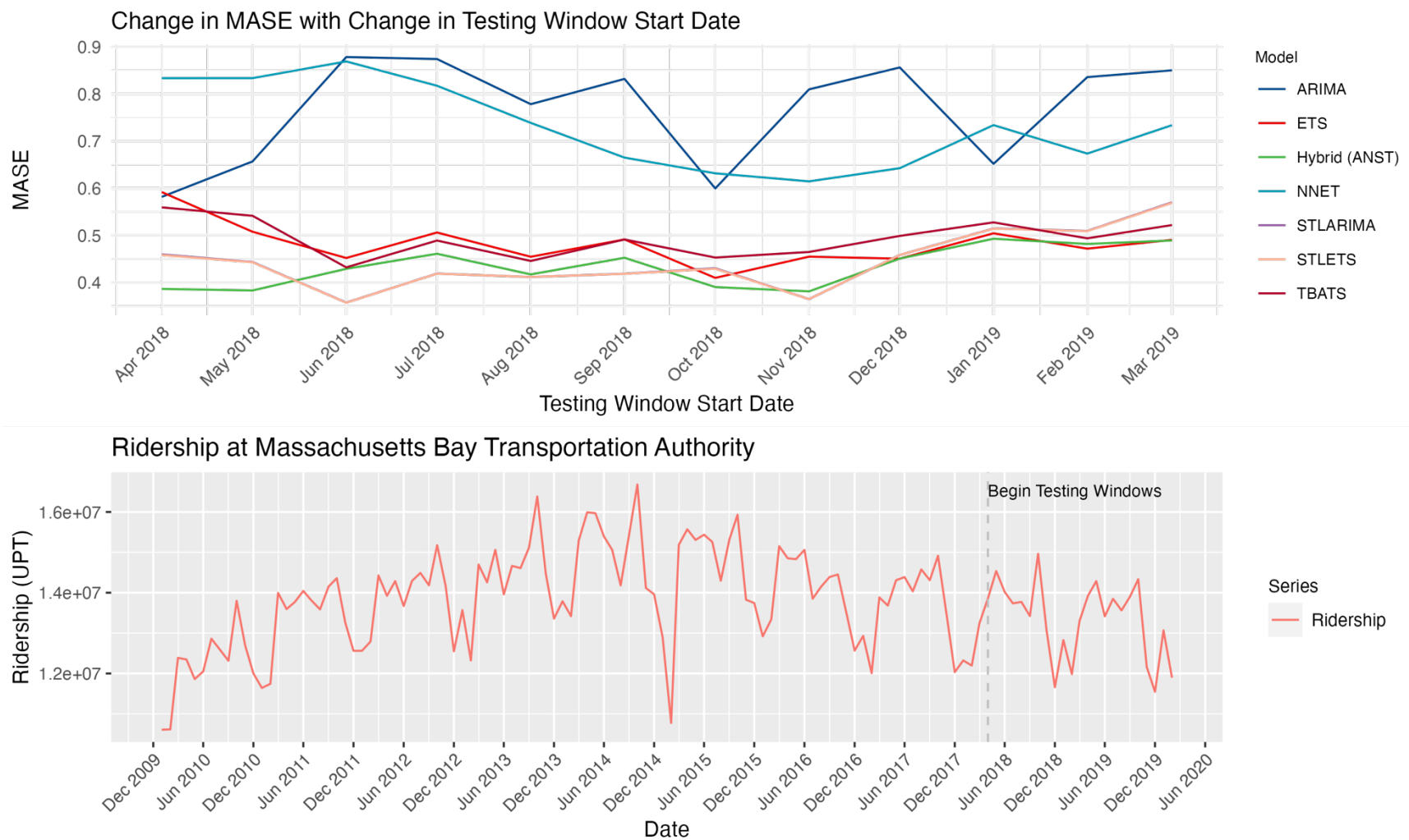


Figure A-17 Pre-COVID Change in MASE at the Massachusetts Bay Transportation Authority Using the Moving Window

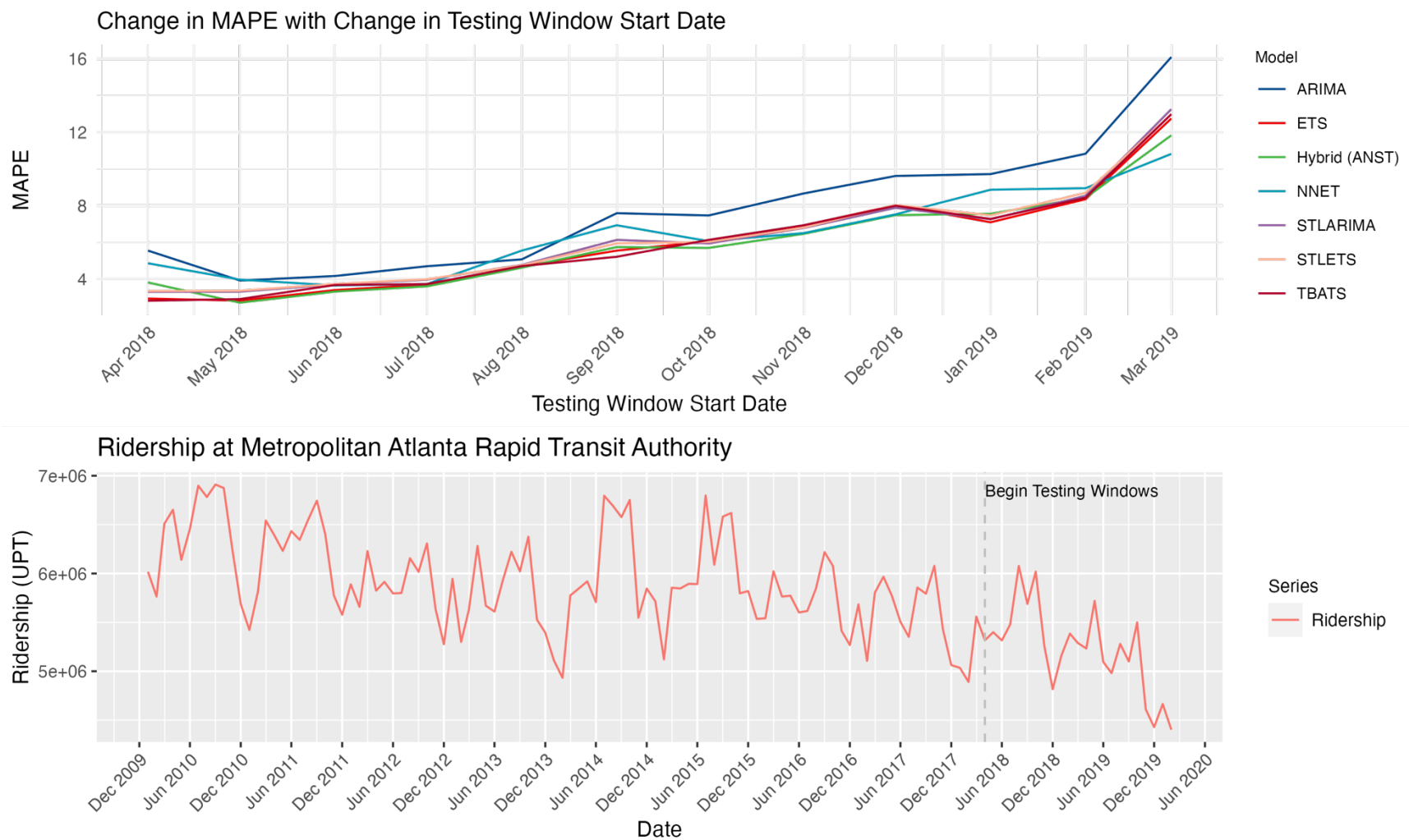


Figure A-18 Pre-COVID Change in MAPE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

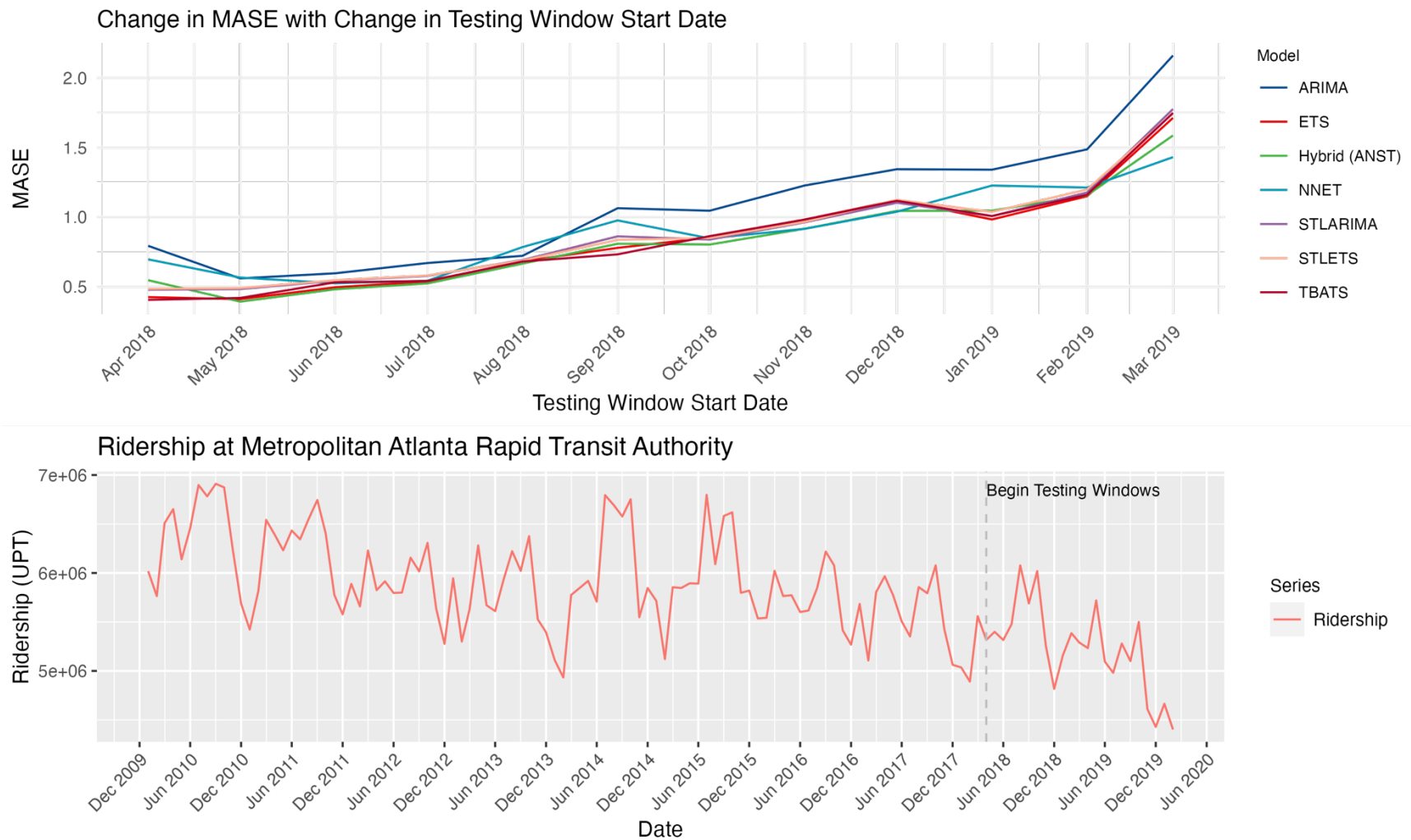


Figure A-19 Pre-COVID Change in MASE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

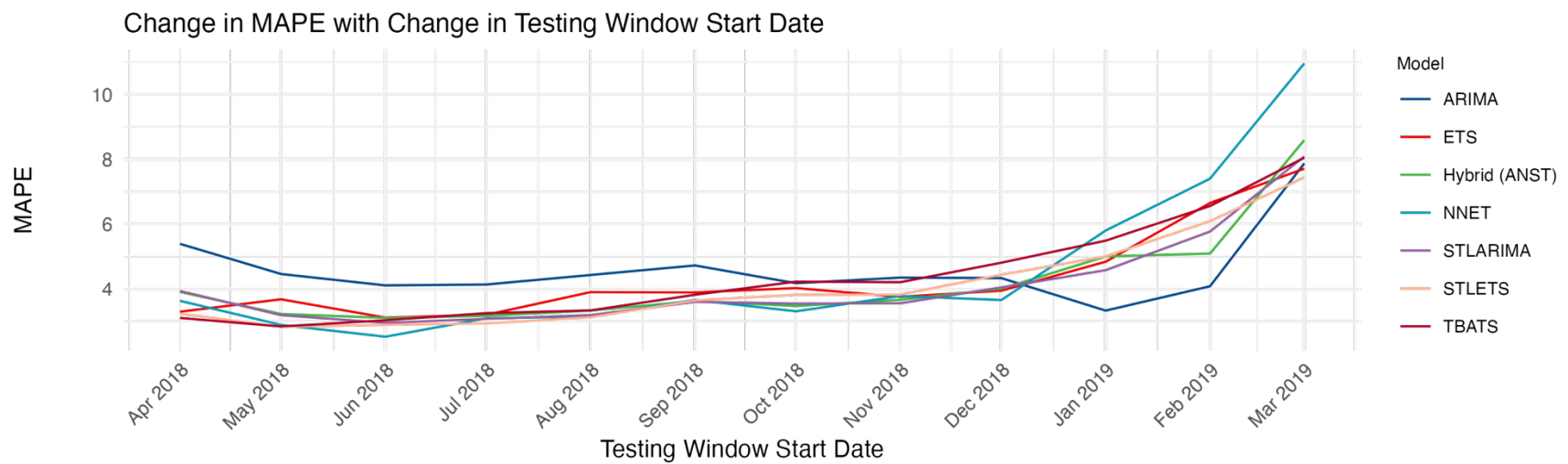
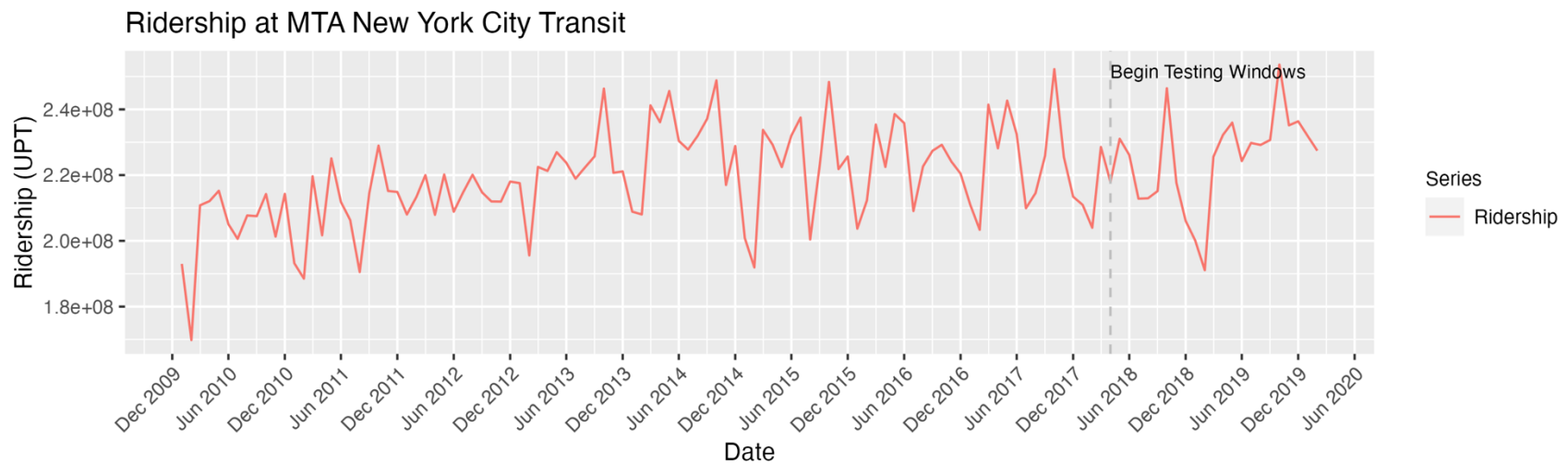


Figure A-20 Pre-COVID Change in MAPE at MTA New York City Transit Using the Moving Window

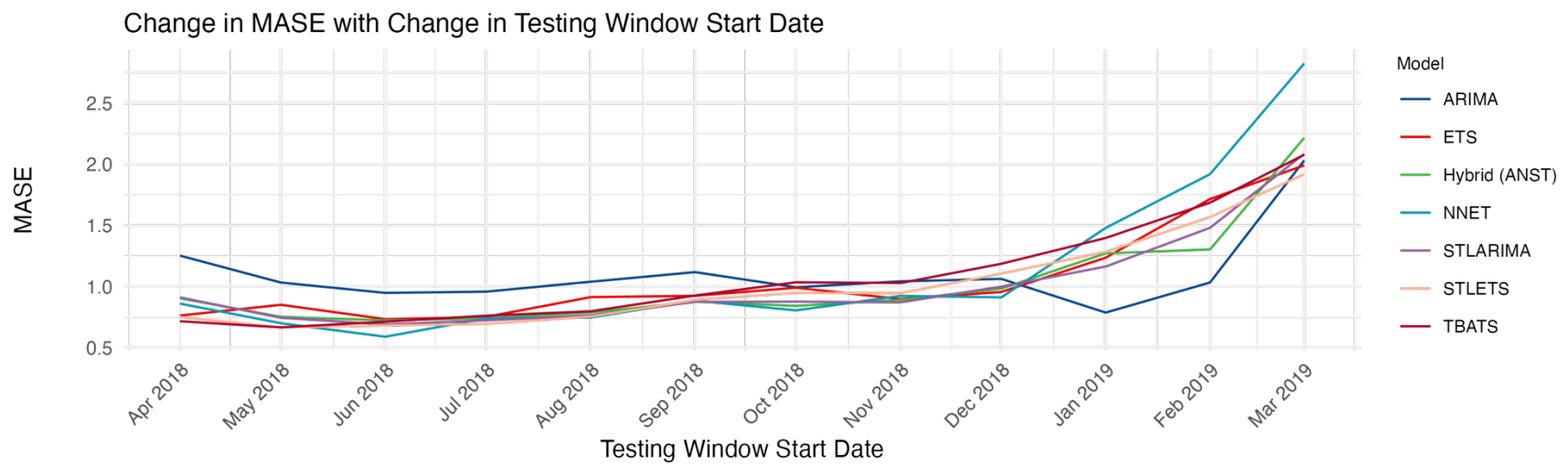
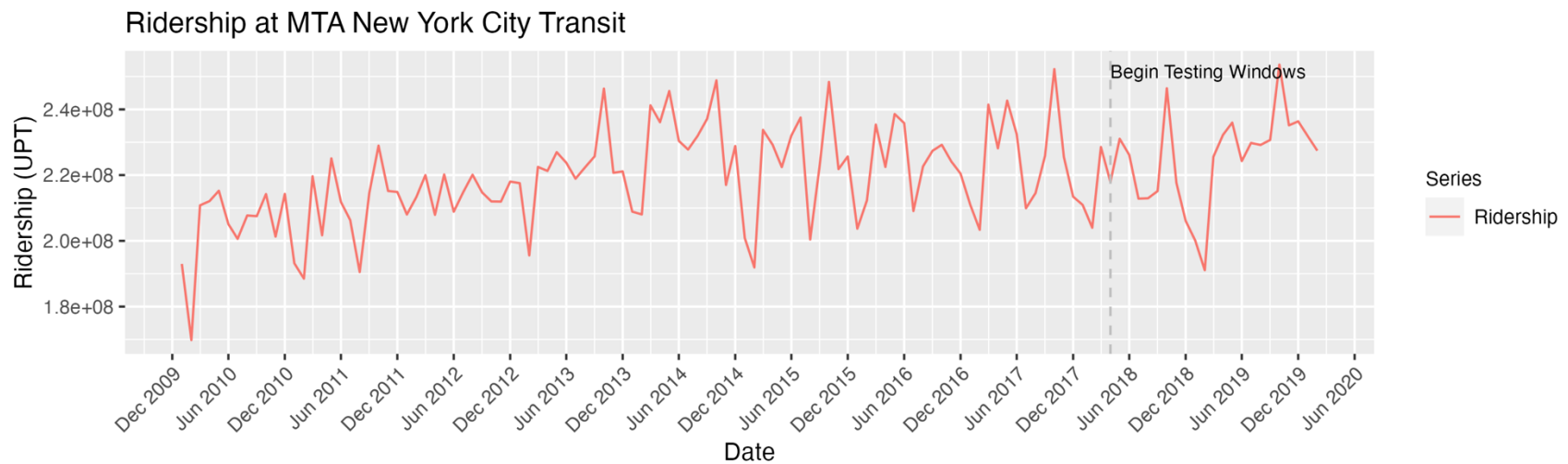


Figure A-21 Pre-COVID Change in MASE at MTA New York City Transit Using the Moving Window

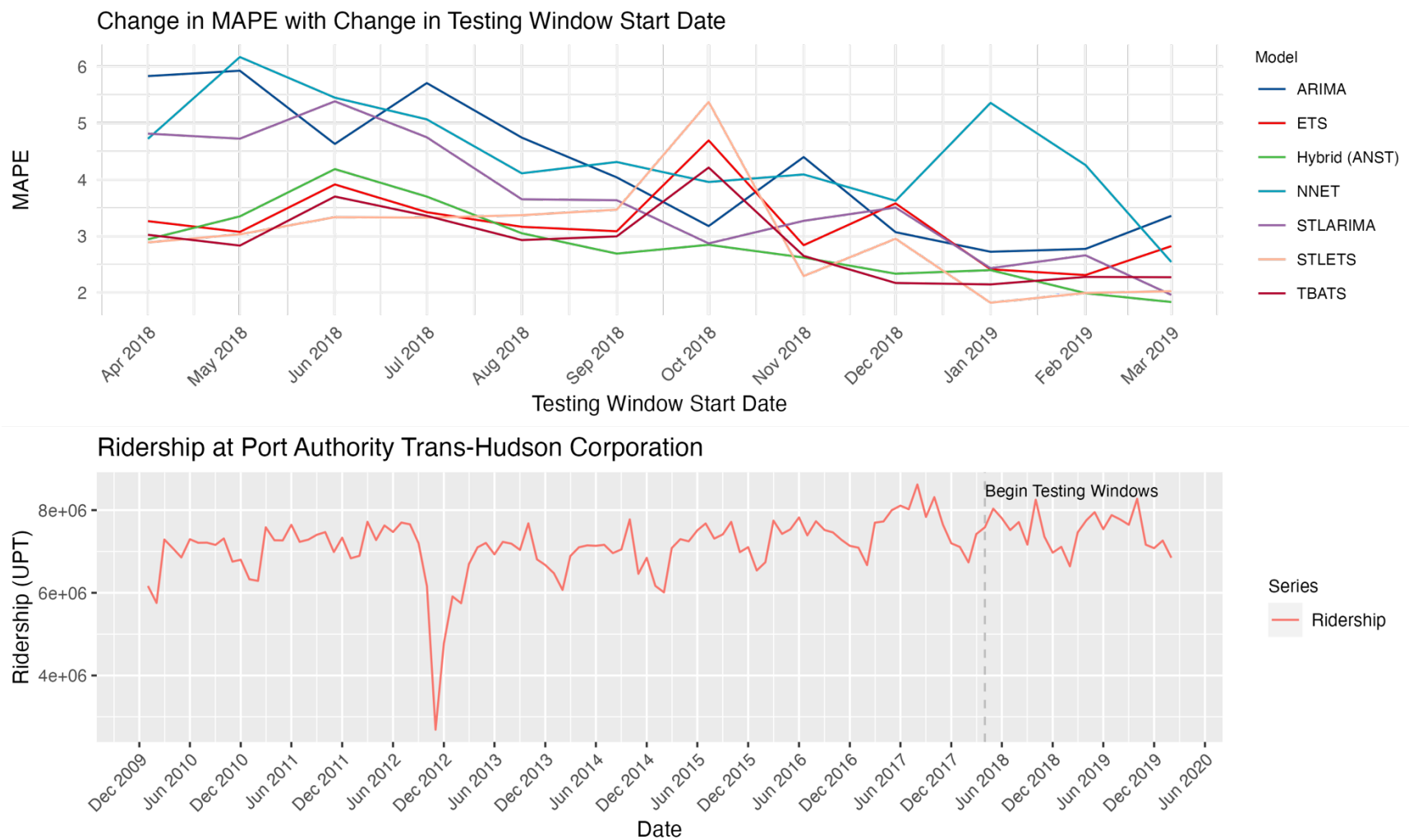


Figure A-22 Pre-COVID Change in MAPE at the Port Authority Trans-Hudson Corporation Using the Moving Window

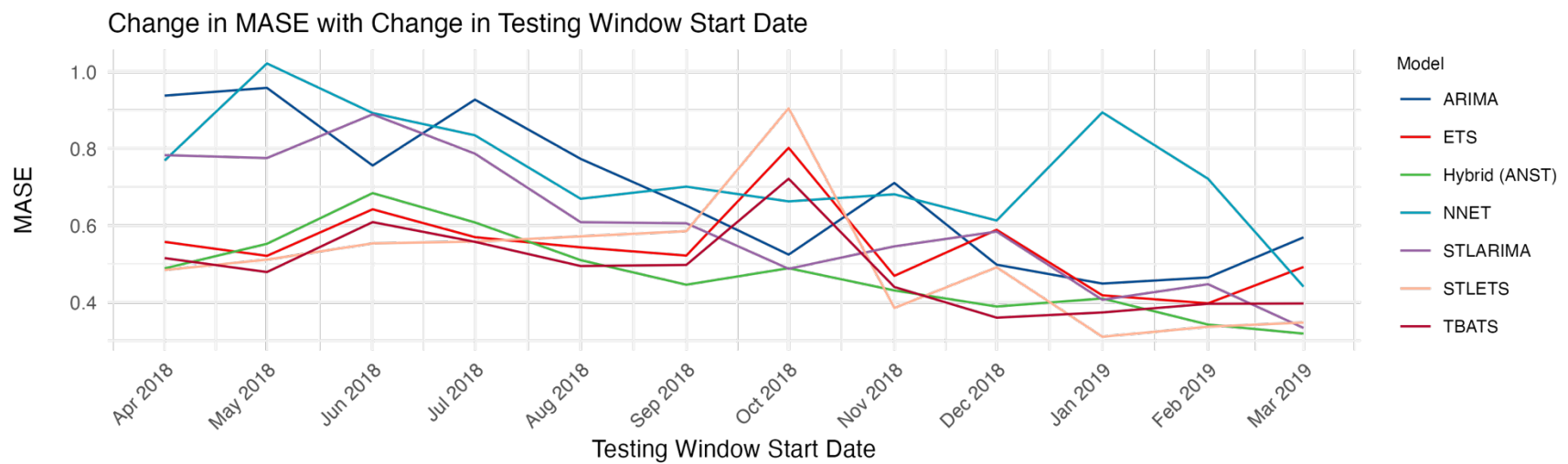
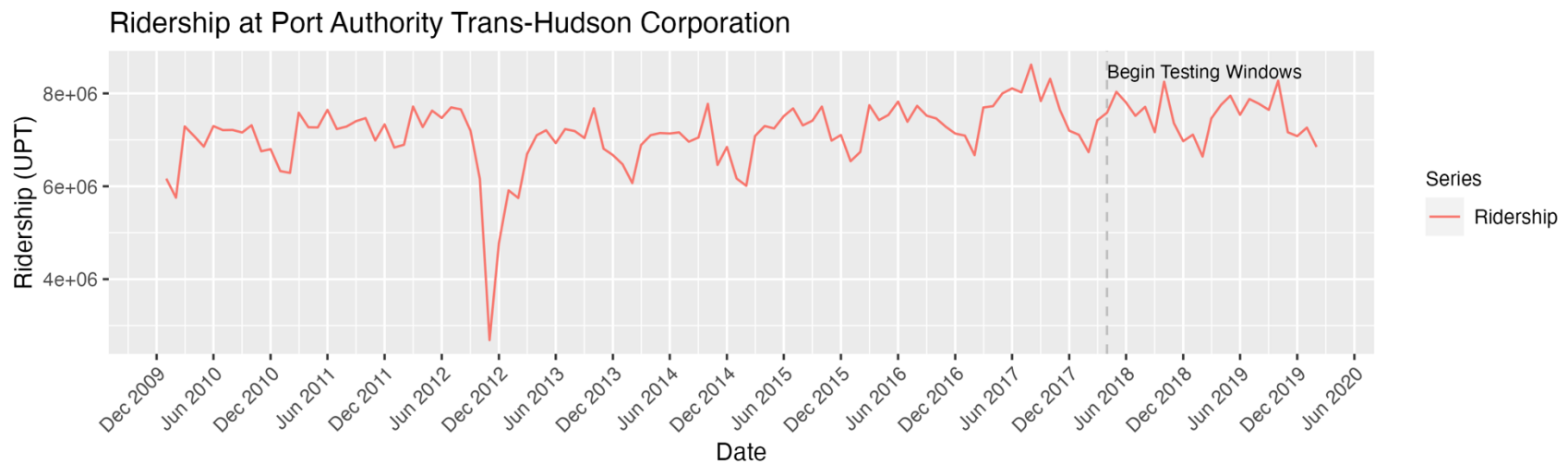


Figure A-23 Pre-COVID Change in MASE at the Port Authority Trans-Hudson Corporation Using the Moving Window

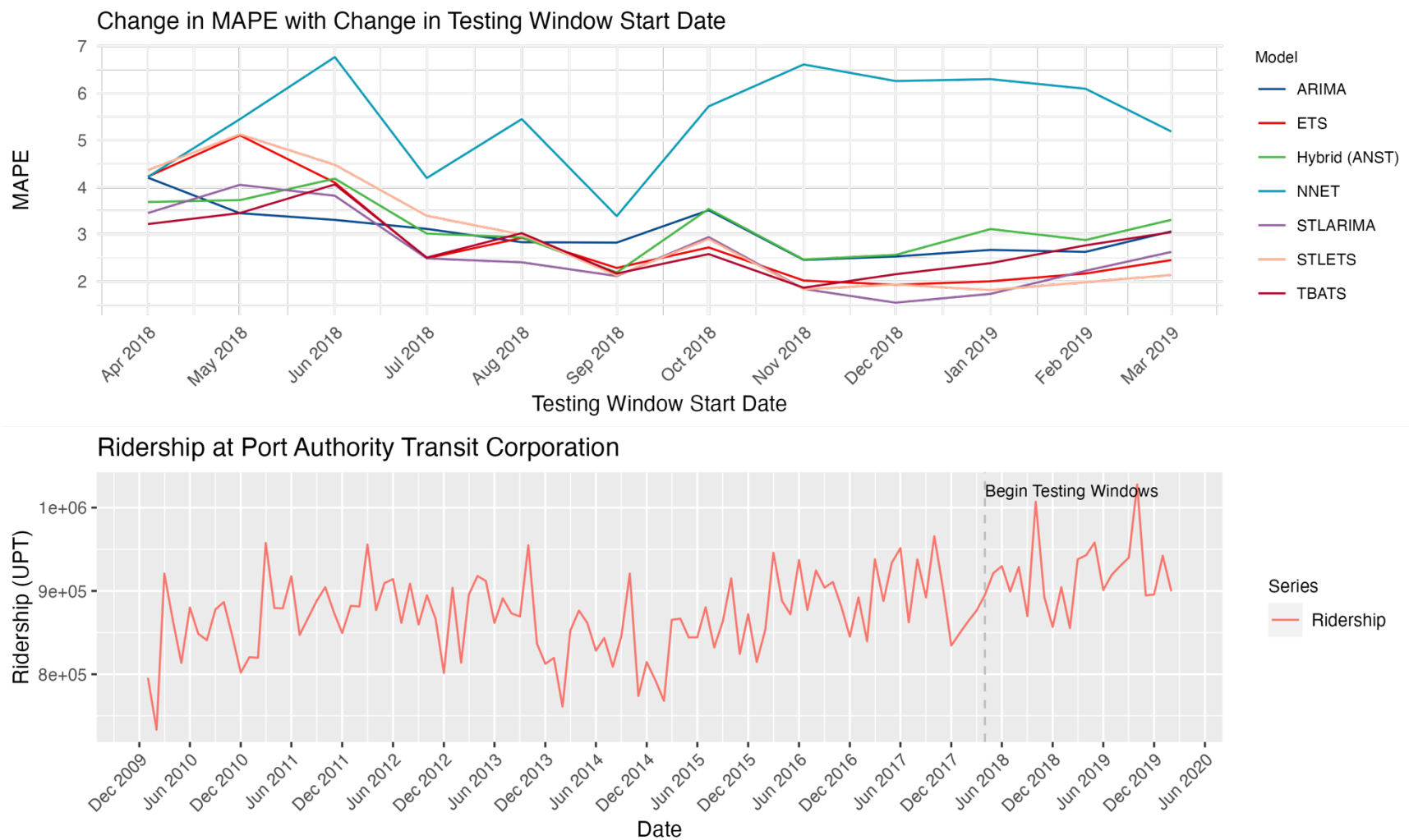


Figure A-24 Pre-COVID Change in MAPE at the Port Authority Transit Corporation Using the Moving Window

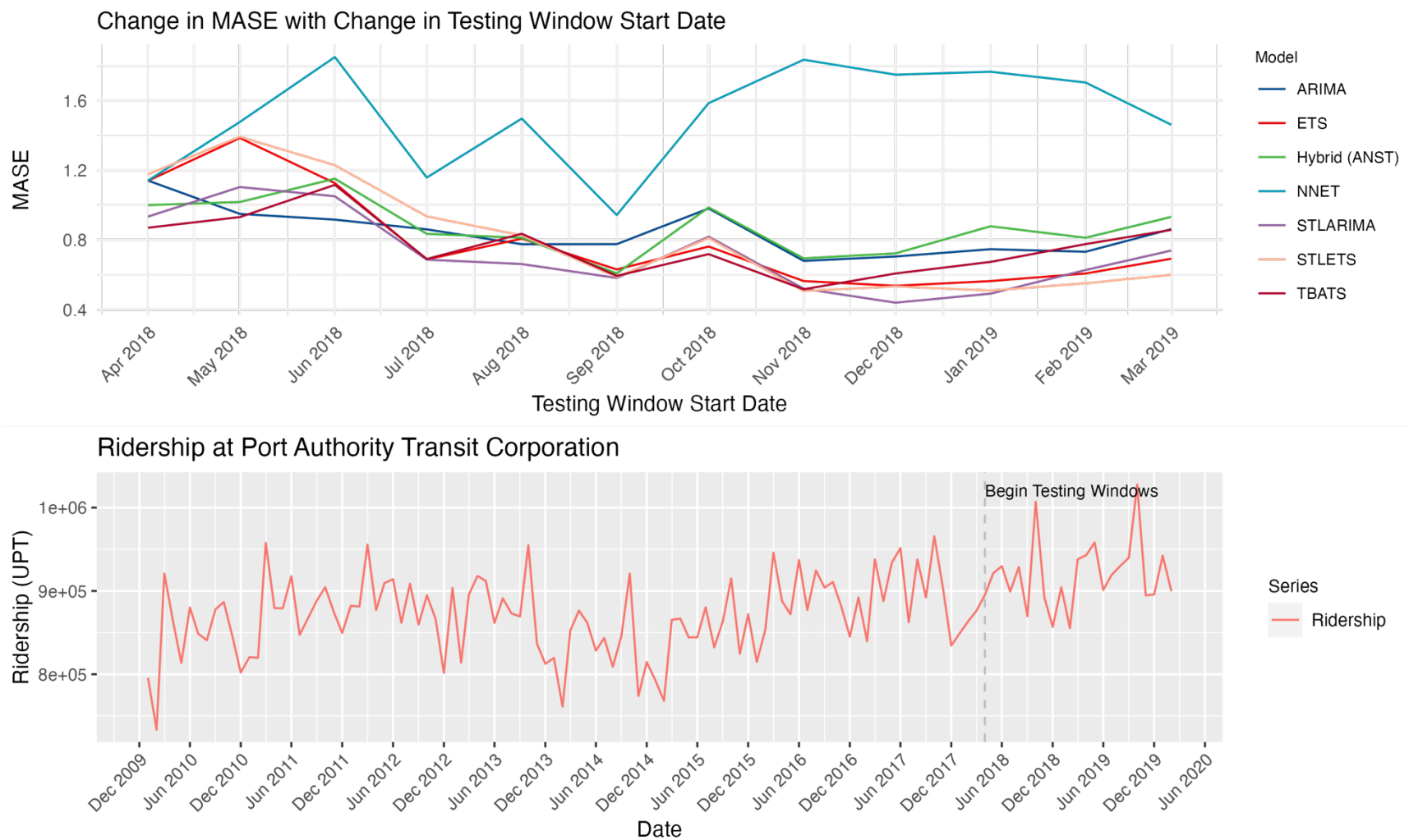


Figure A-25 Pre-COVID Change in MASE at the Port Authority Transit Corporation Using the Moving Window

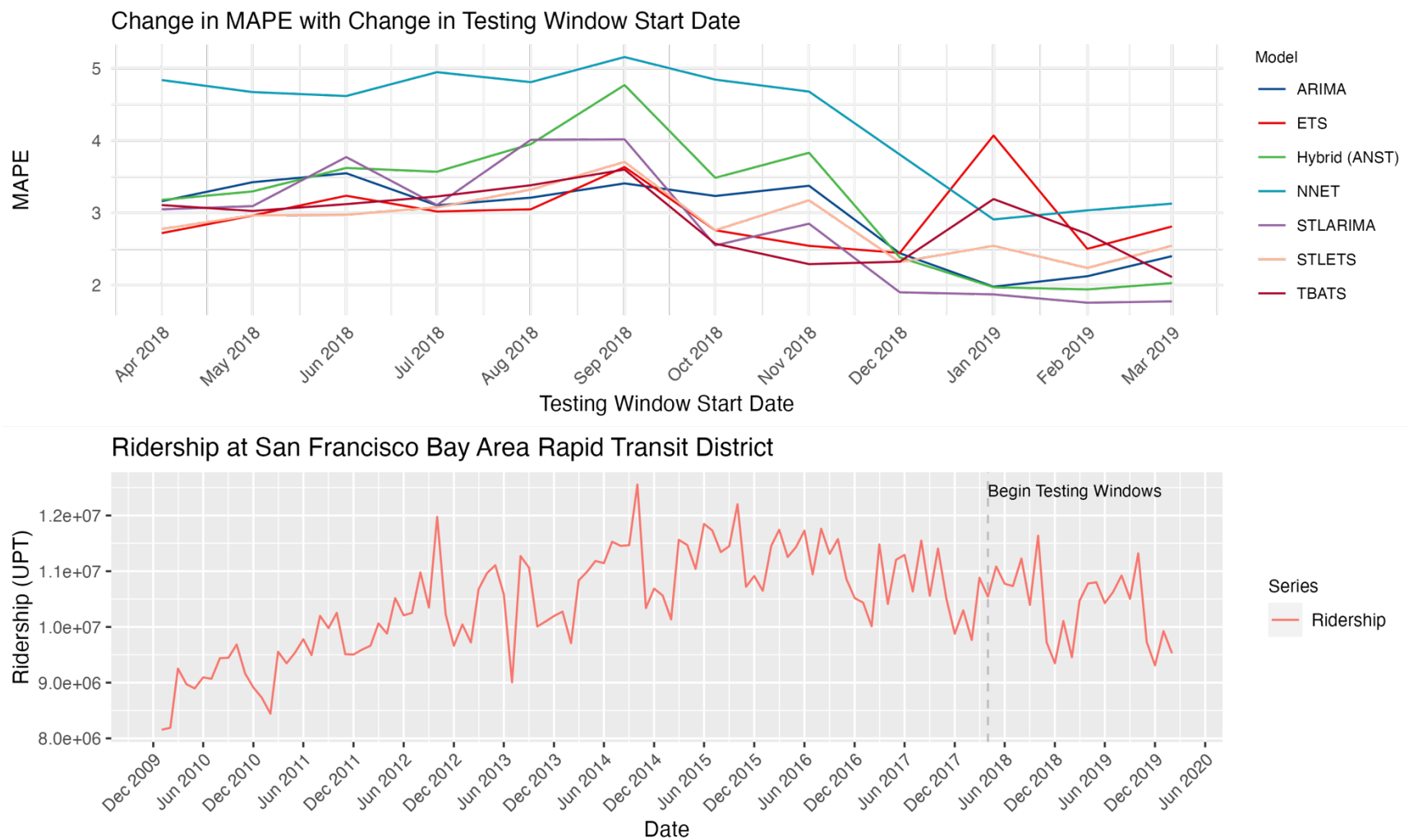


Figure A-26 Pre-COVID Change in MAPE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

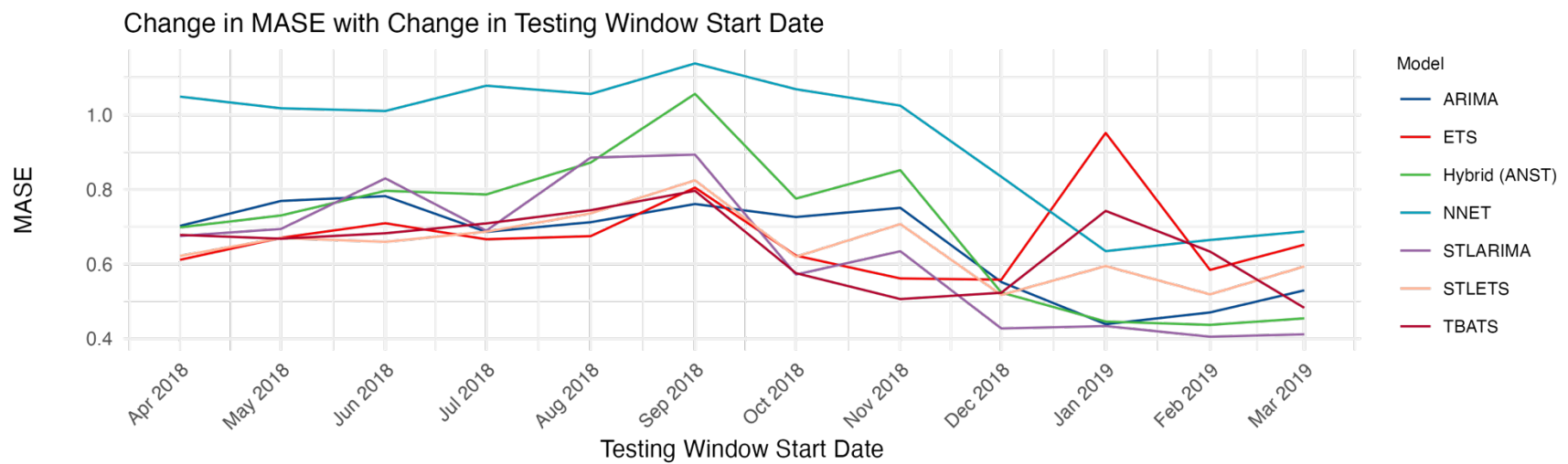
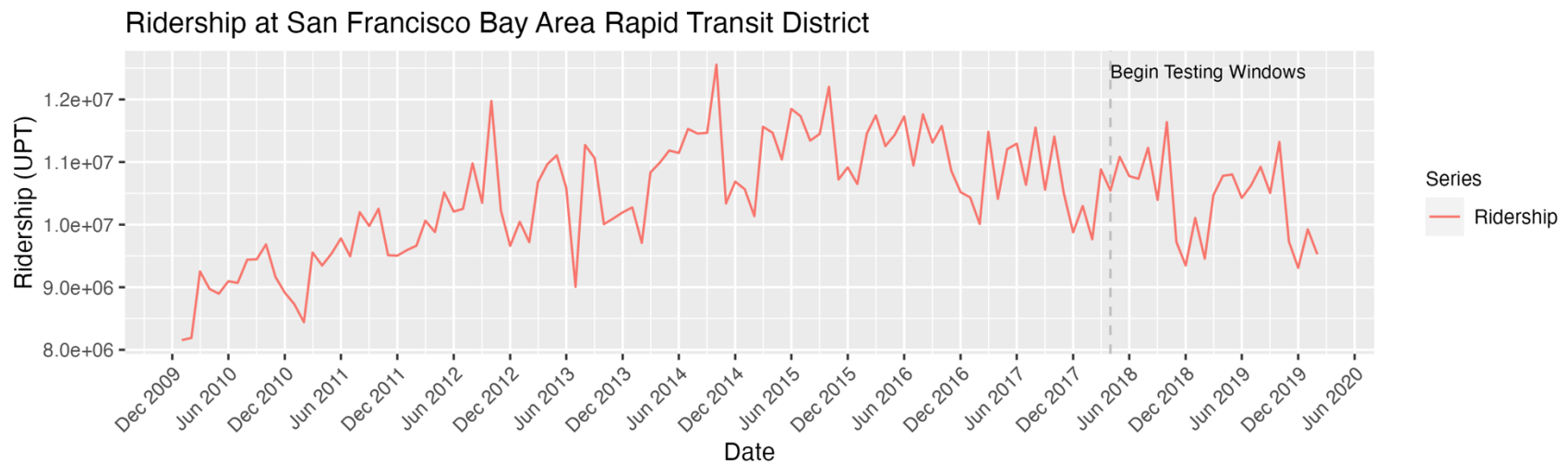


Figure A-27 Pre-COVID Change in MASE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

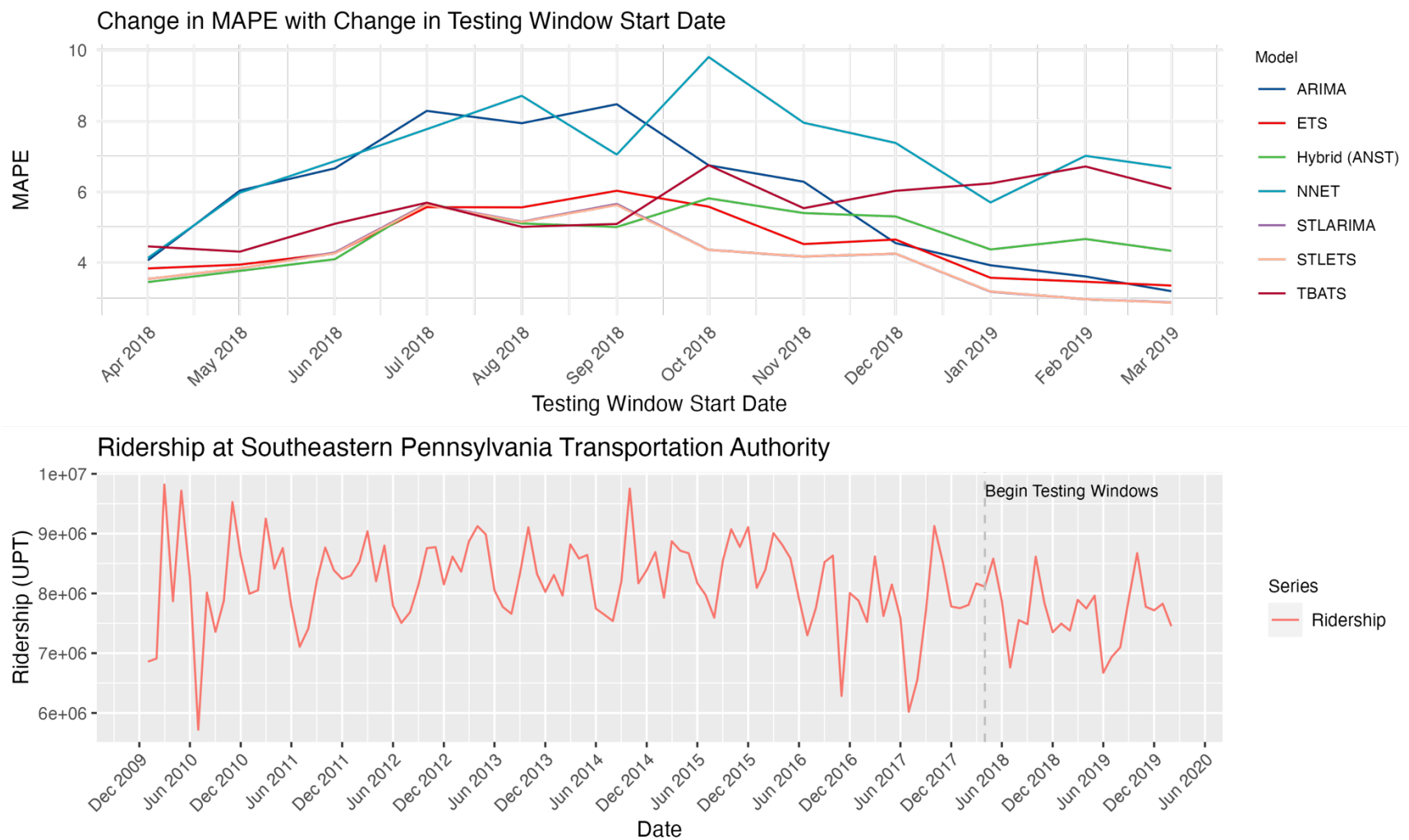


Figure A-28 Pre-COVID Change in MAPE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

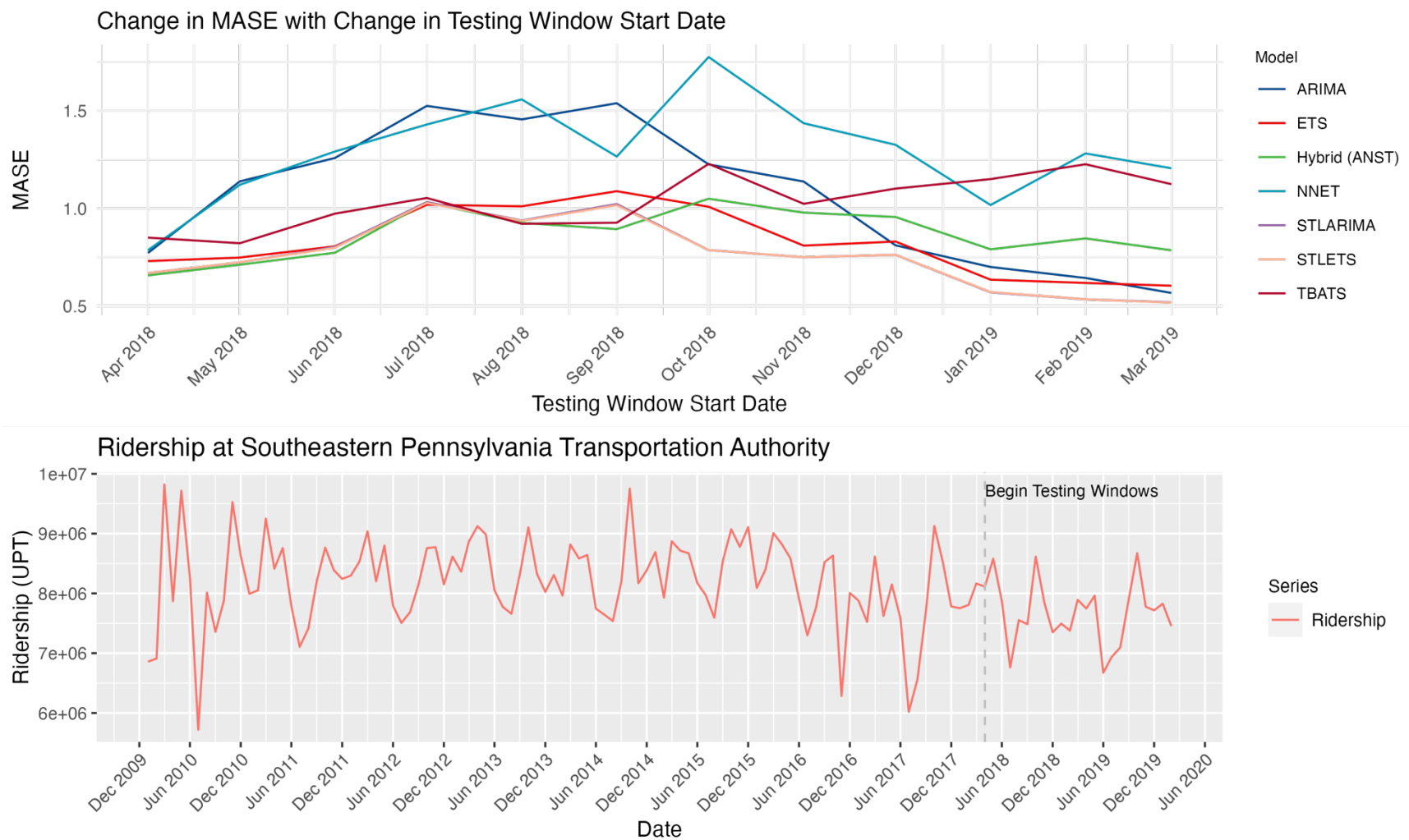


Figure A-29 Pre-COVID Change in MASE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

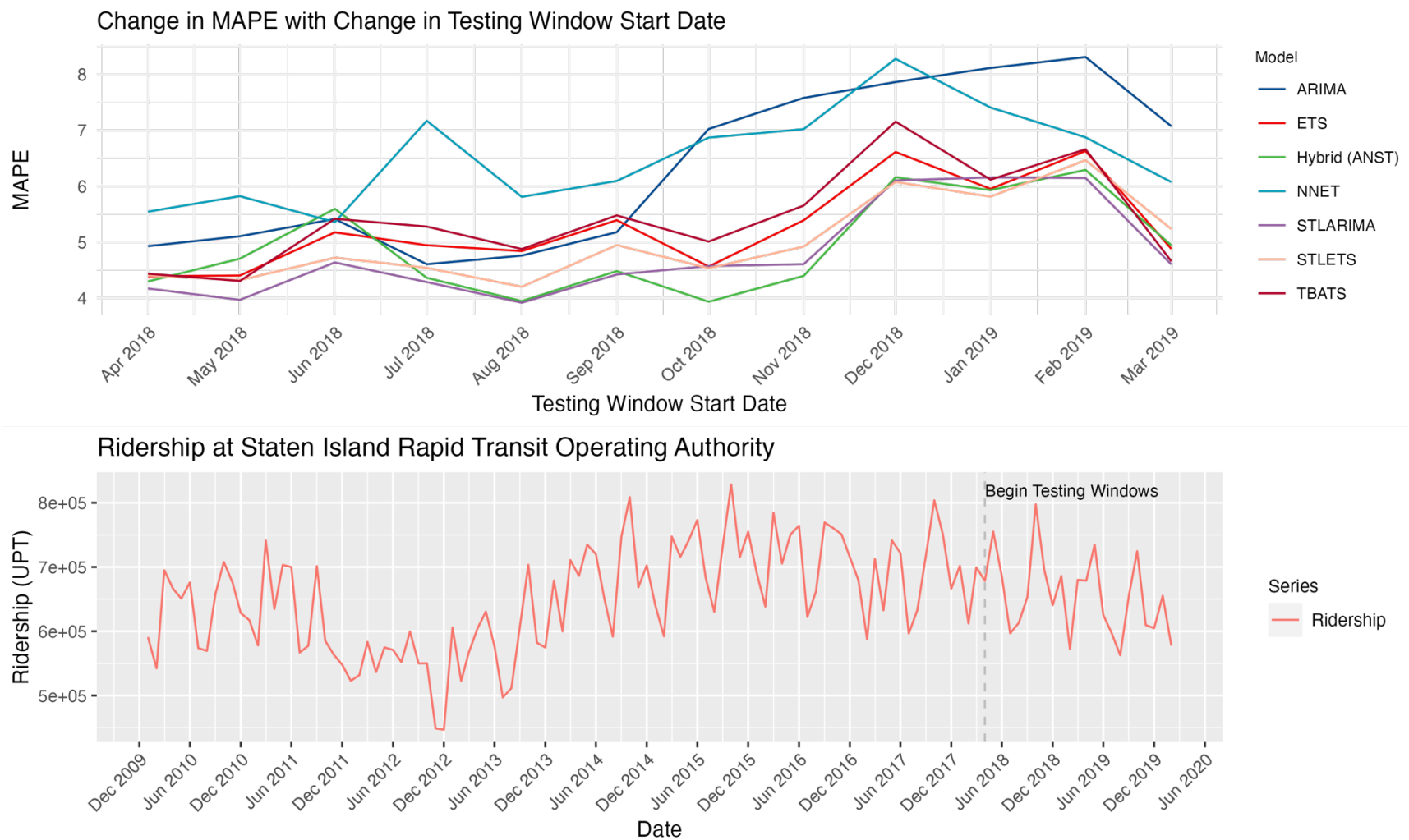


Figure A-30 Pre-COVID Change in MAPE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

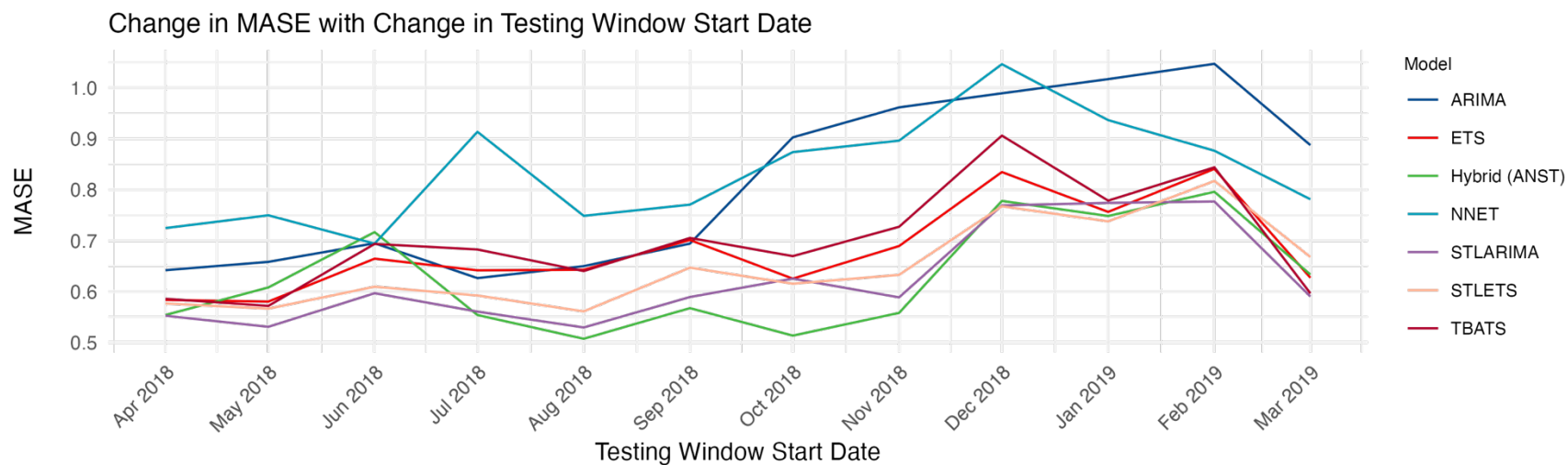
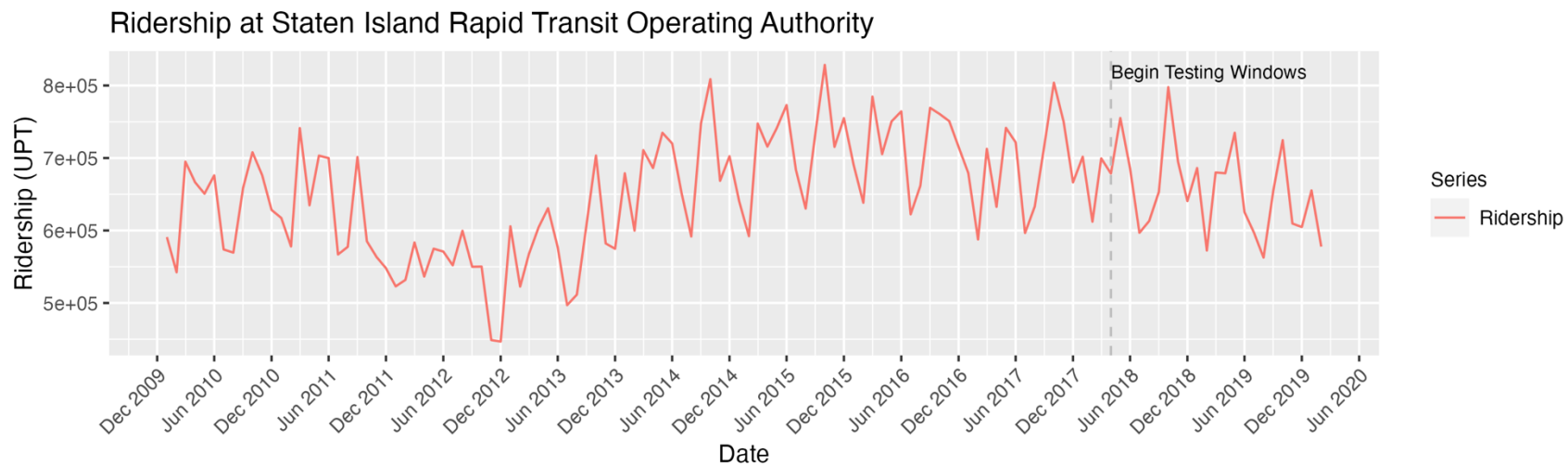


Figure A-31 Pre-COVID Change in MASE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

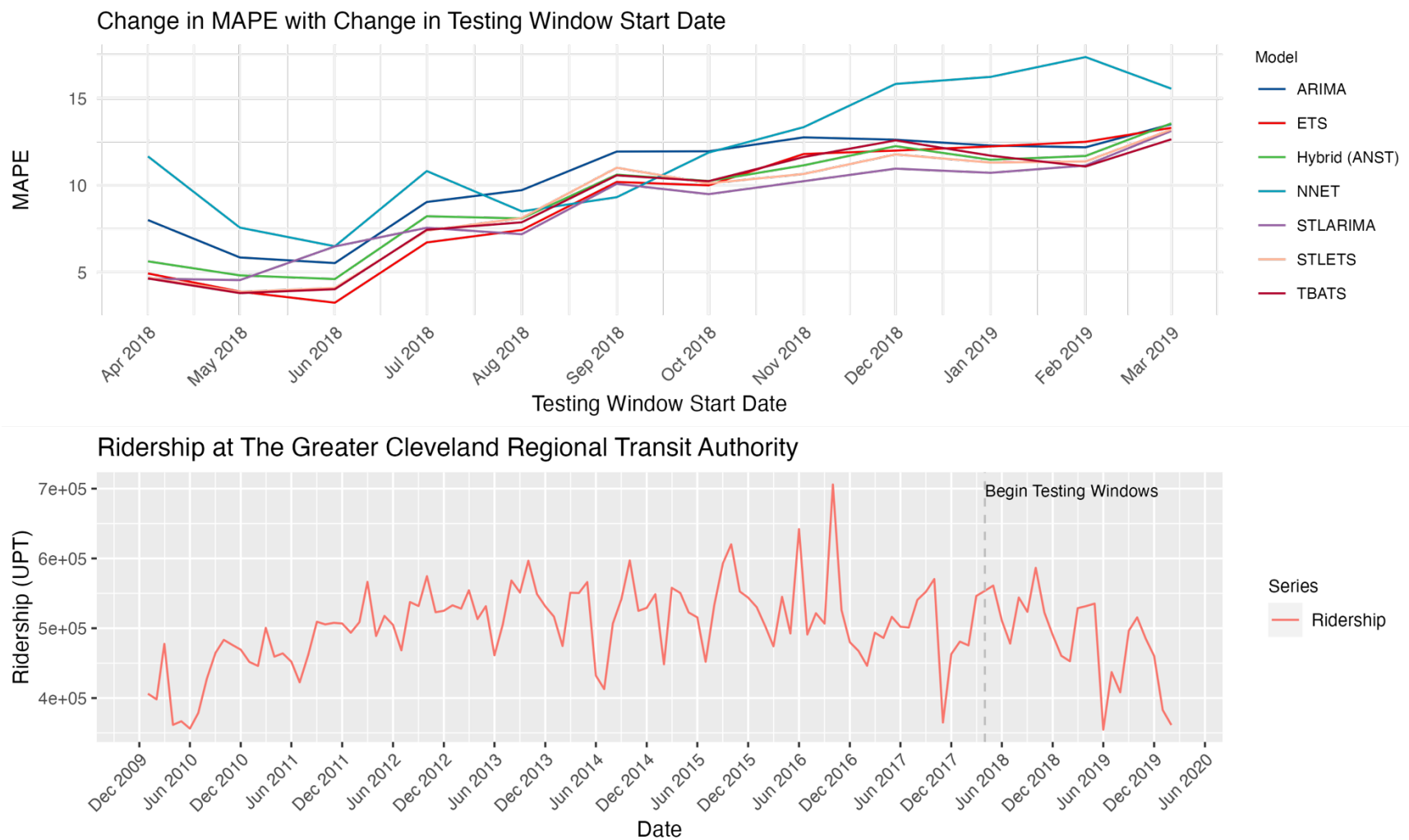


Figure A-32 Pre-COVID Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

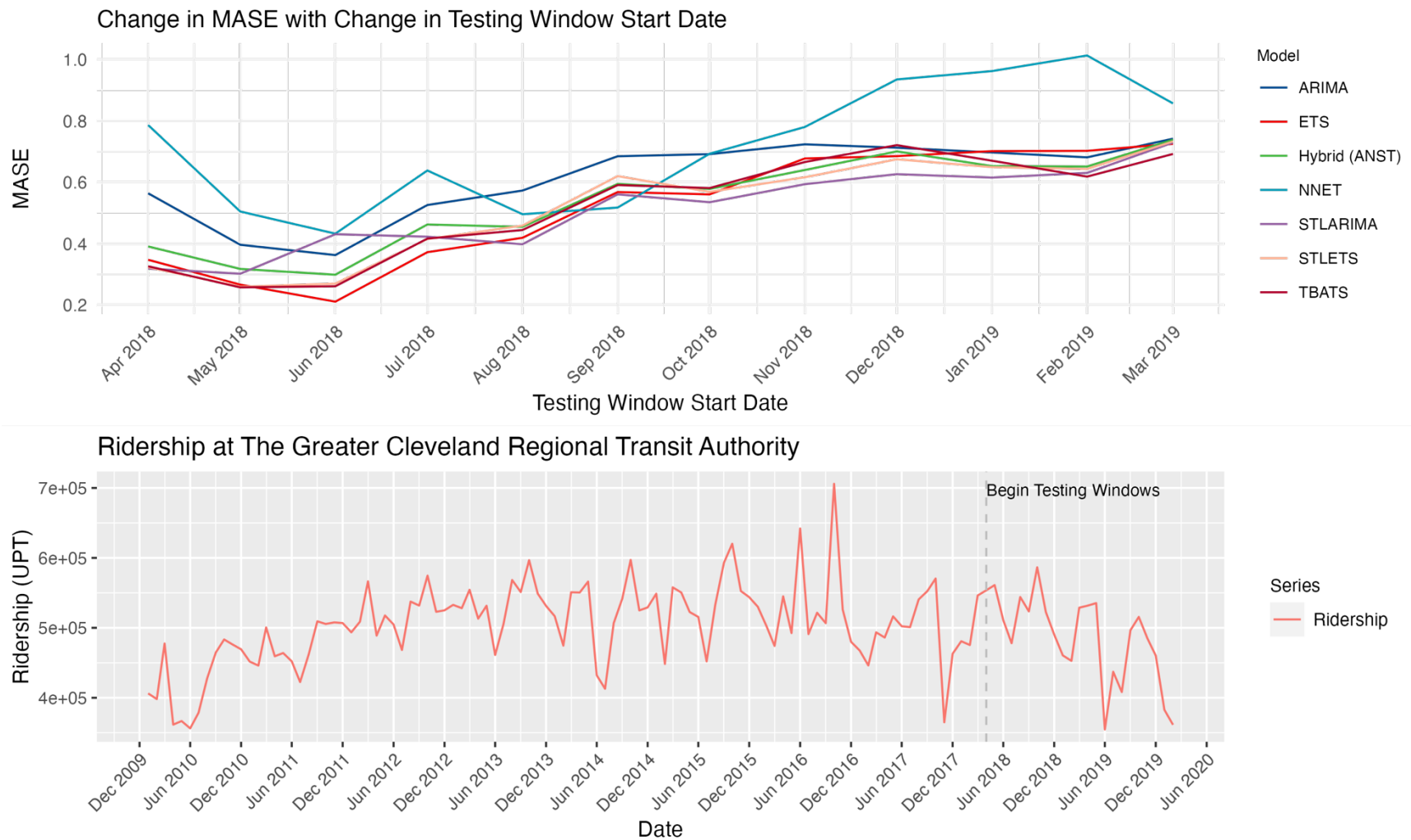


Figure A-33 Pre-COVID Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

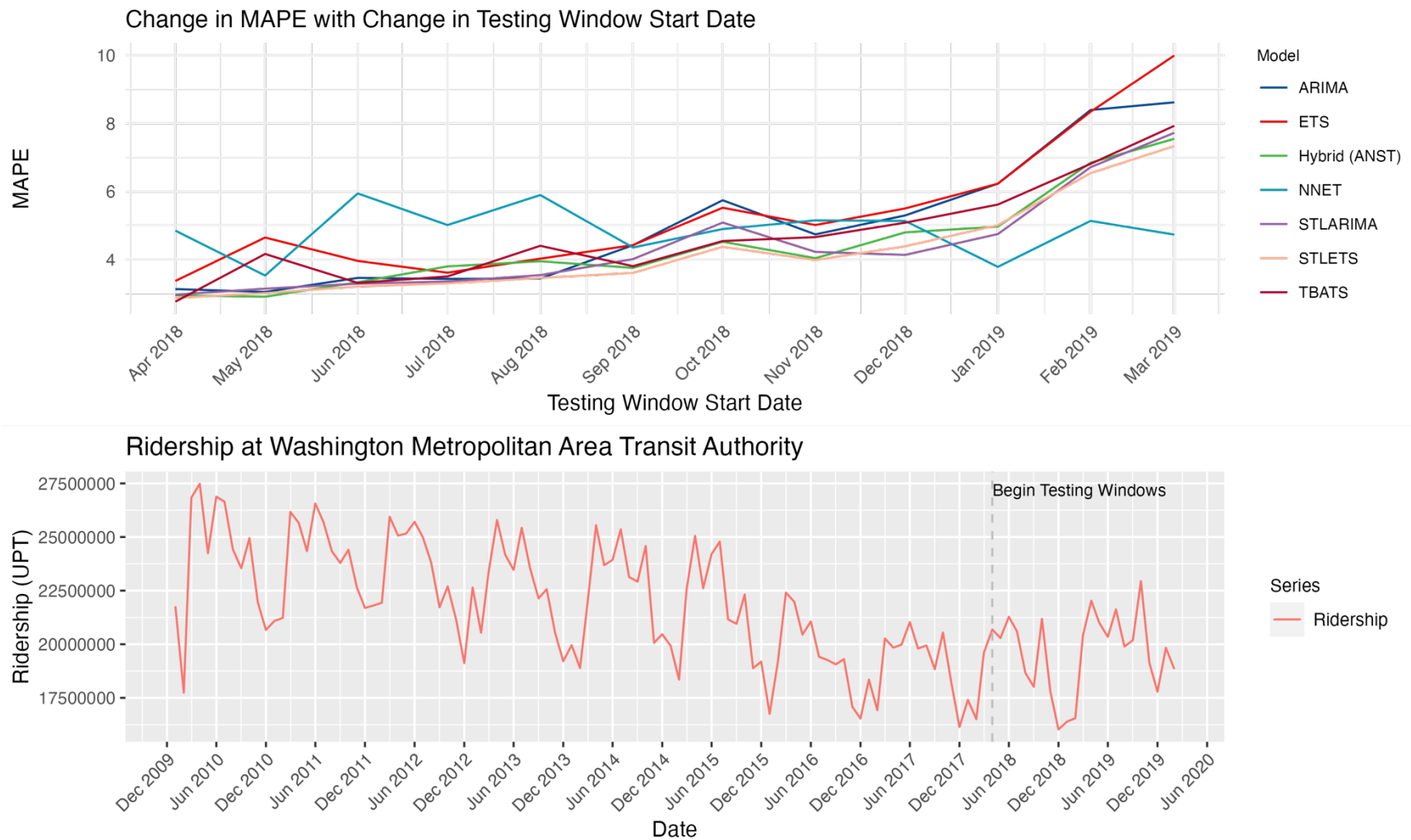


Figure A-34 Pre-COVID Change in MAPE at the Washington Metropolitan Area Transit Authority Using the Moving Window

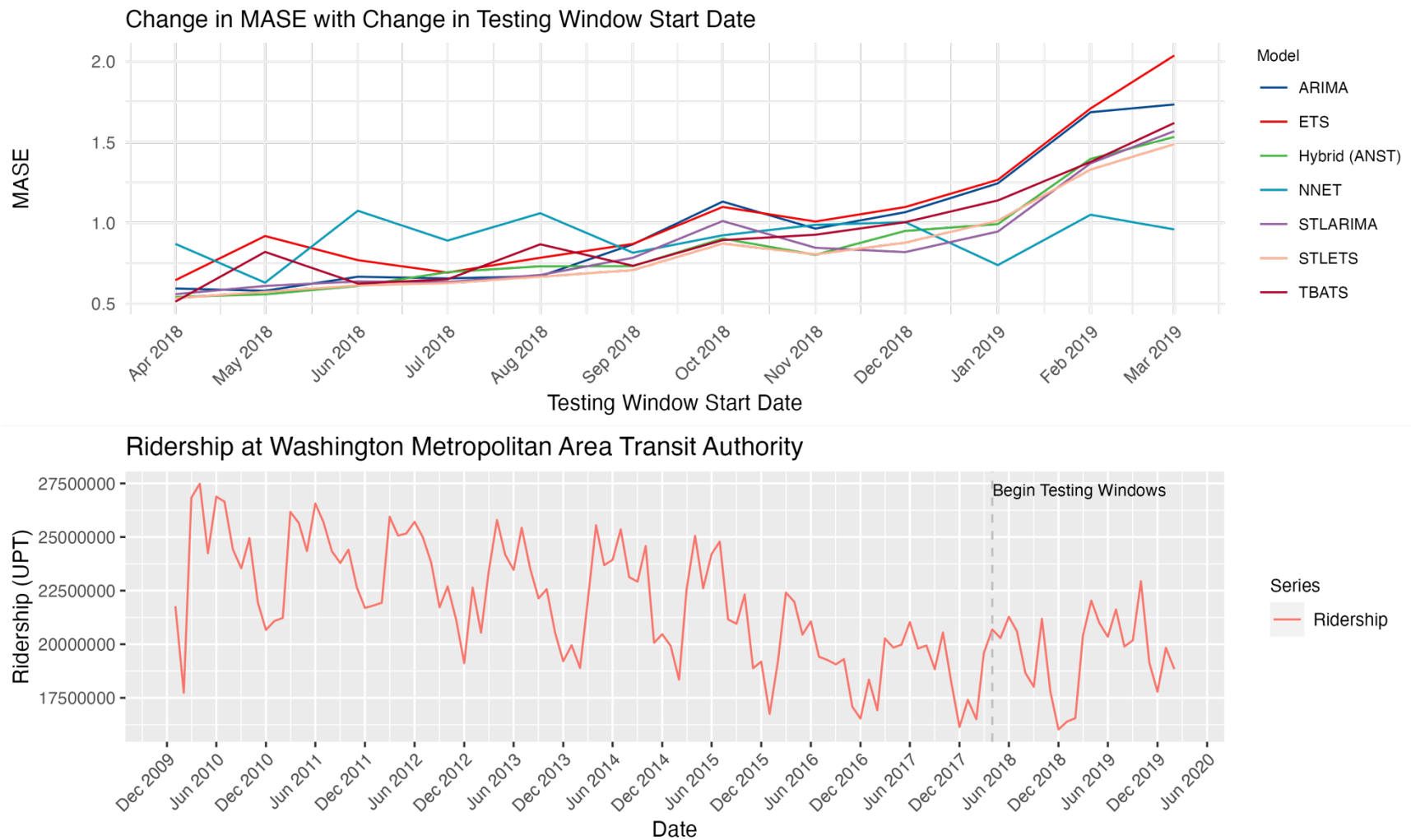


Figure A-35 Pre-COVID Change in MASE at the Washington Metropolitan Area Transit Authority Using the Moving Window

Part B: Full Series Moving Window Forecasts

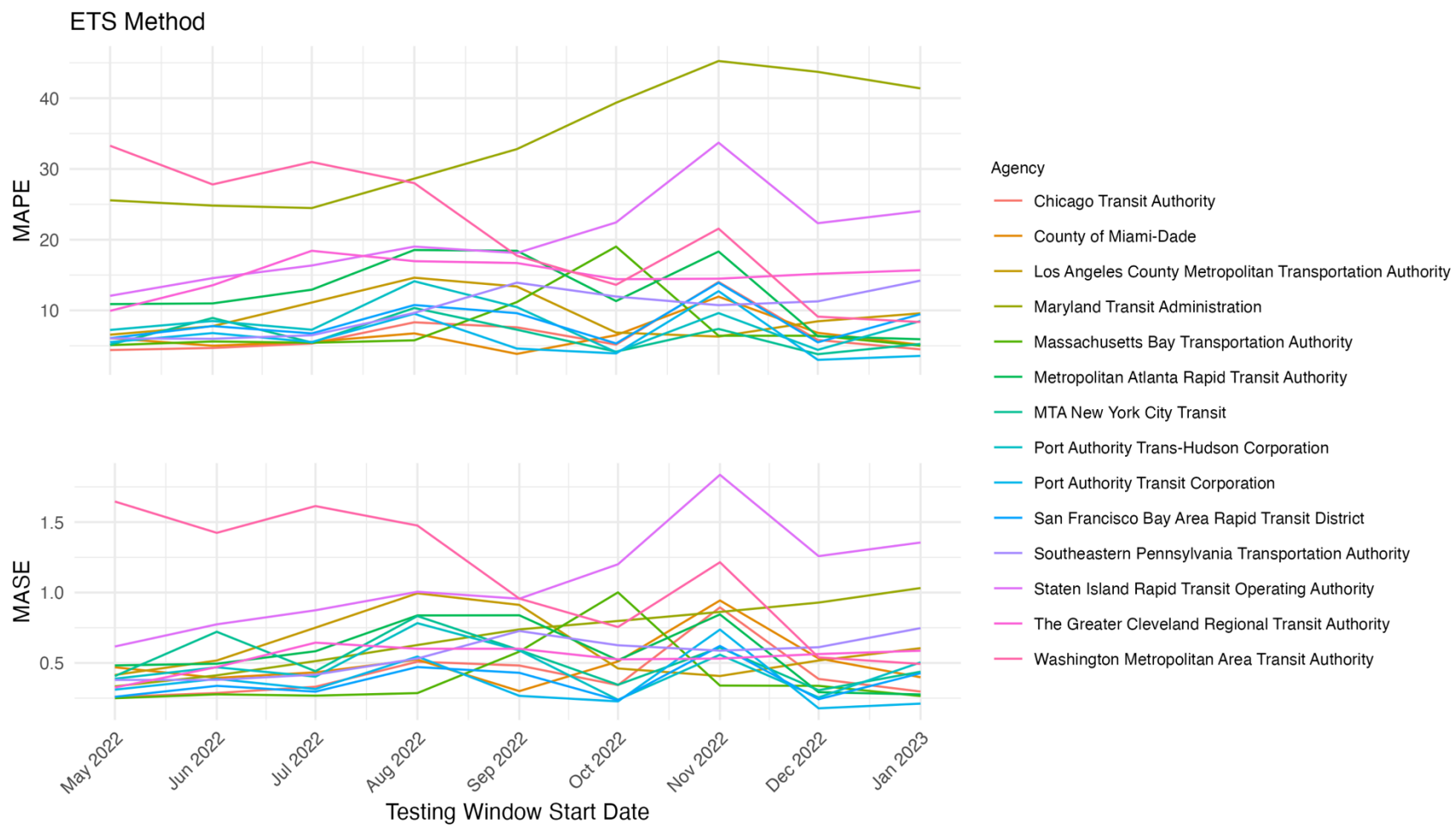


Figure B-1 Full Series Performance of the ETS Method

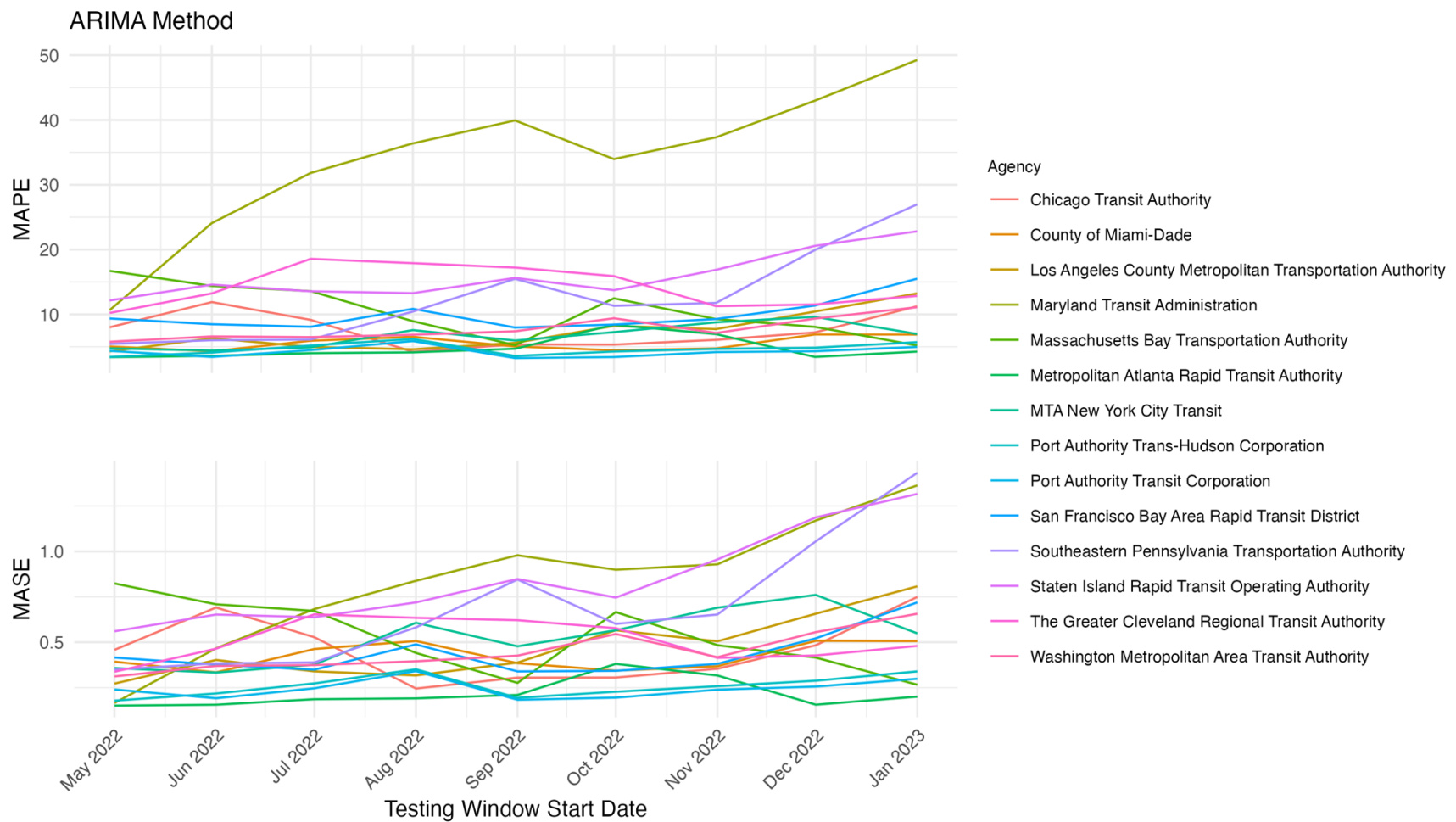


Figure B-2 Full Series Performance of the ARIMA Method

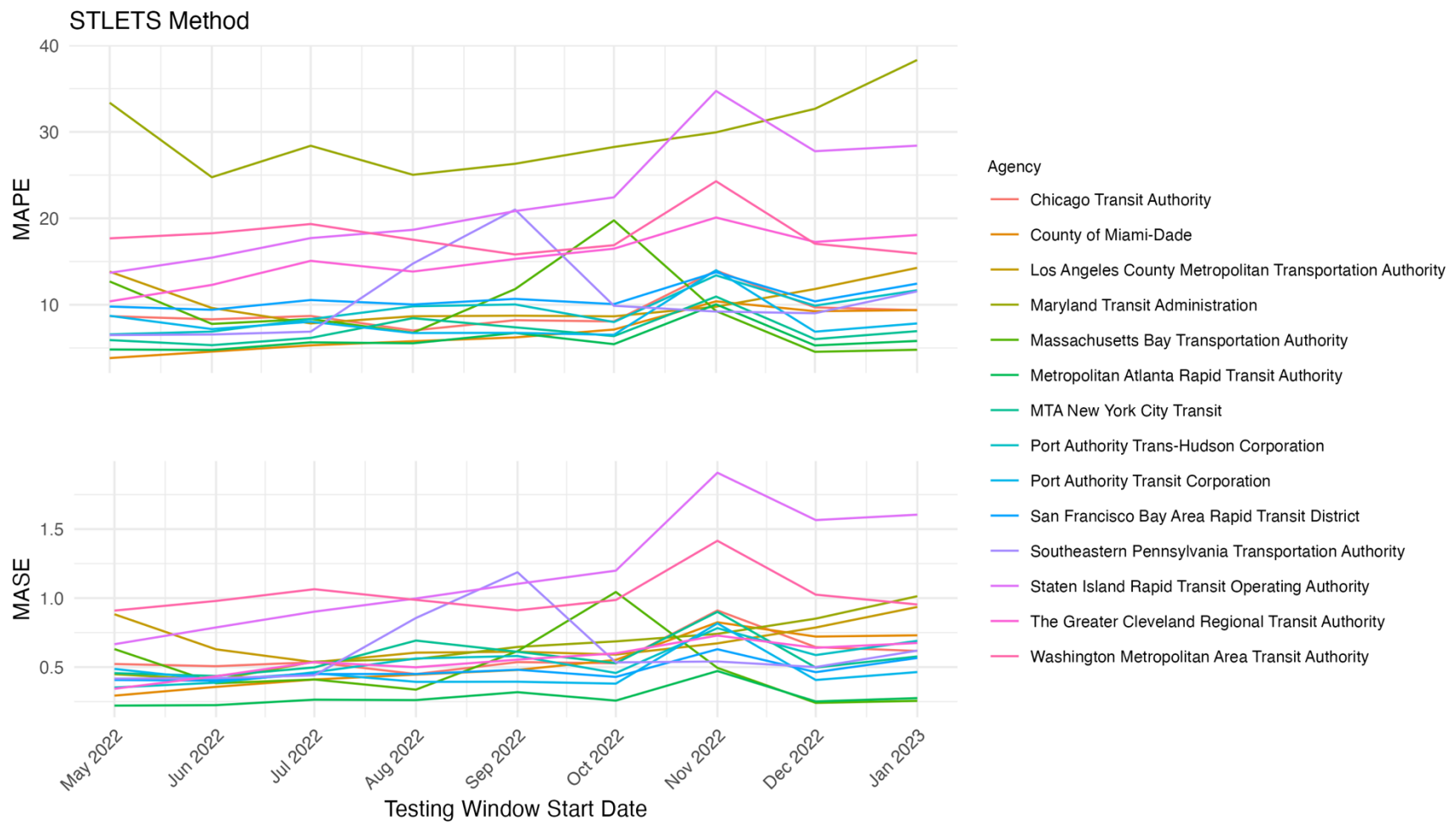


Figure B-3 Full Series Performance of the STL-ETS Method

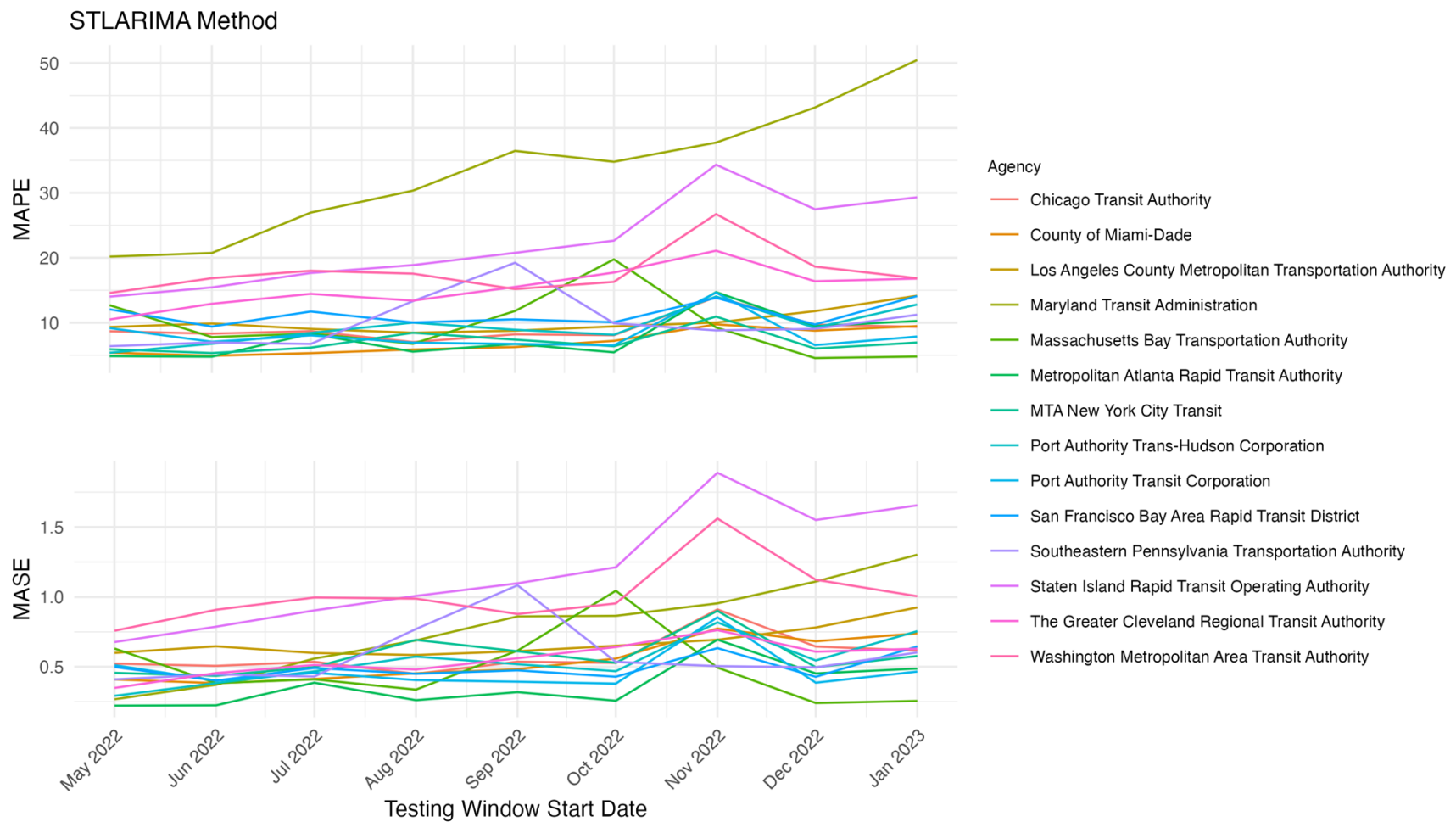


Figure B-4 Full Series Performance of the STL-ARIMA Method

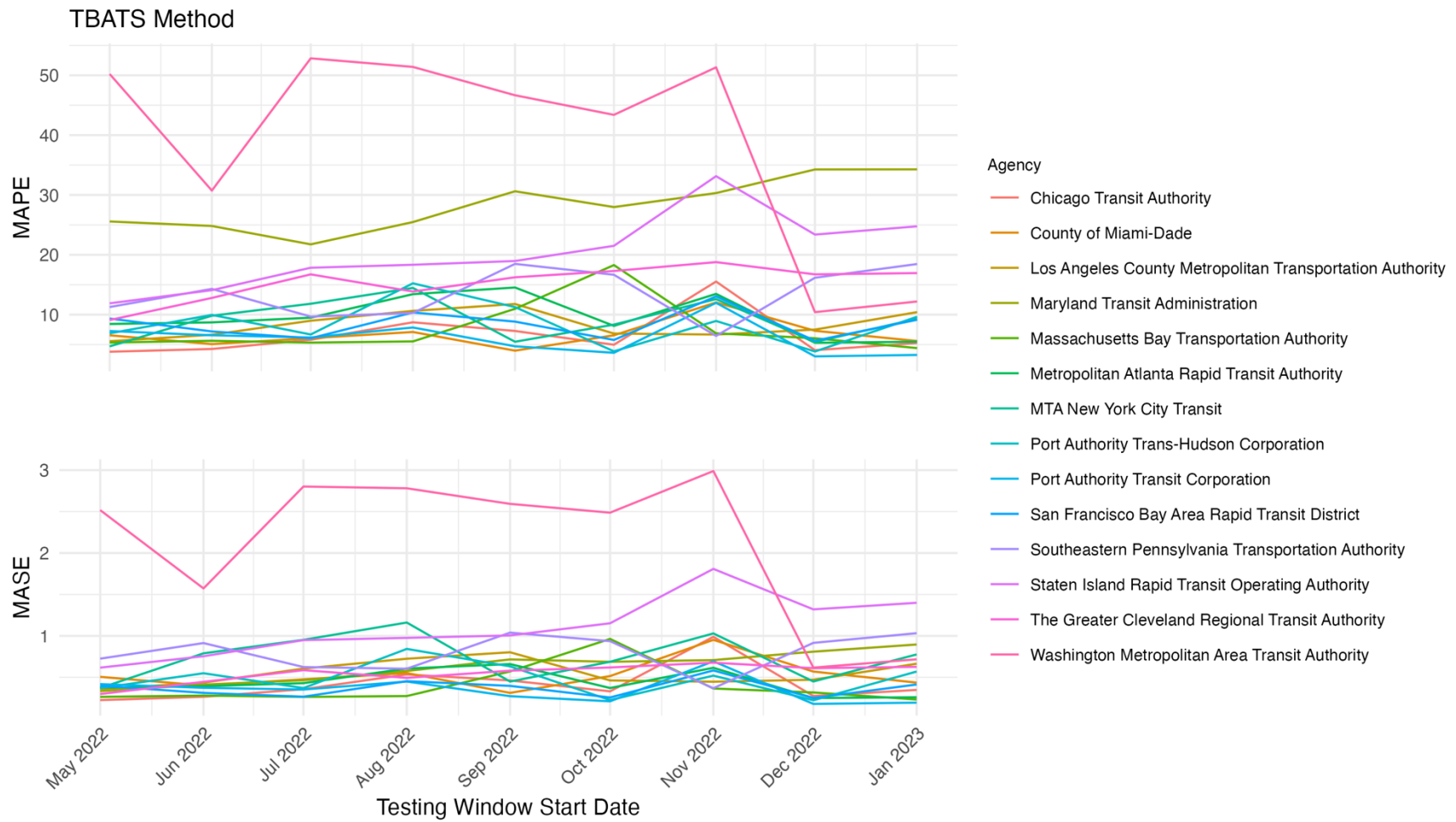


Figure B-5 Full Series Performance of the TBATS Method

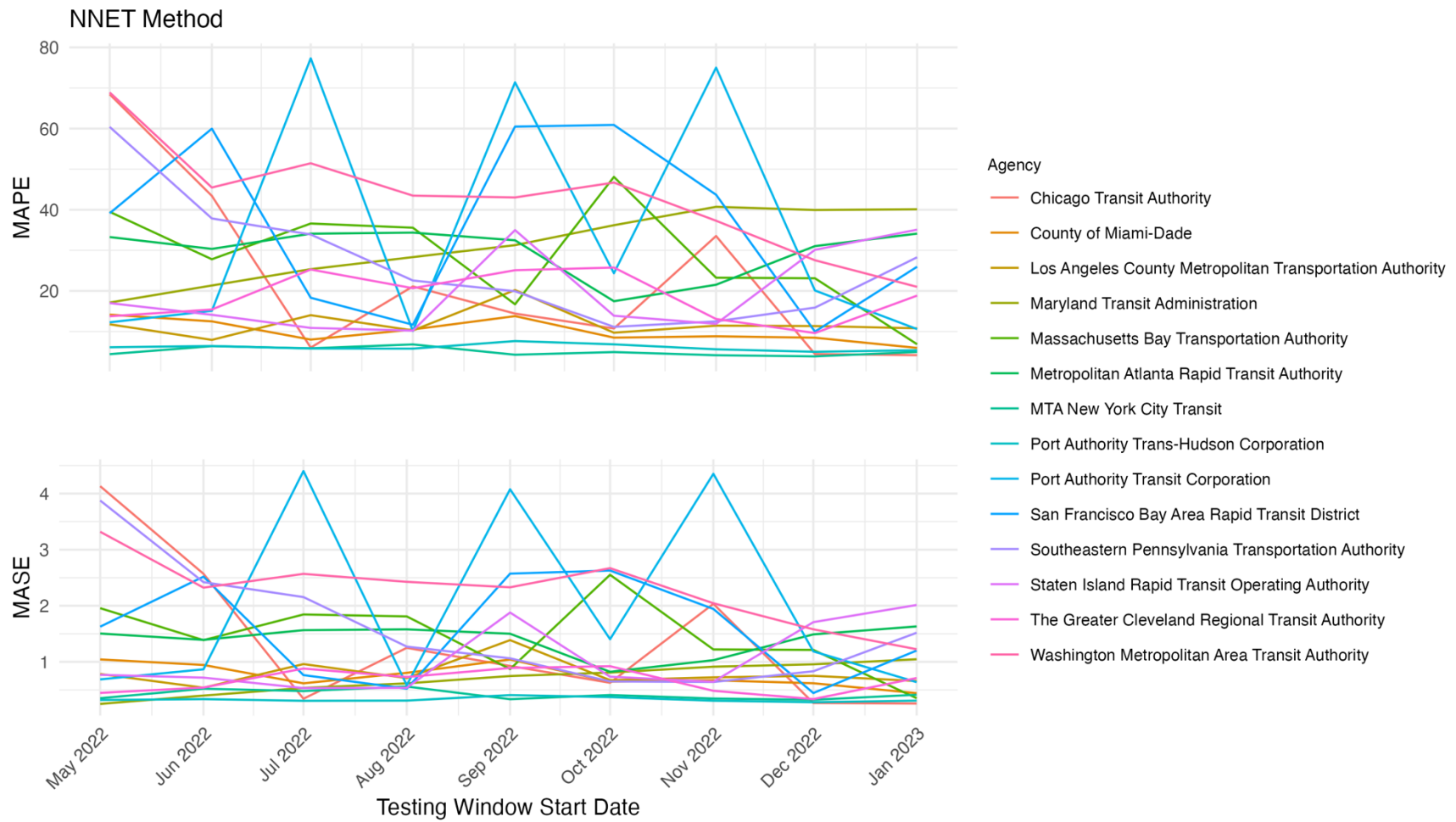


Figure B-6 Full Series Performance of the NNET Method

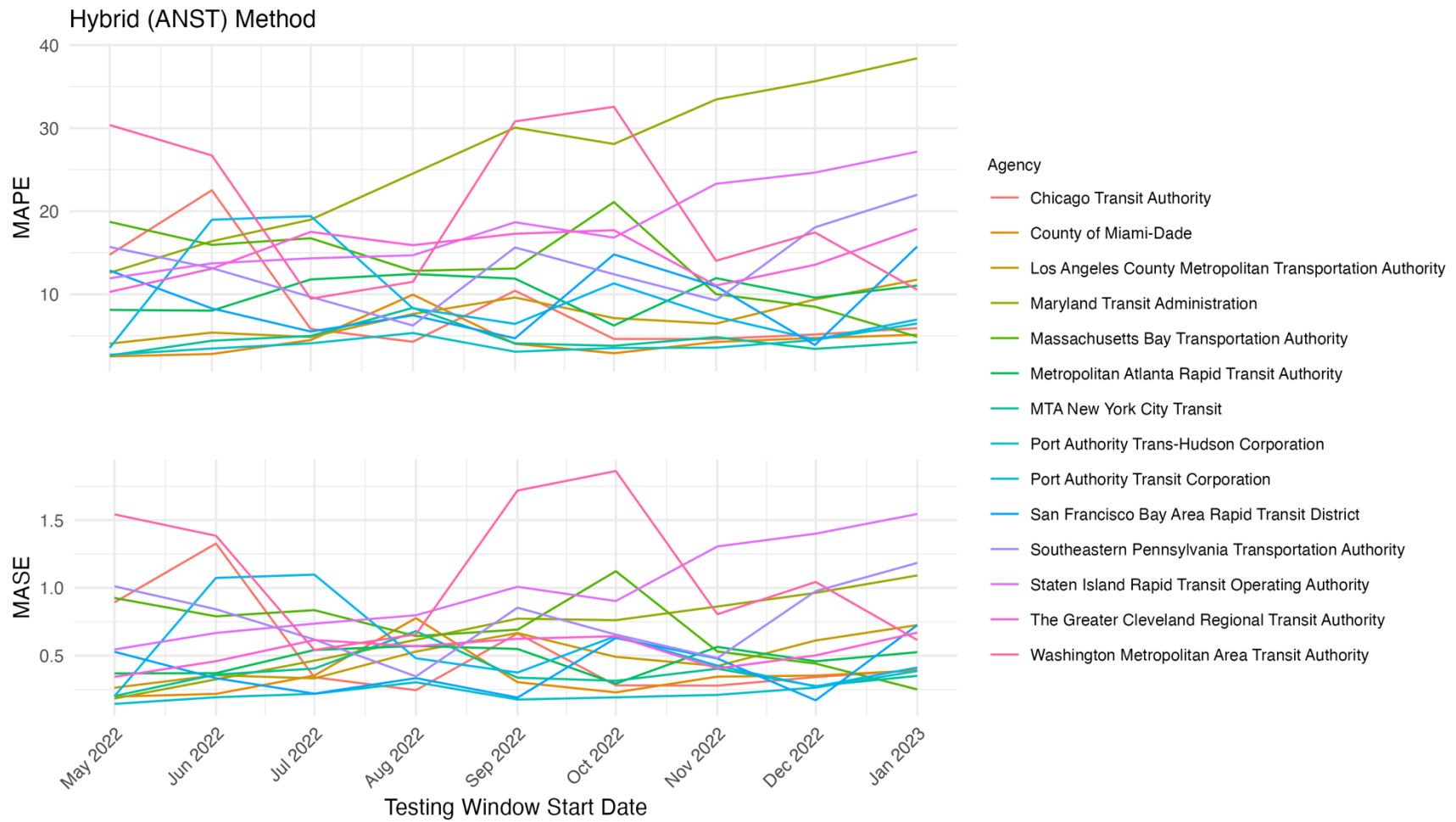


Figure B-7 Full Series Performance of the Hybrid Method

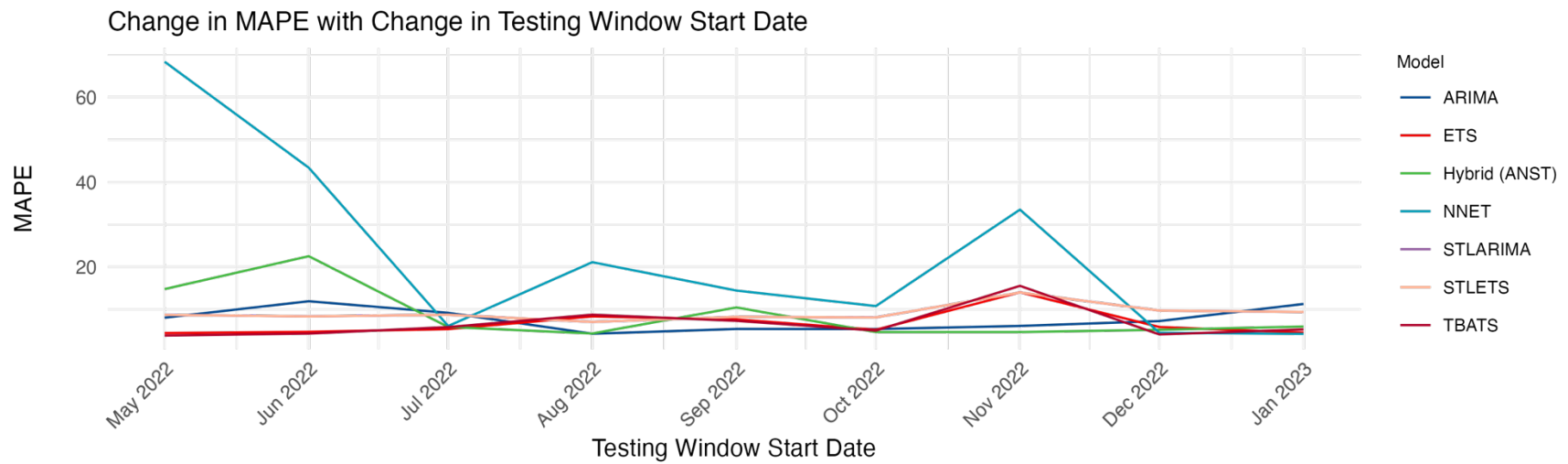
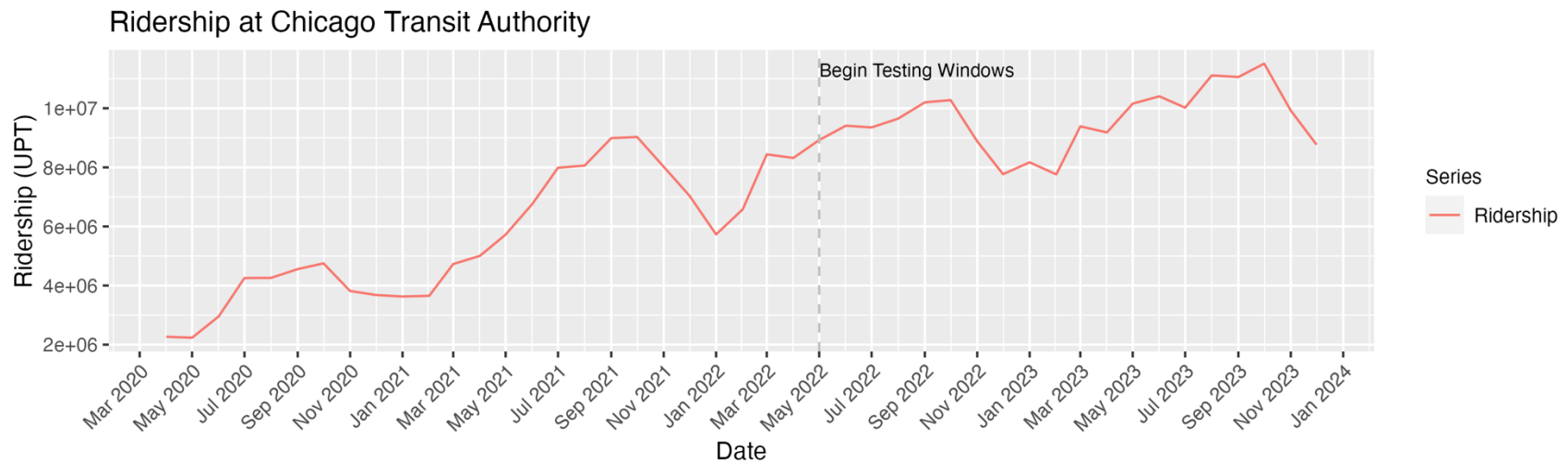


Figure B-8 Full Series Change in MAPE at the Chicago Transit Authority Using the Moving Window

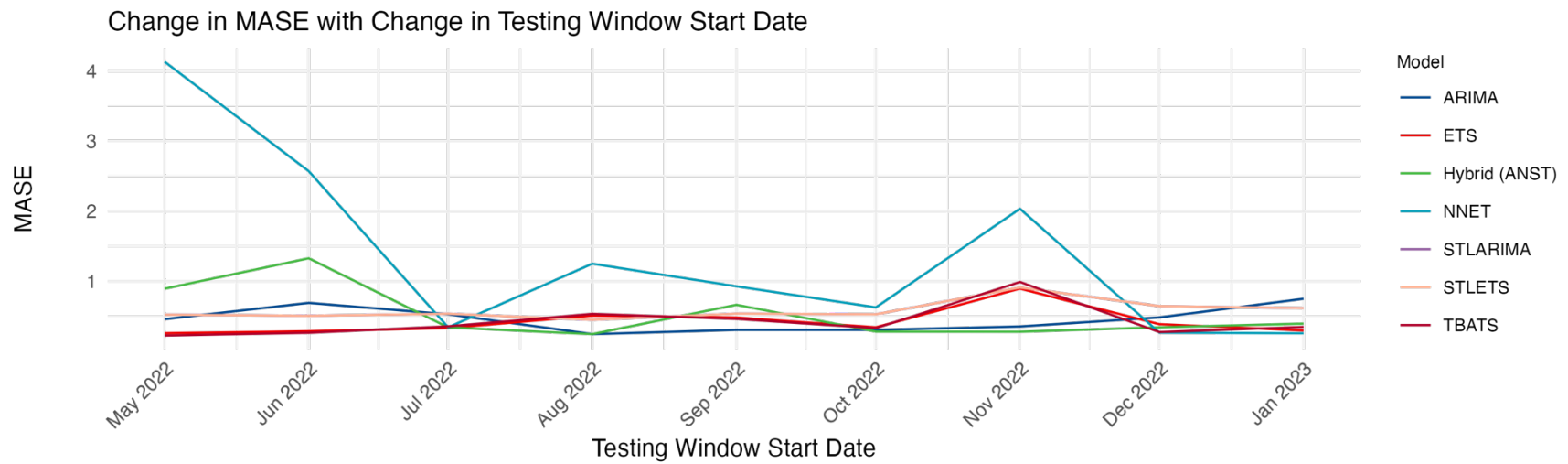
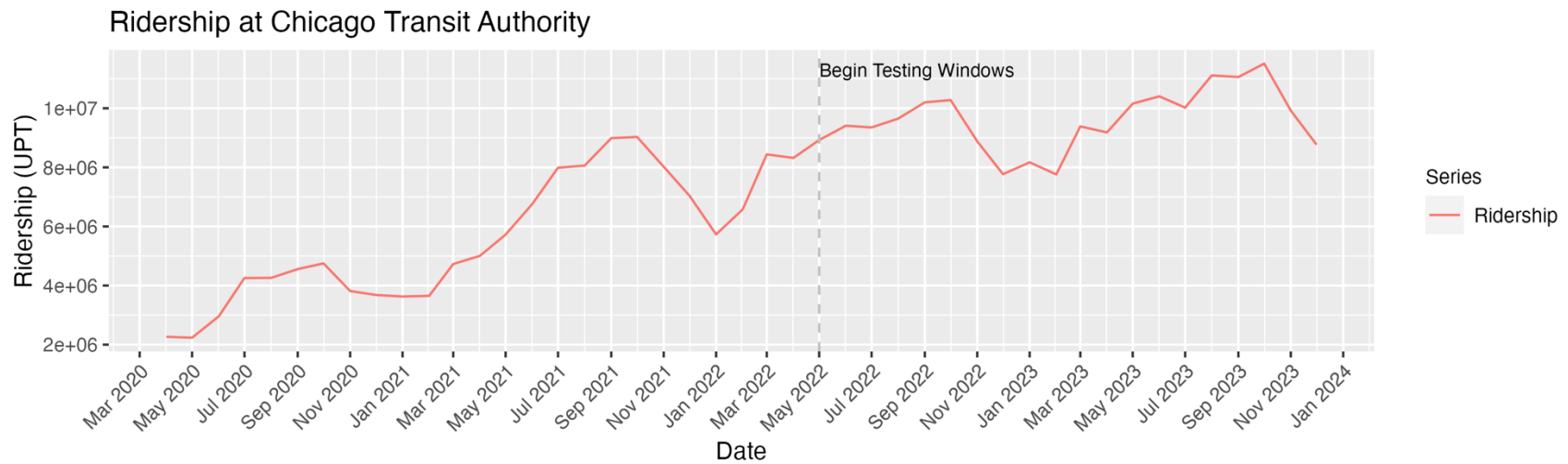


Figure B-9 Full Series Change in MASE at the Chicago Transit Authority Using the Moving Window

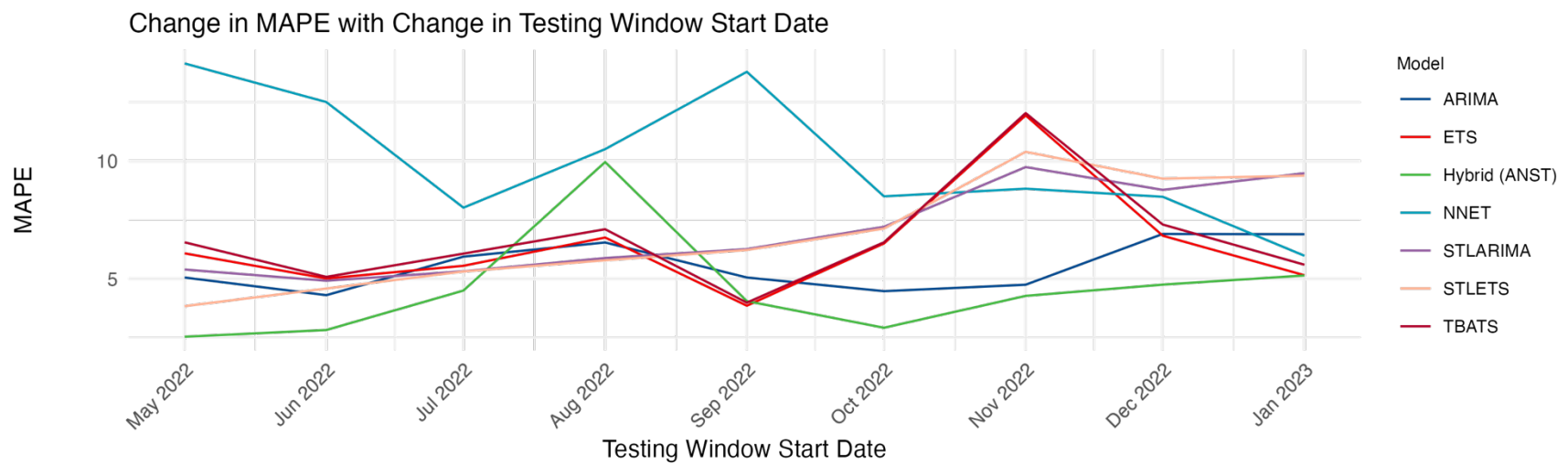
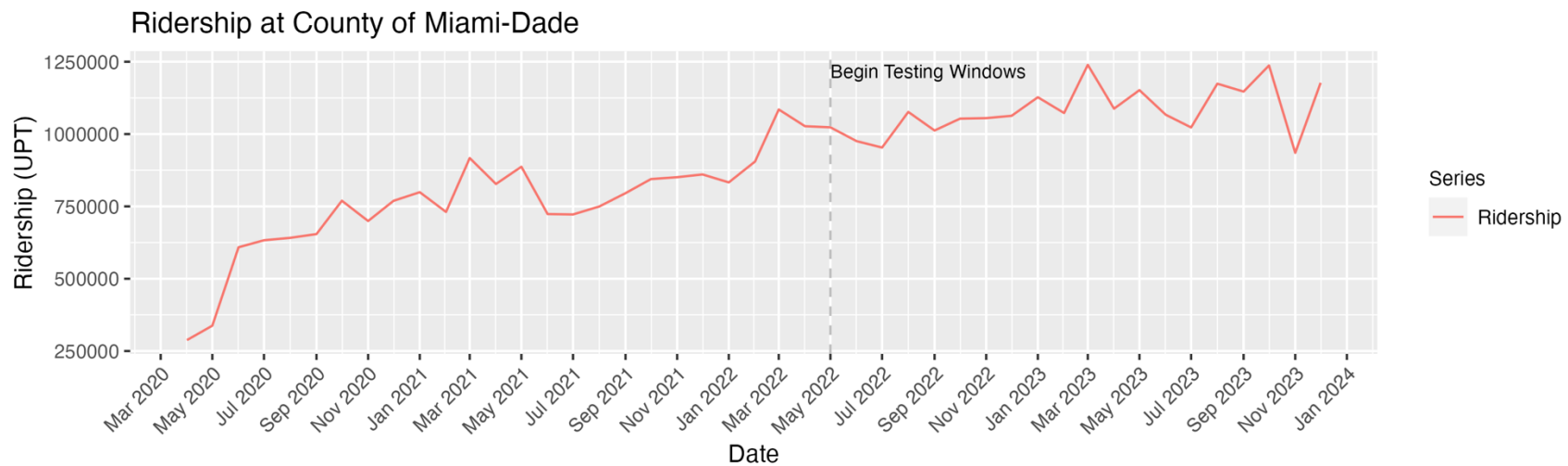


Figure B-10 Full Series Change in MAPE at the County of Miami-Dade Using the Moving Window

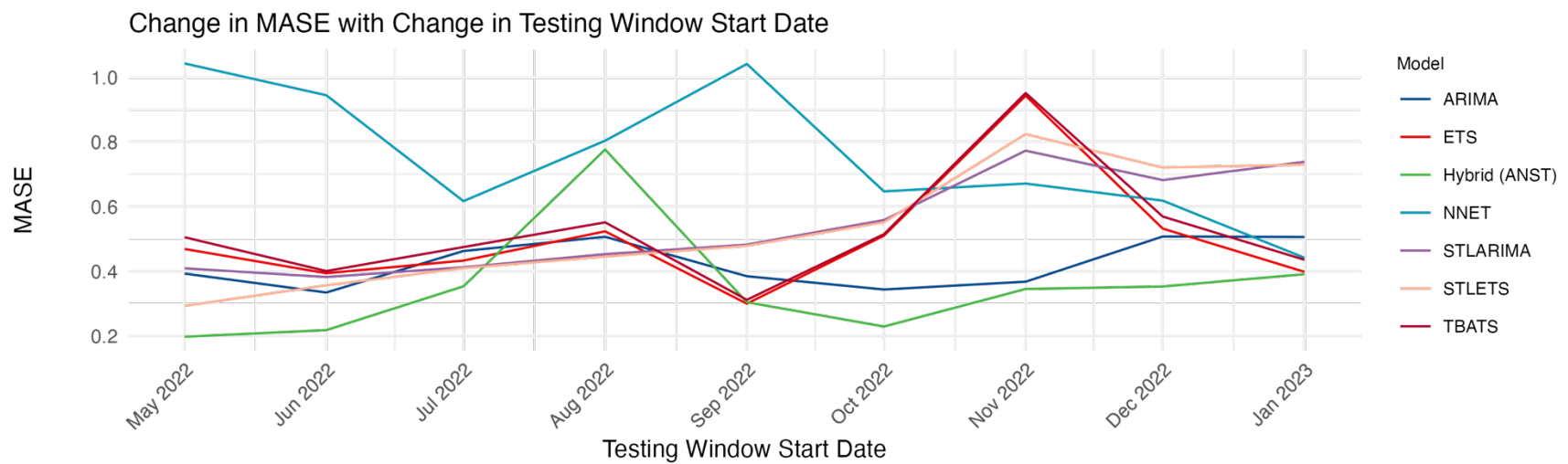
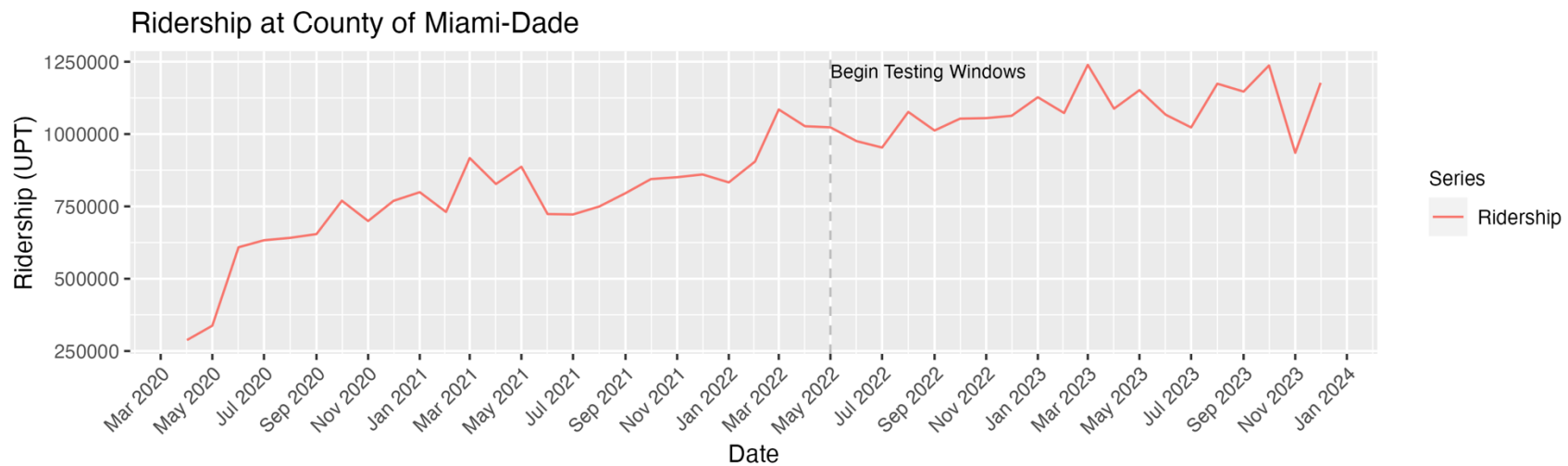


Figure B-11 Full Series Change in MASE at the County of Miami-Dade Using the Moving Window

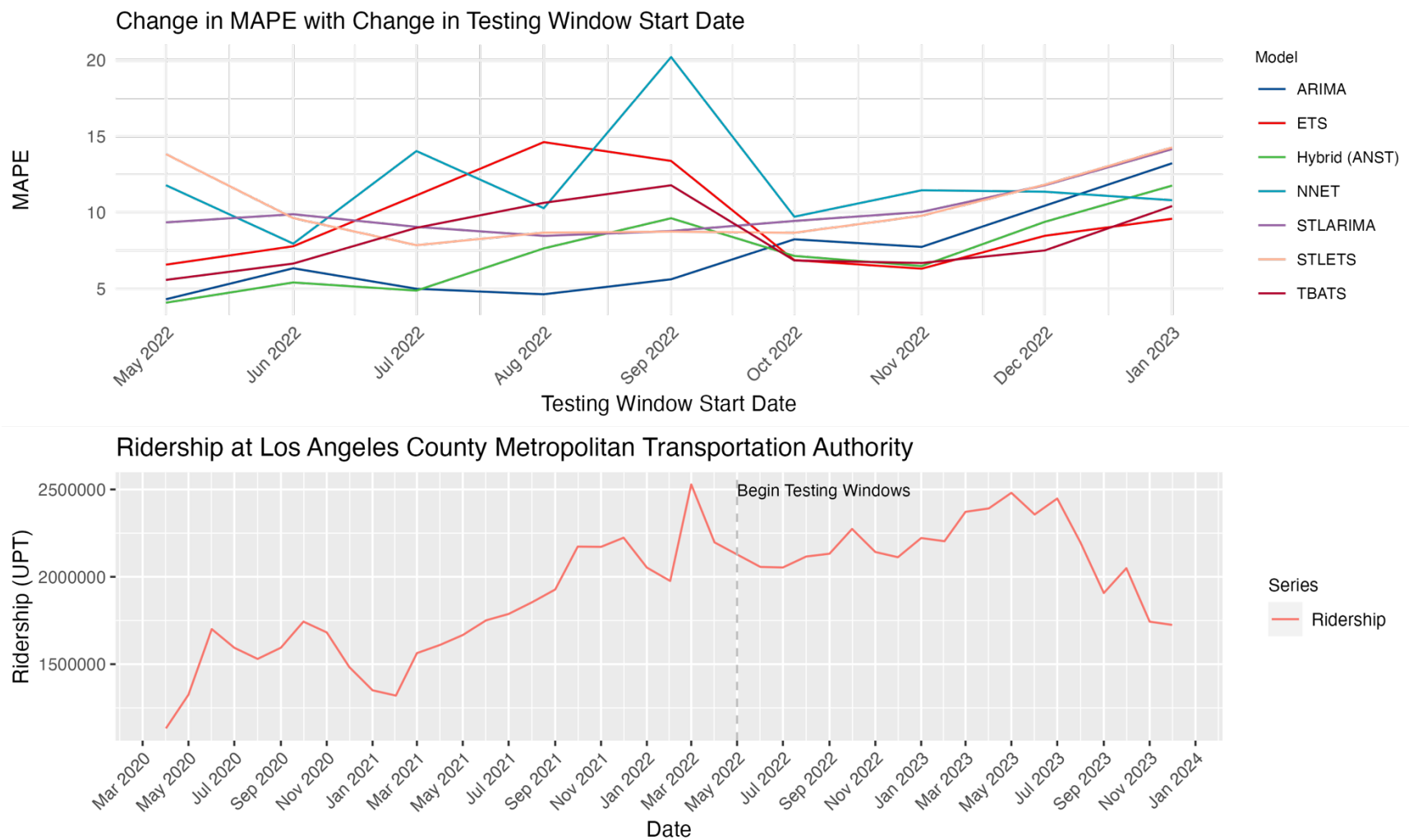


Figure B-12 Full Series Change in MAPE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

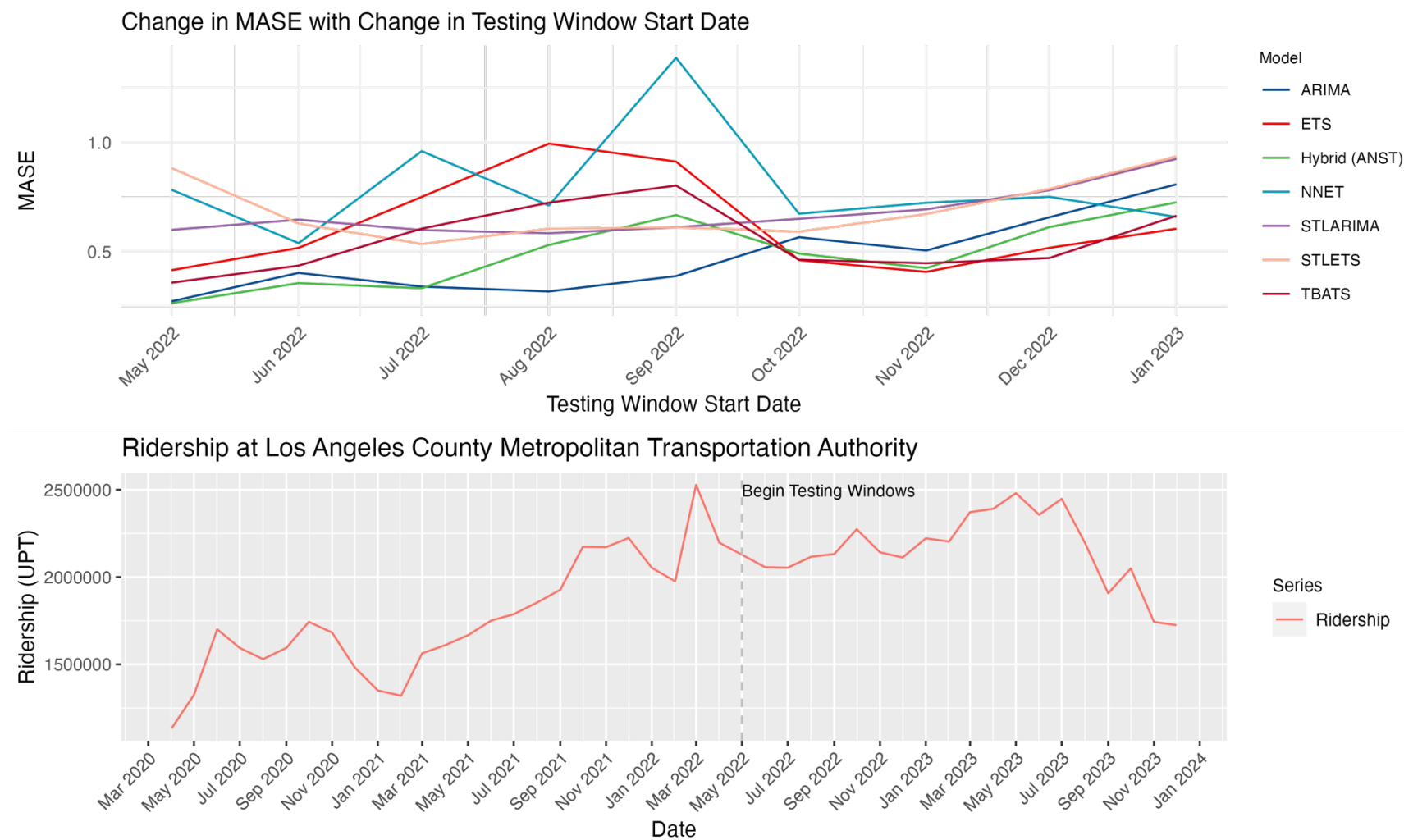


Figure B-13 Full Series Change in MASE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

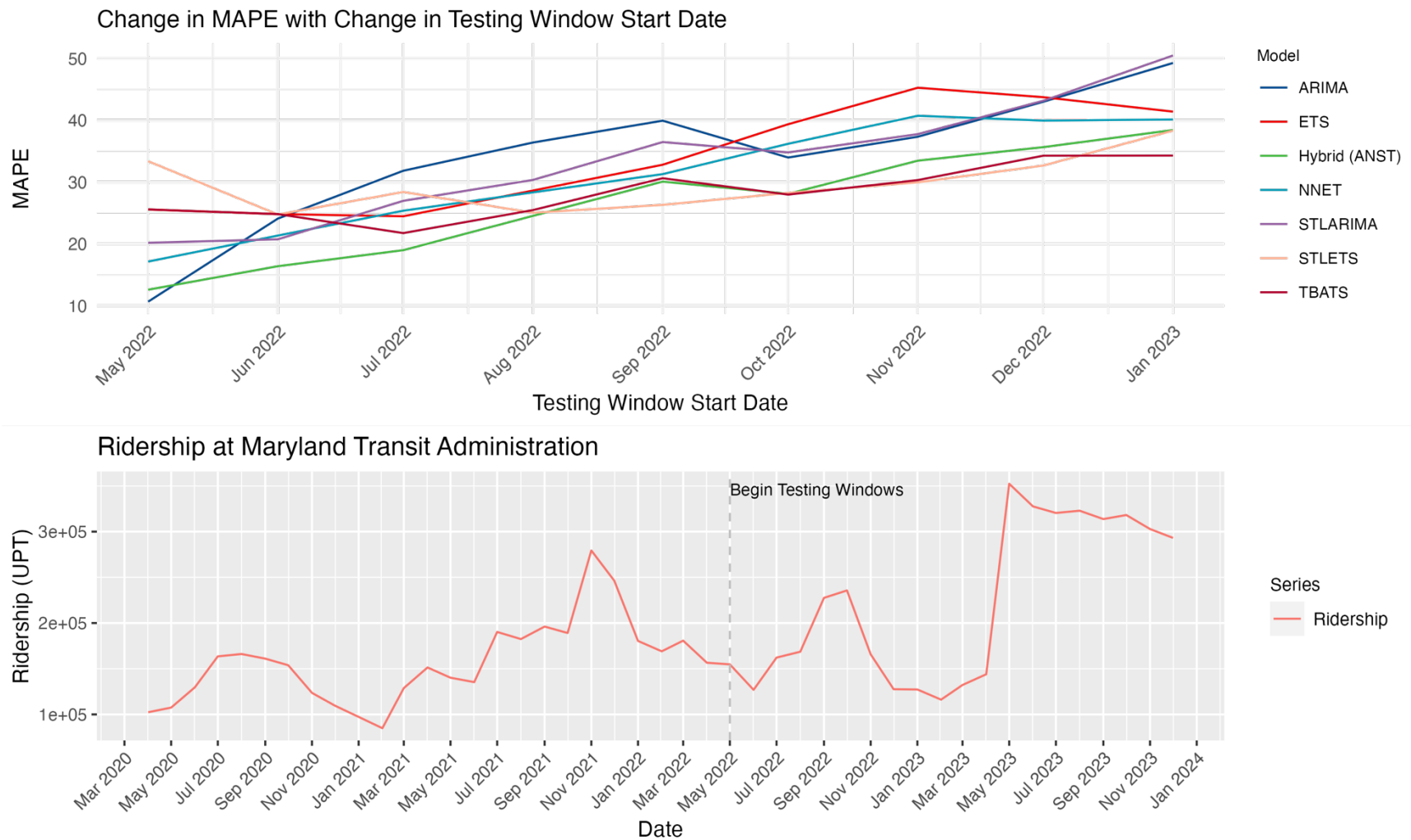


Figure B-14 Full Series Change in MAPE at the Maryland Transit Administration Using the Moving Window

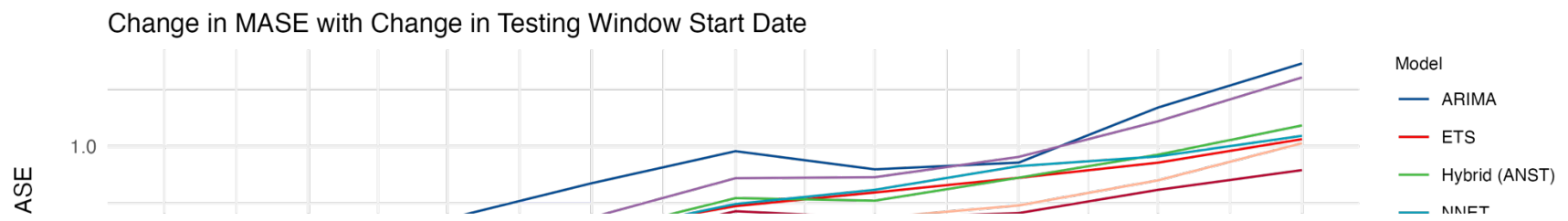


Figure B-15 Full Series Change in MASE at the Maryland Transit Administration Using the Moving Window

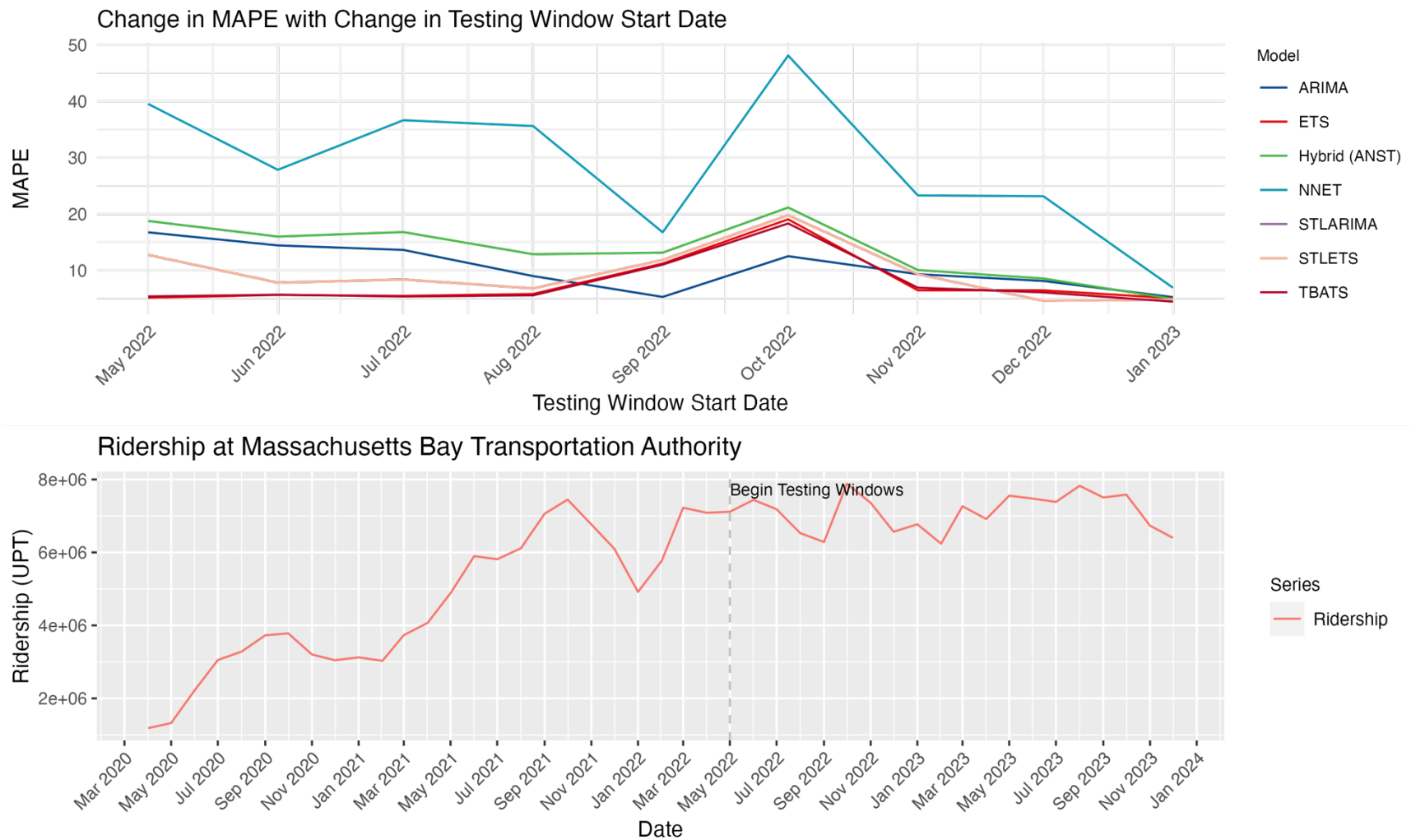


Figure B-16 Full Series Change in MAPE at the Massachusetts Bay Transportation Authority Using the Moving Window

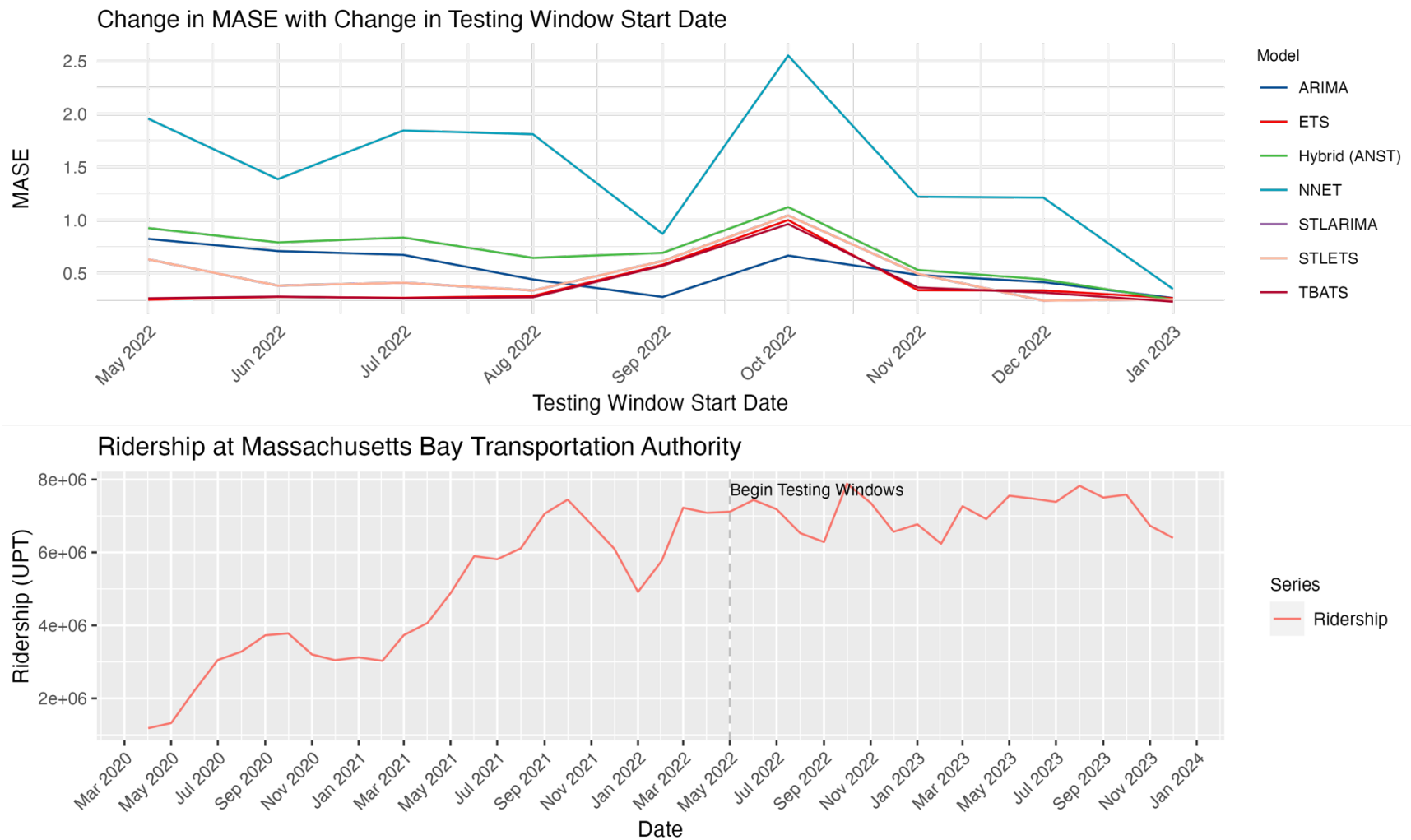


Figure B-17 Full Series Change in MASE at the Massachusetts Bay Transportation Authority Using the Moving Window

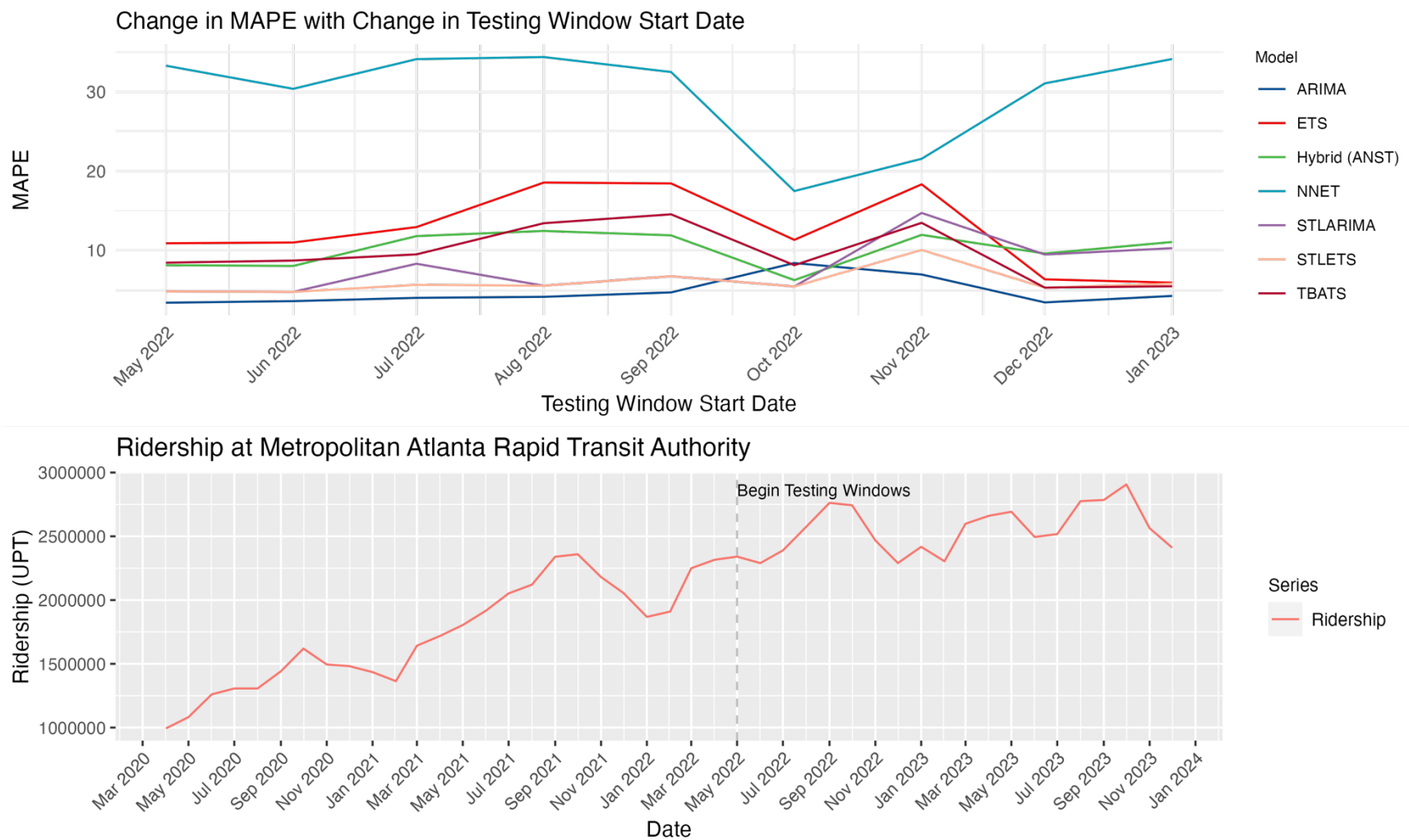


Figure B-18 Full Series Change in MAPE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

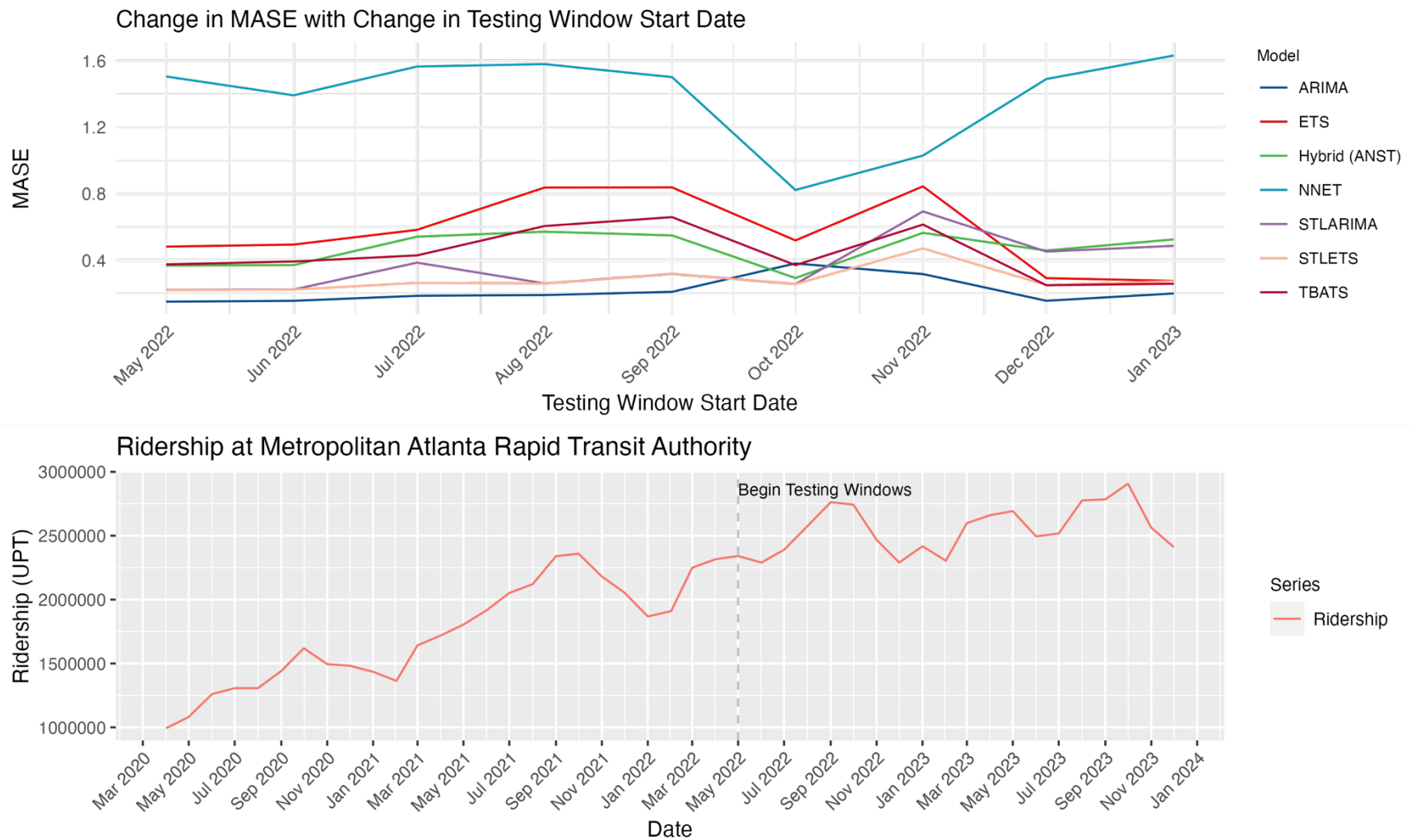


Figure B-19 Full Series Change in MASE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

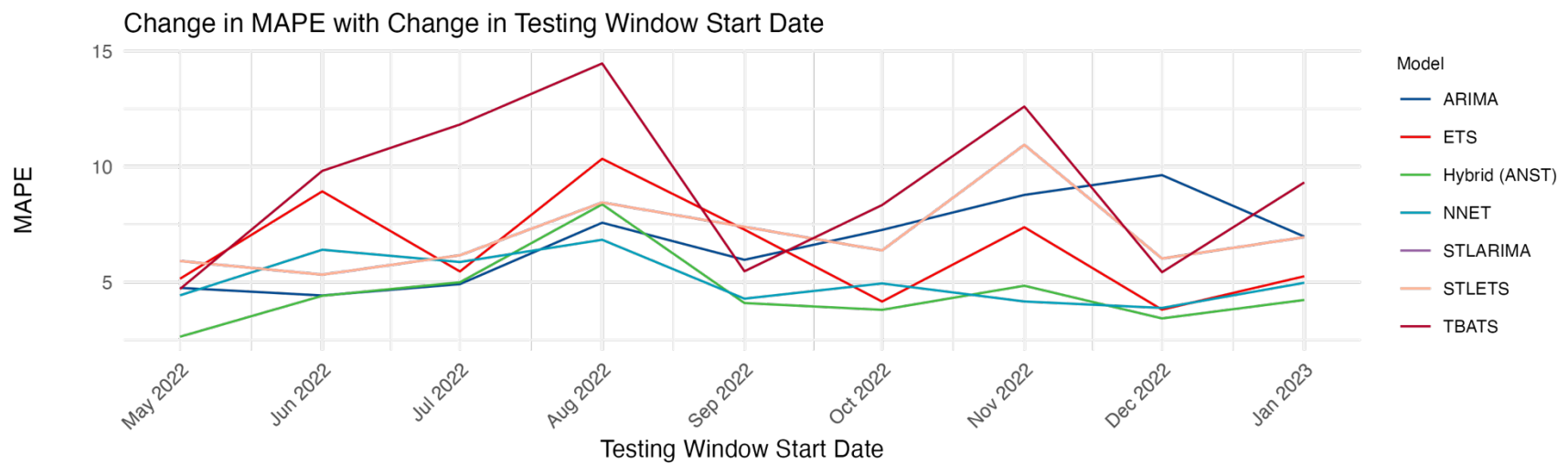
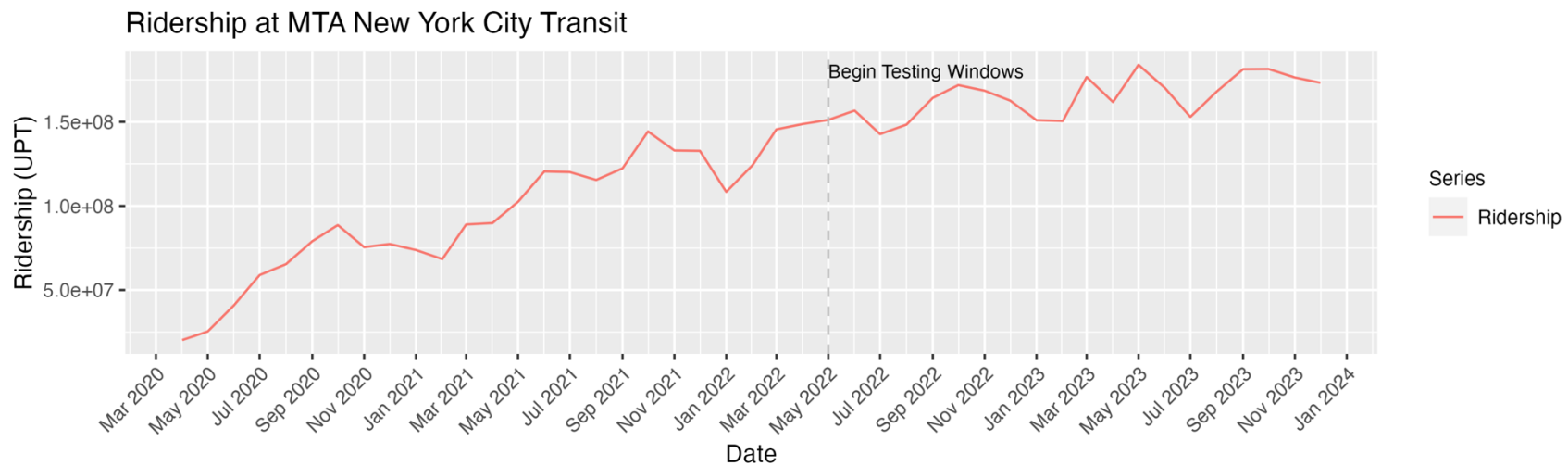


Figure B-20 Full Series Change in MAPE at MTA New York City Transit Using the Moving Window

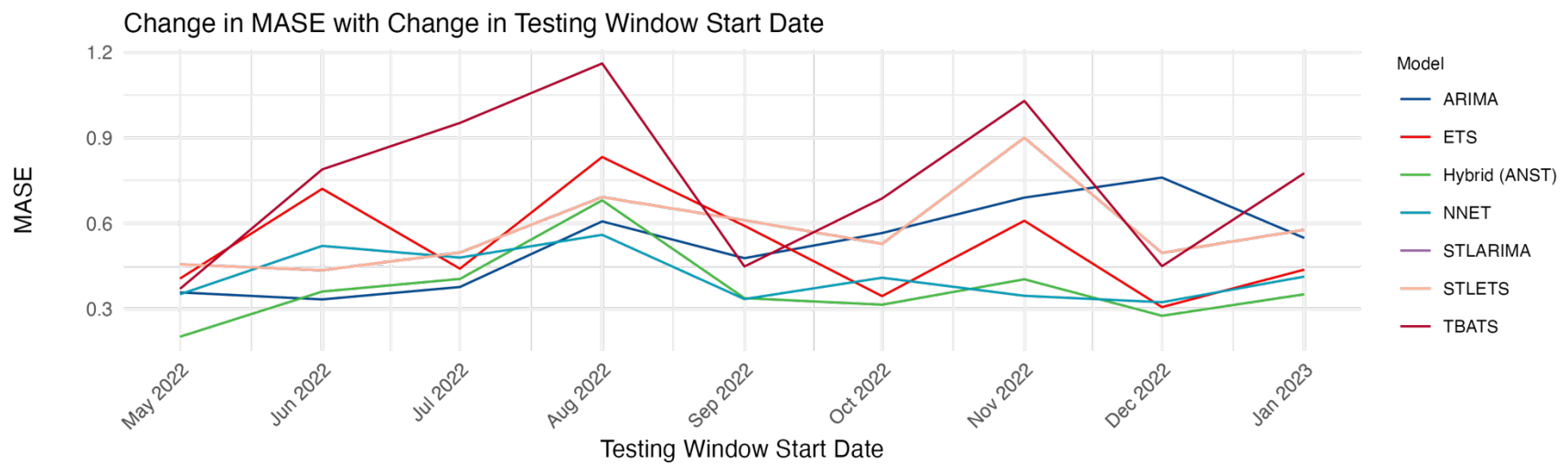
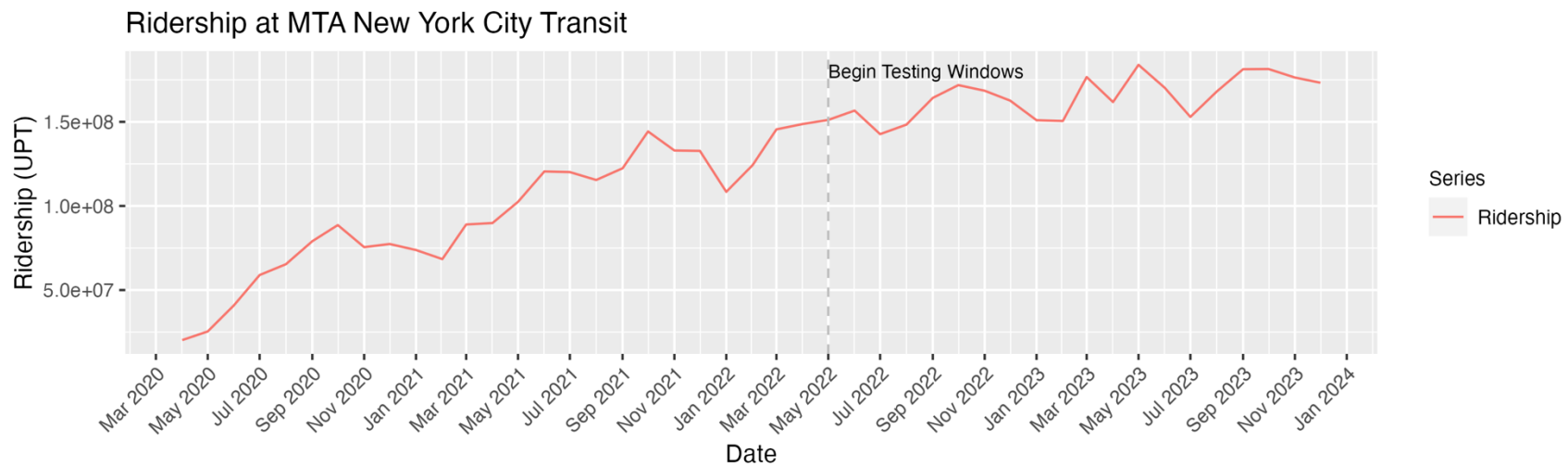


Figure B-21 Full Series Change in MASE at MTA New York City Transit Using the Moving Window

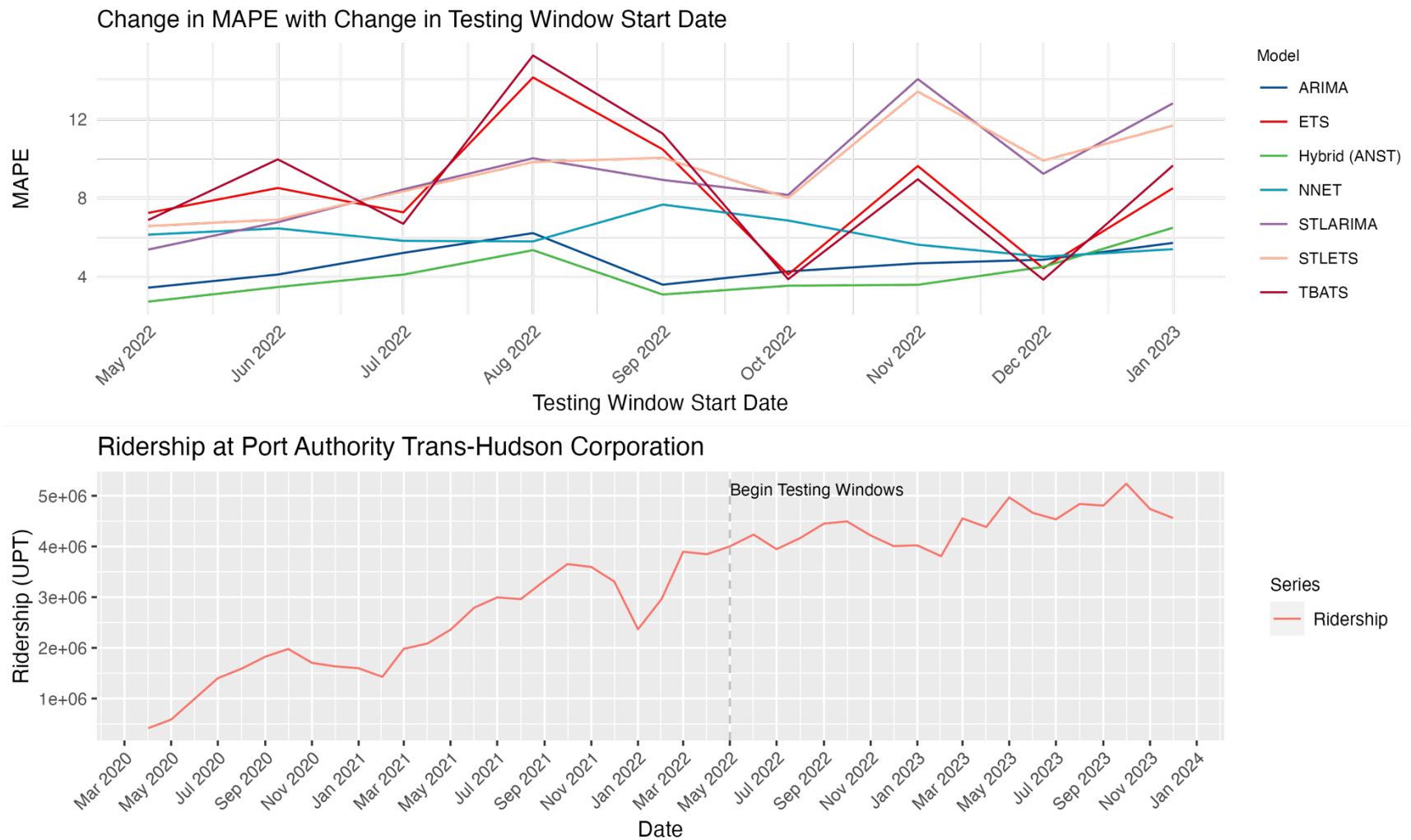


Figure B-22 Full Series Change in MAPE at the Port Authority Trans-Hudson Corporation Using the Moving Window

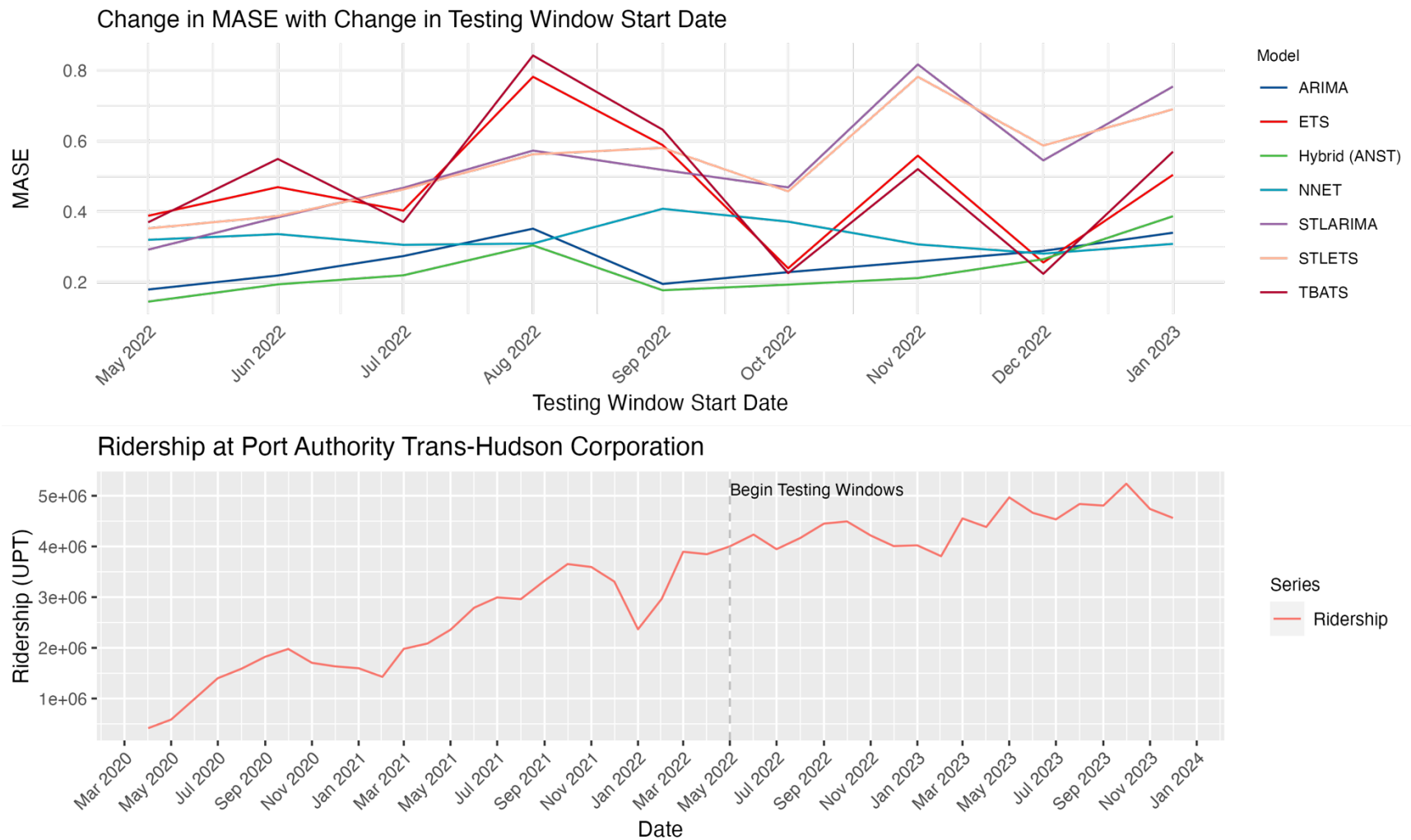


Figure B-23 Full Series Change in MASE at the Port Authority Trans-Hudson Corporation Using the Moving Window

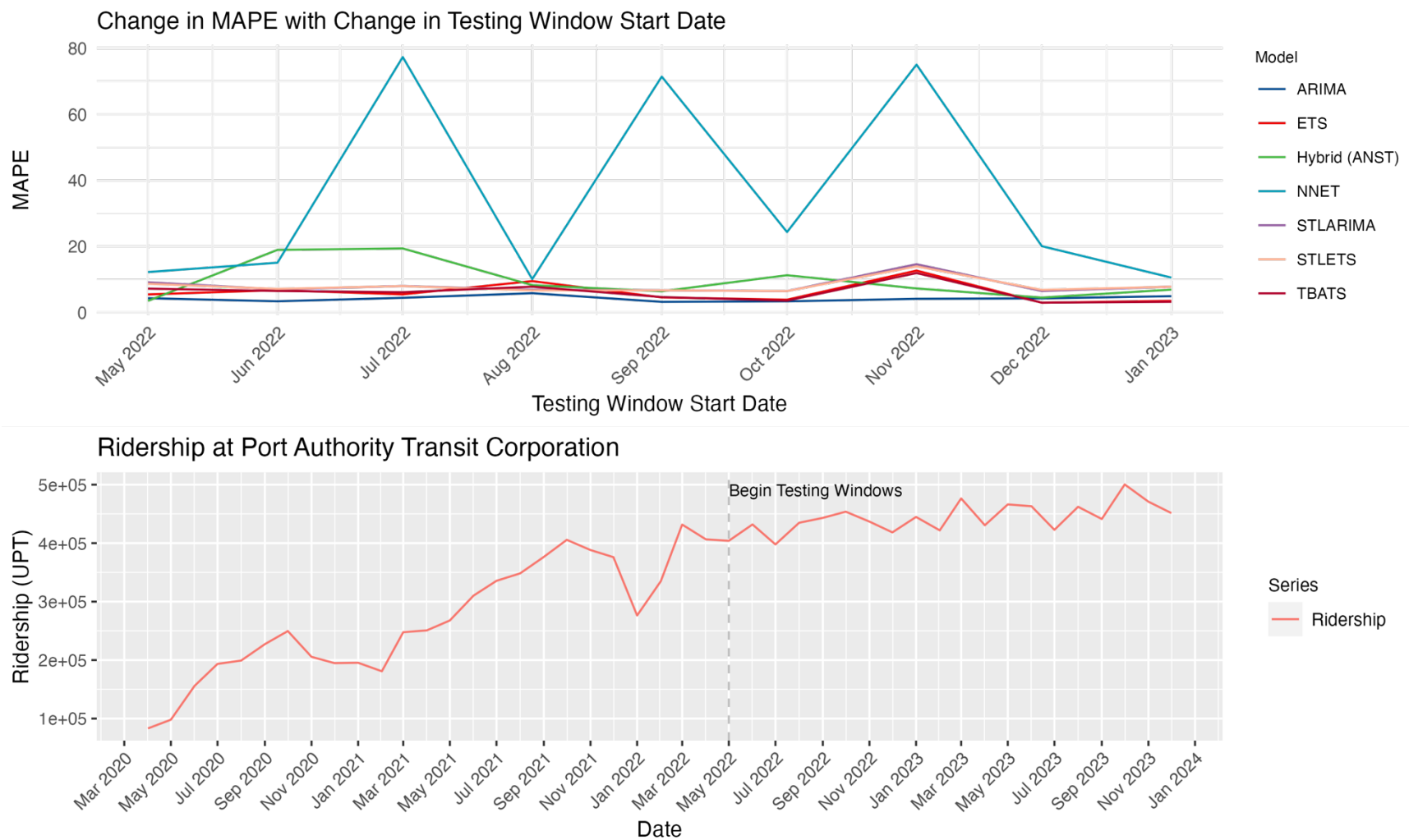


Figure B-24 Full Series Change in MAPE at the Port Authority Transit Corporation Using the Moving Window

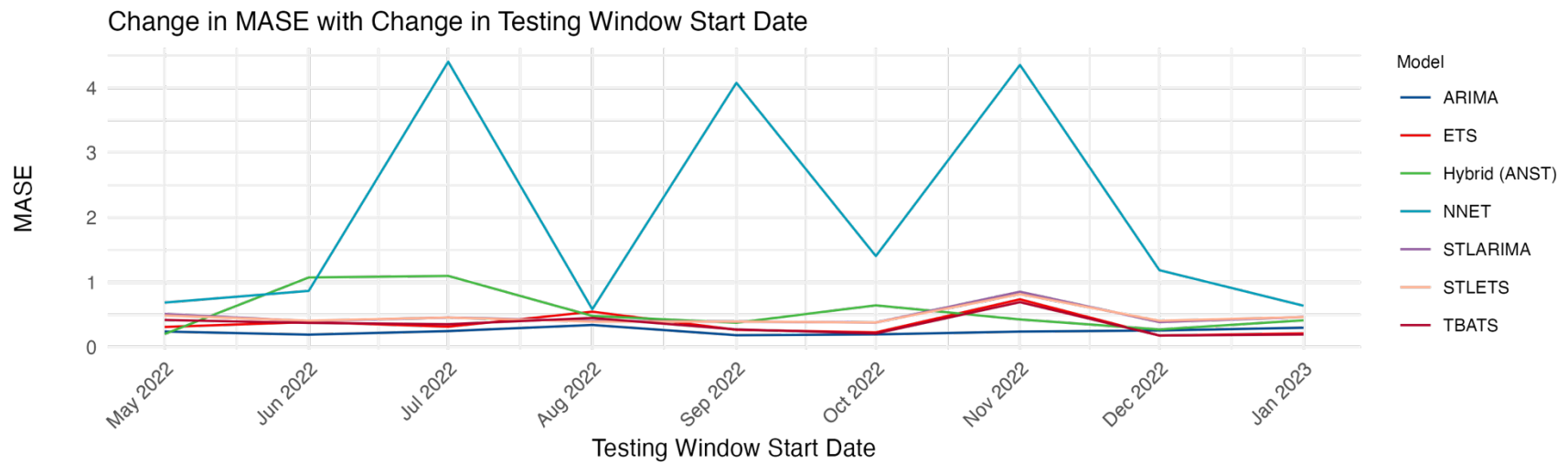
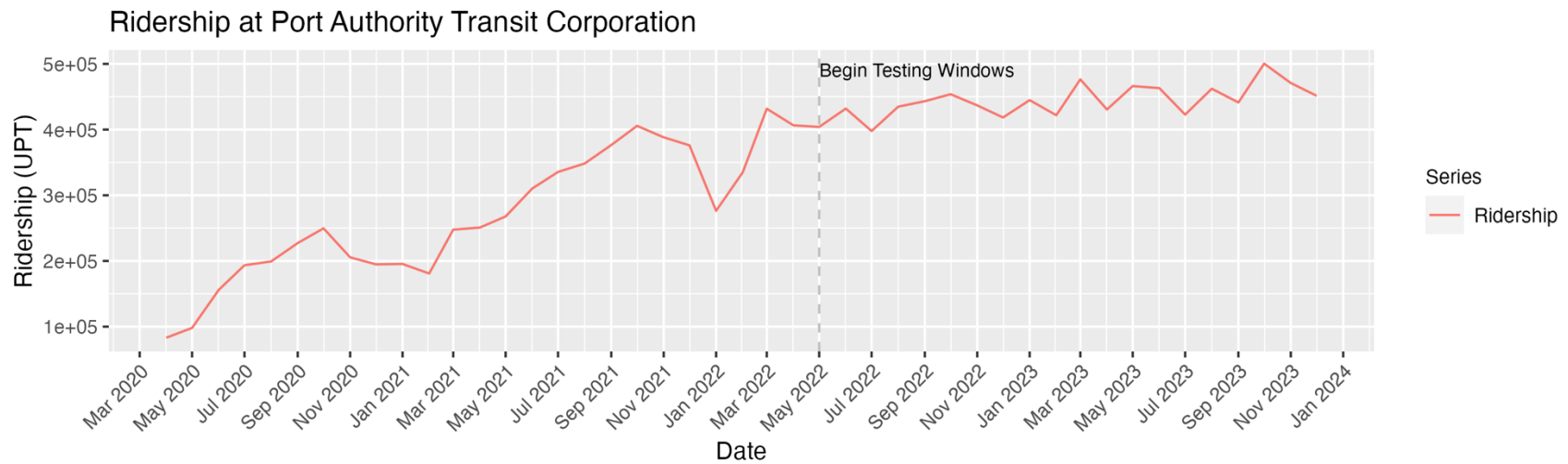


Figure B-25 Full Series Change in MASE at the Port Authority Transit Corporation Using the Moving Window

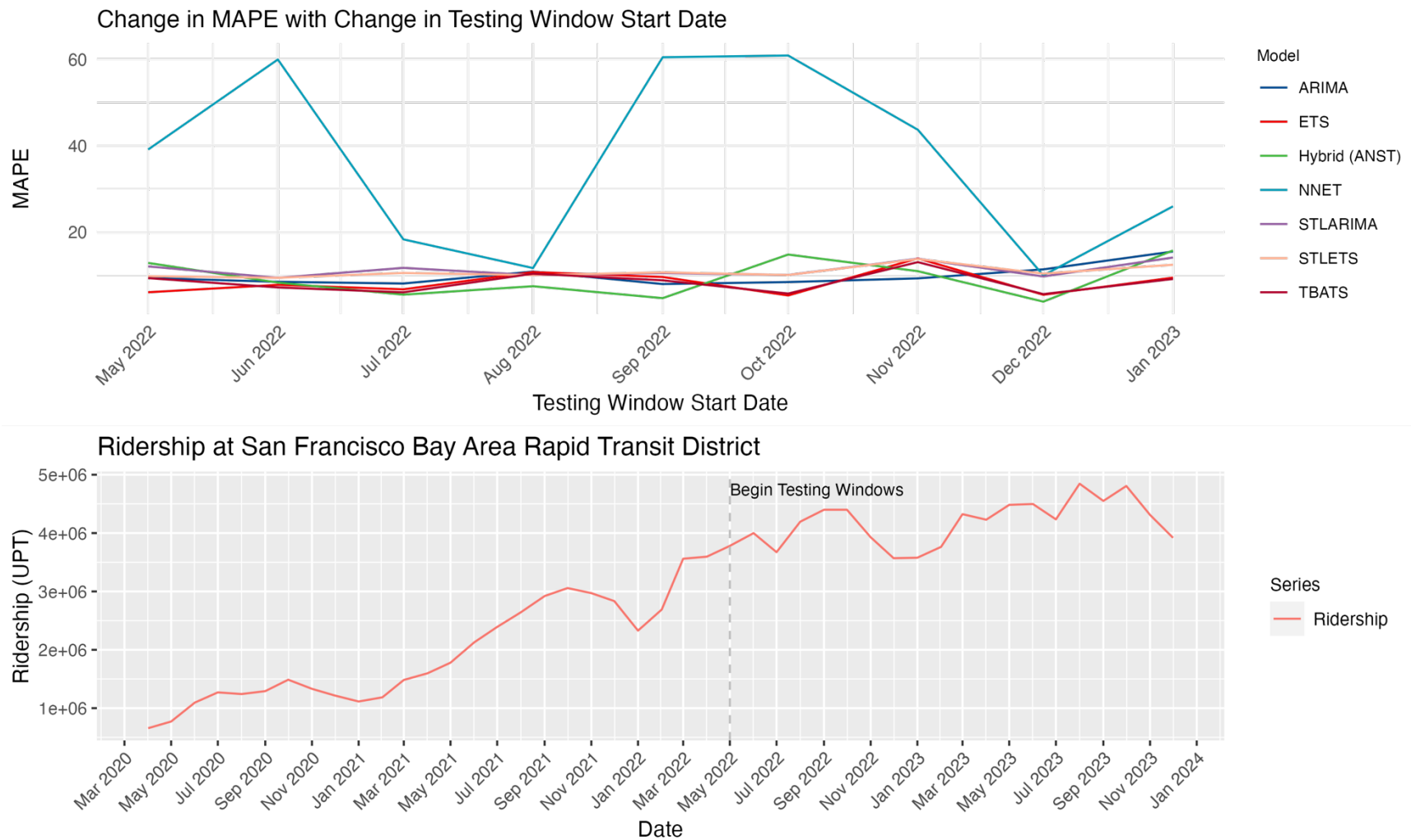


Figure B-26 Full Series Change in MAPE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

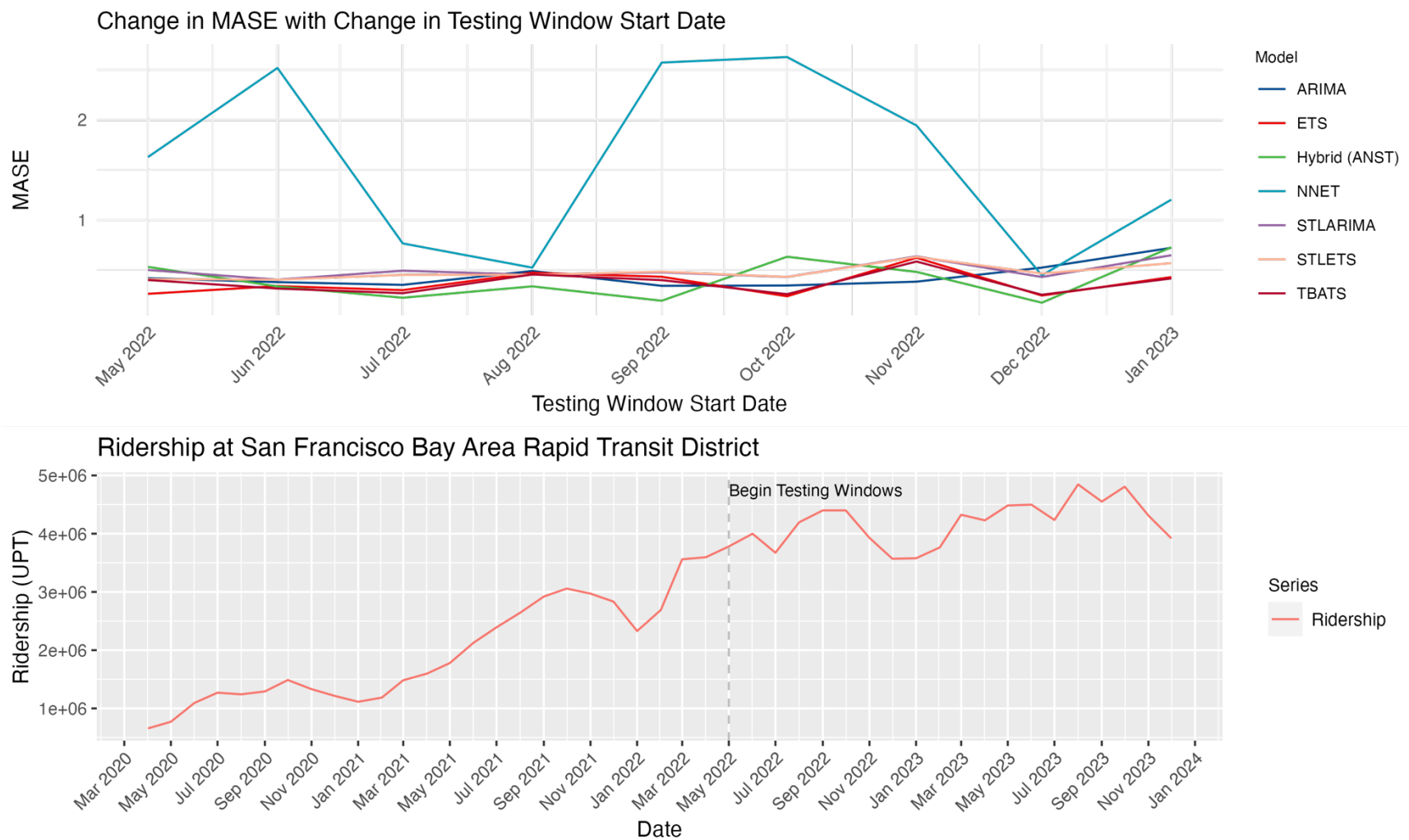


Figure B-27 Full Series Change in MASE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

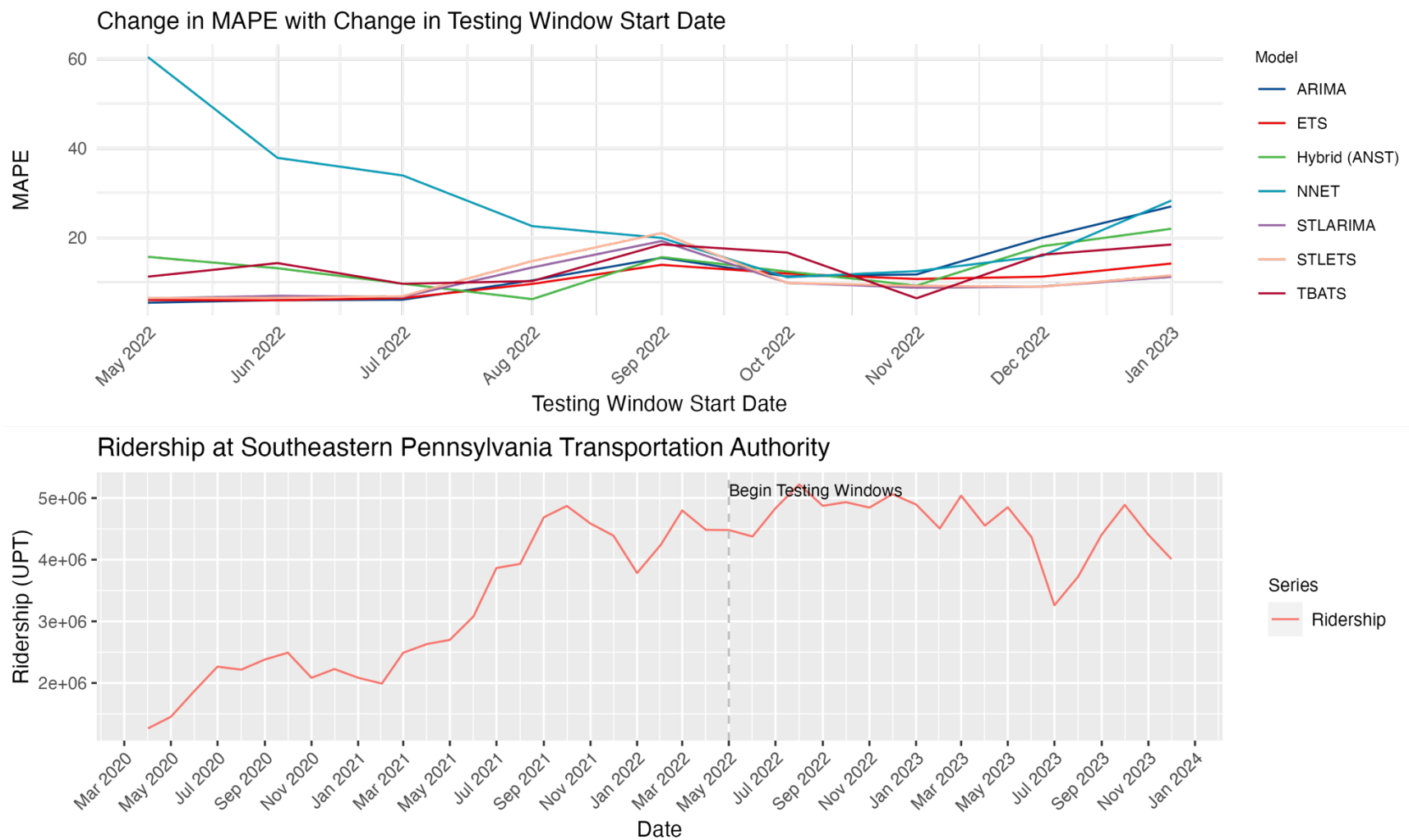


Figure B-28 Full Series Change in MAPE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

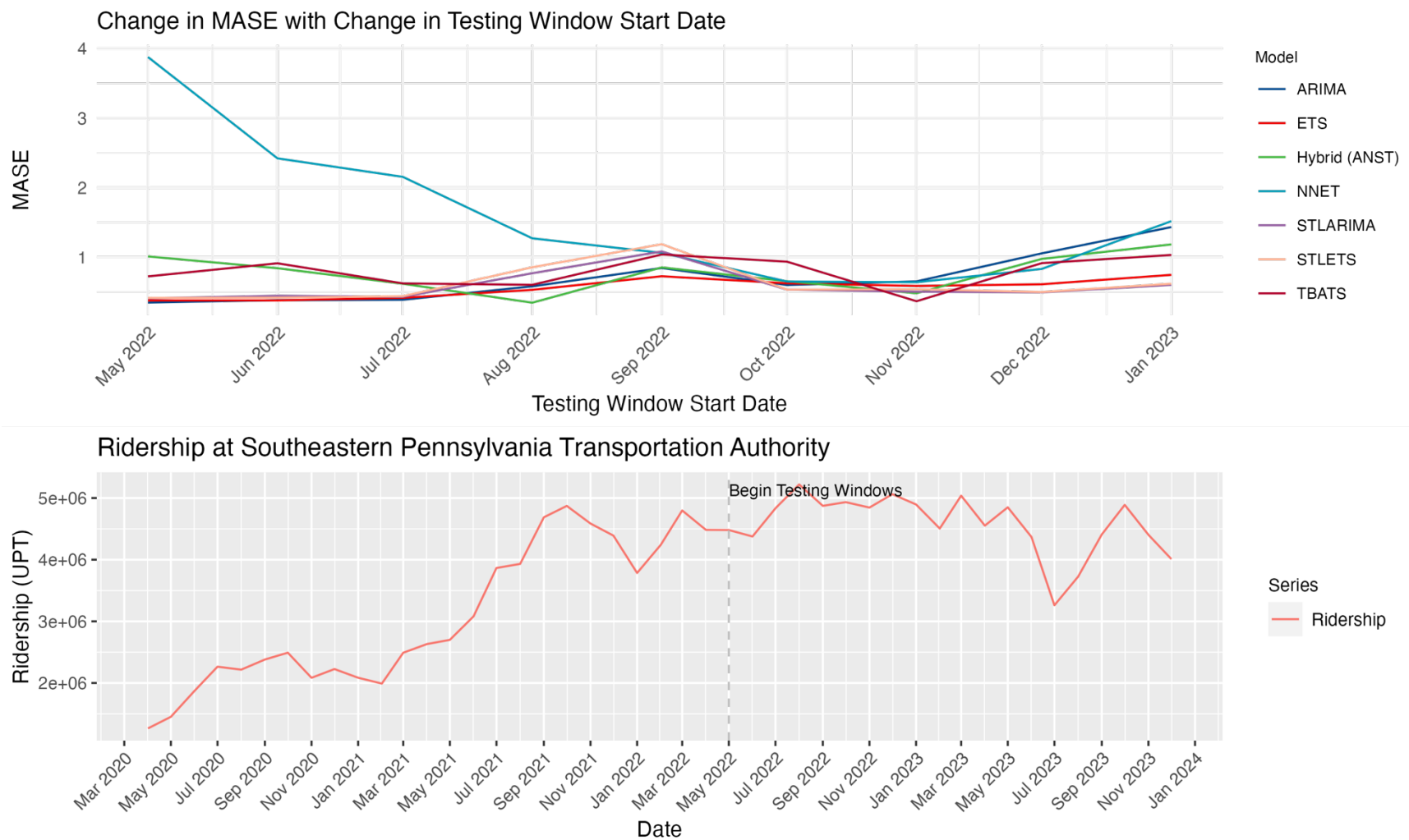


Figure B-29 Full Series Change in MASE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

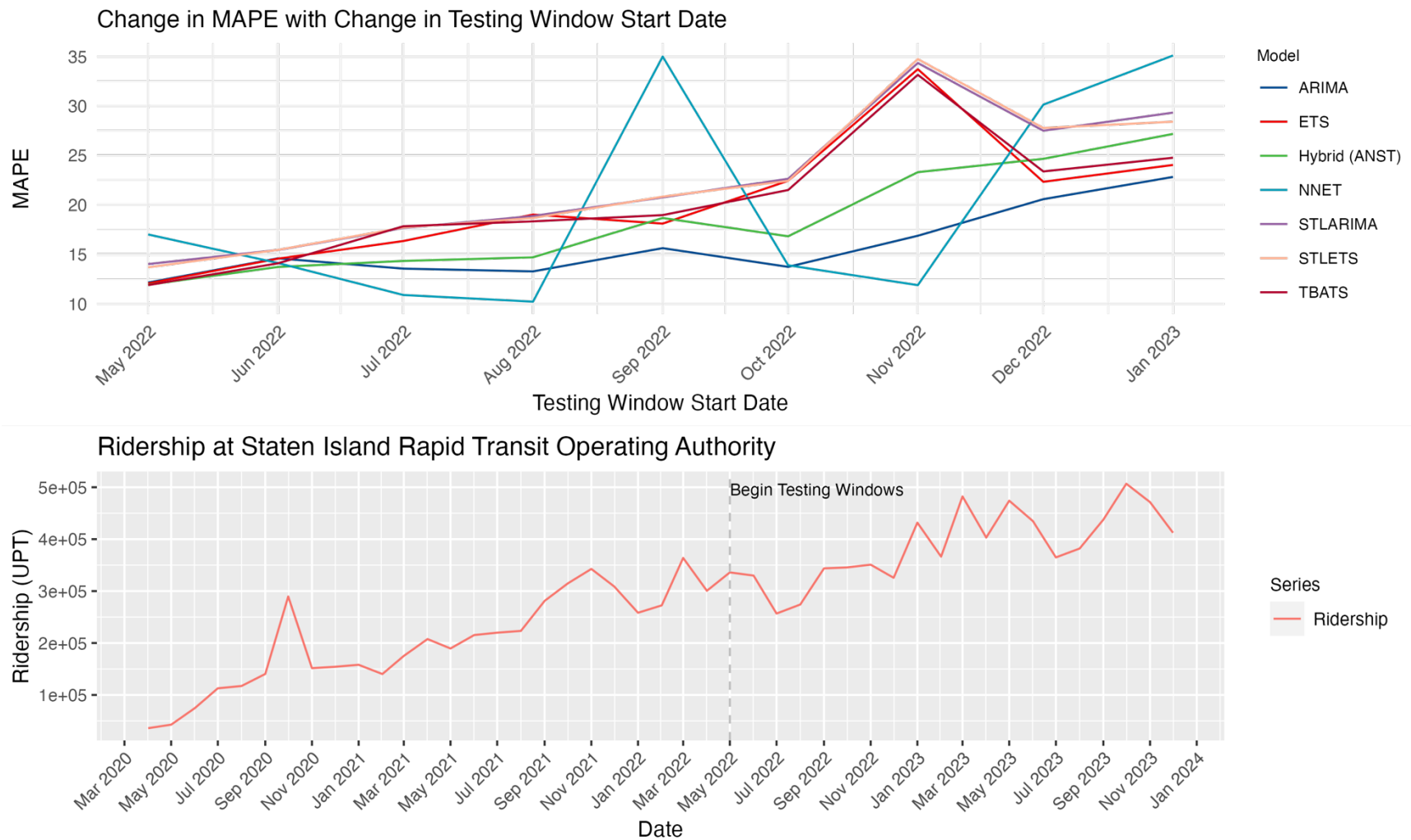


Figure B-30 Full Series Change in MAPE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

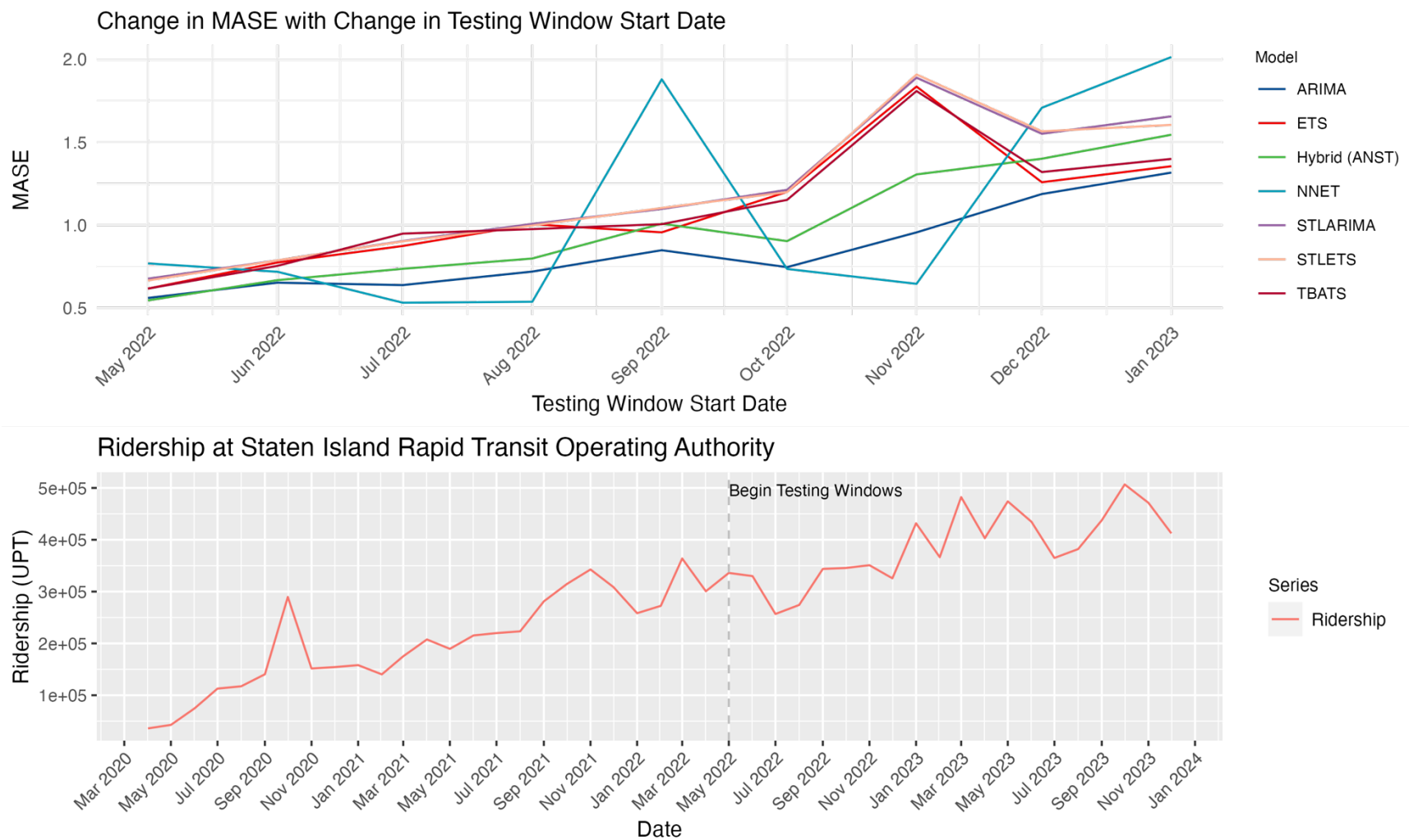


Figure B-31 Full Series Change in MASE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

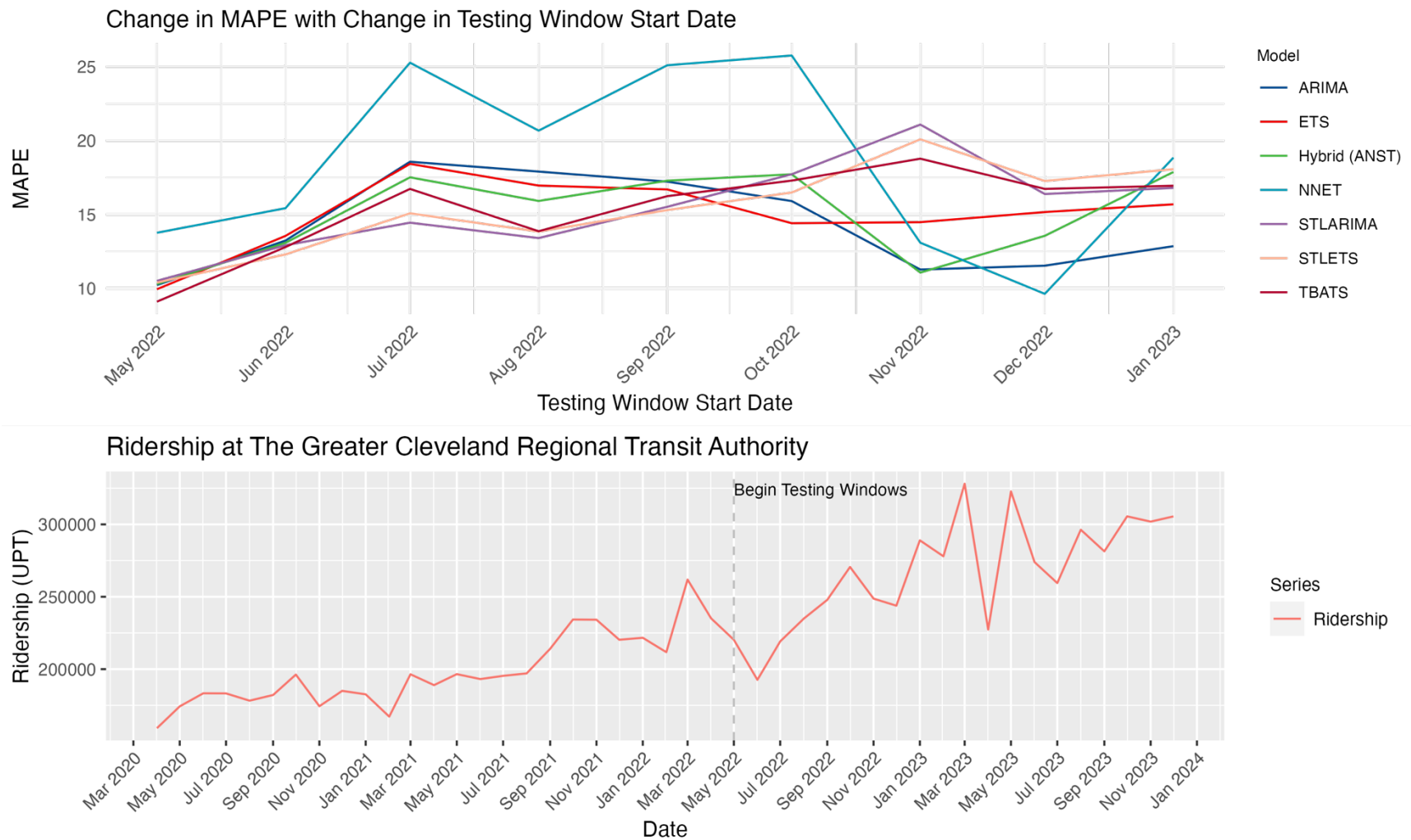


Figure B-32 Full Series Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

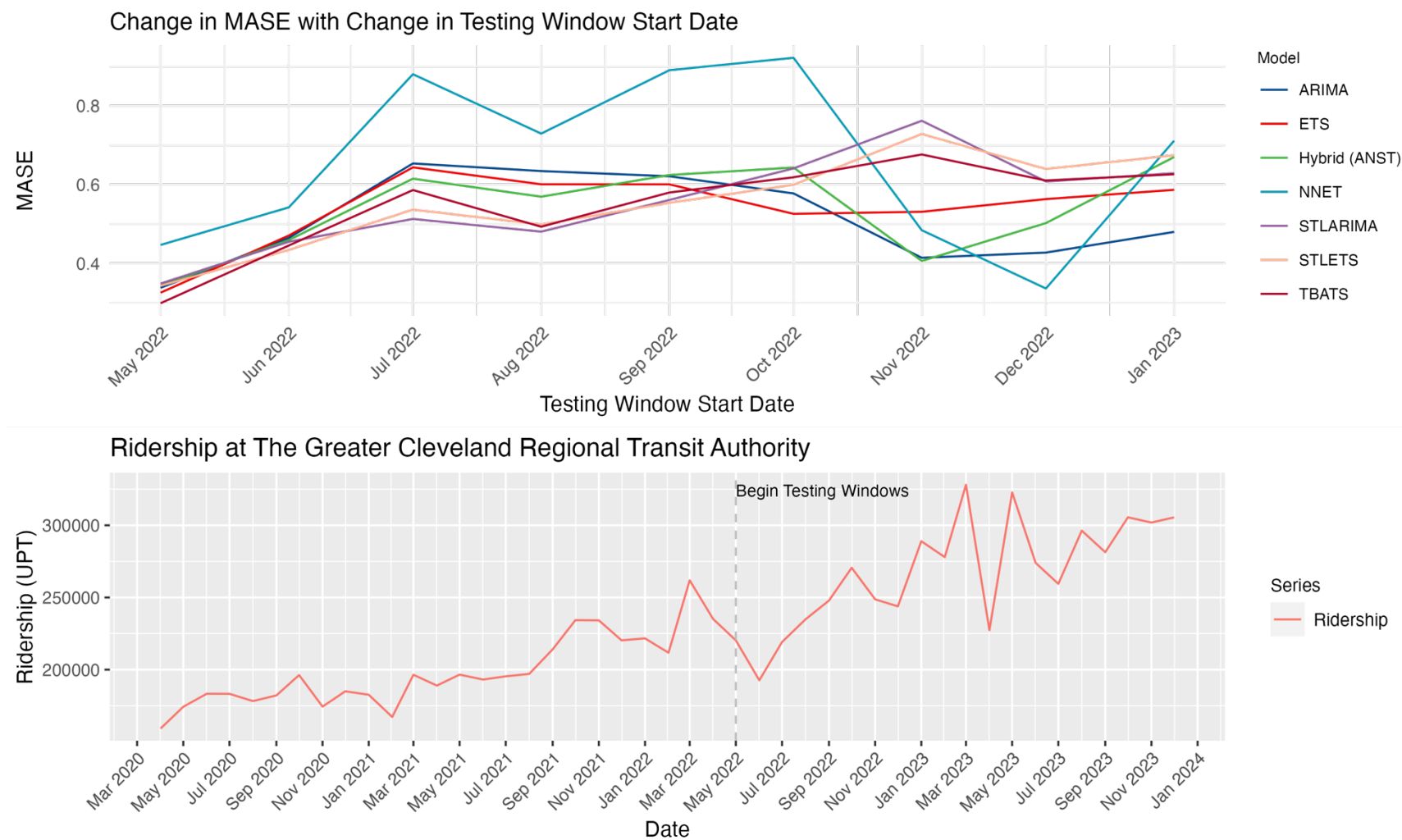


Figure B-33 Full Series Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

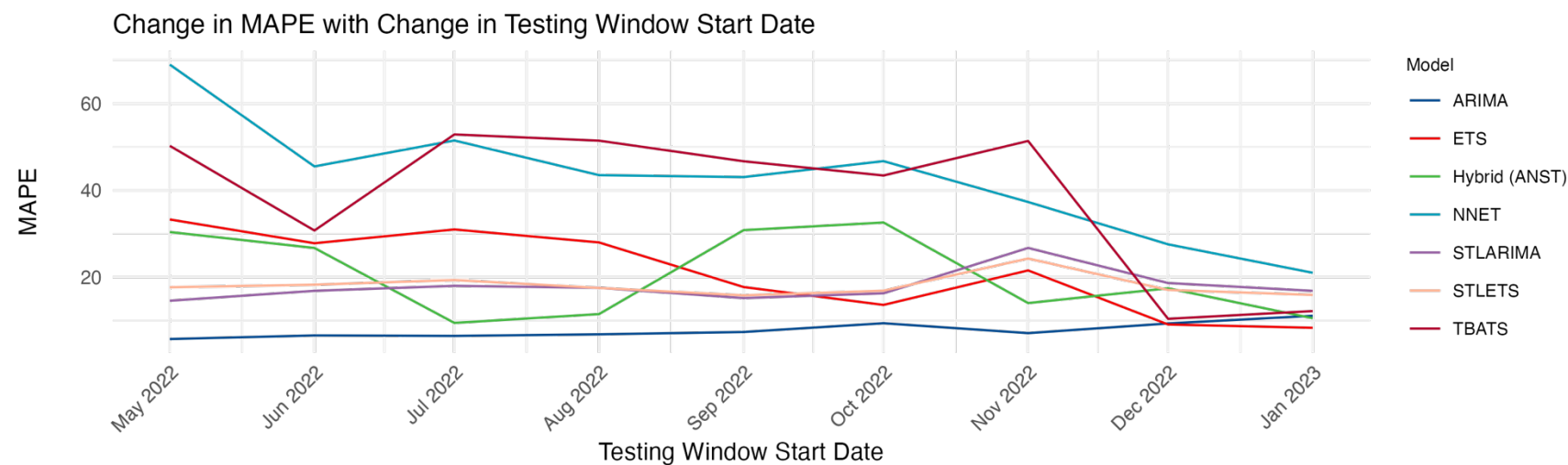
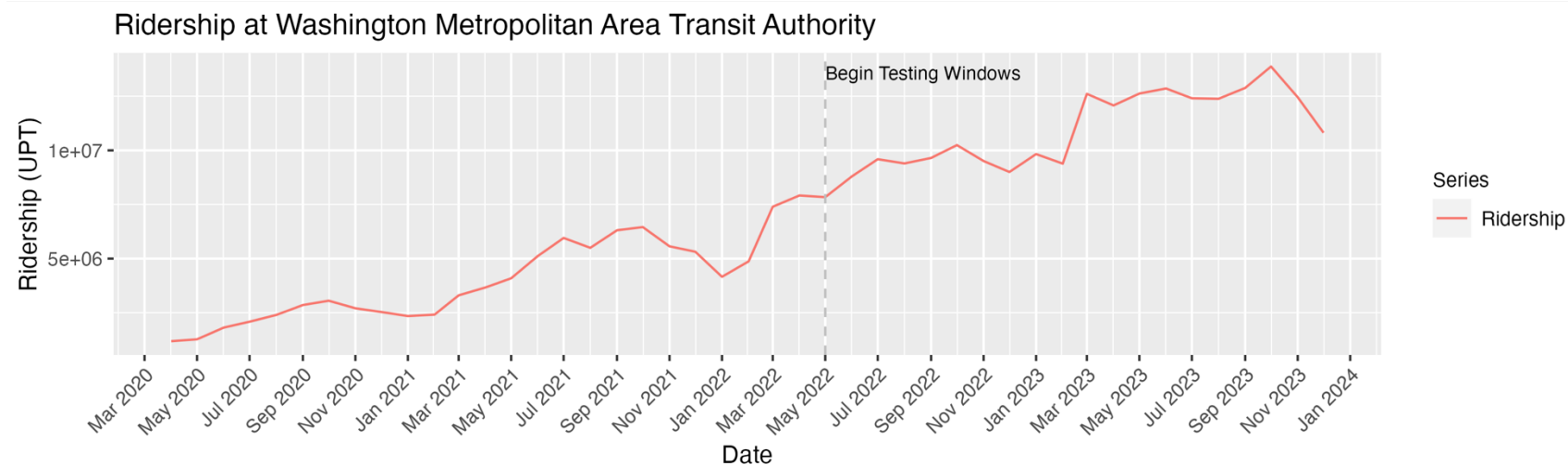


Figure B-34 Full Series Change in MAPE at the Washington Metropolitan Area Transit Authority Using the Moving Window

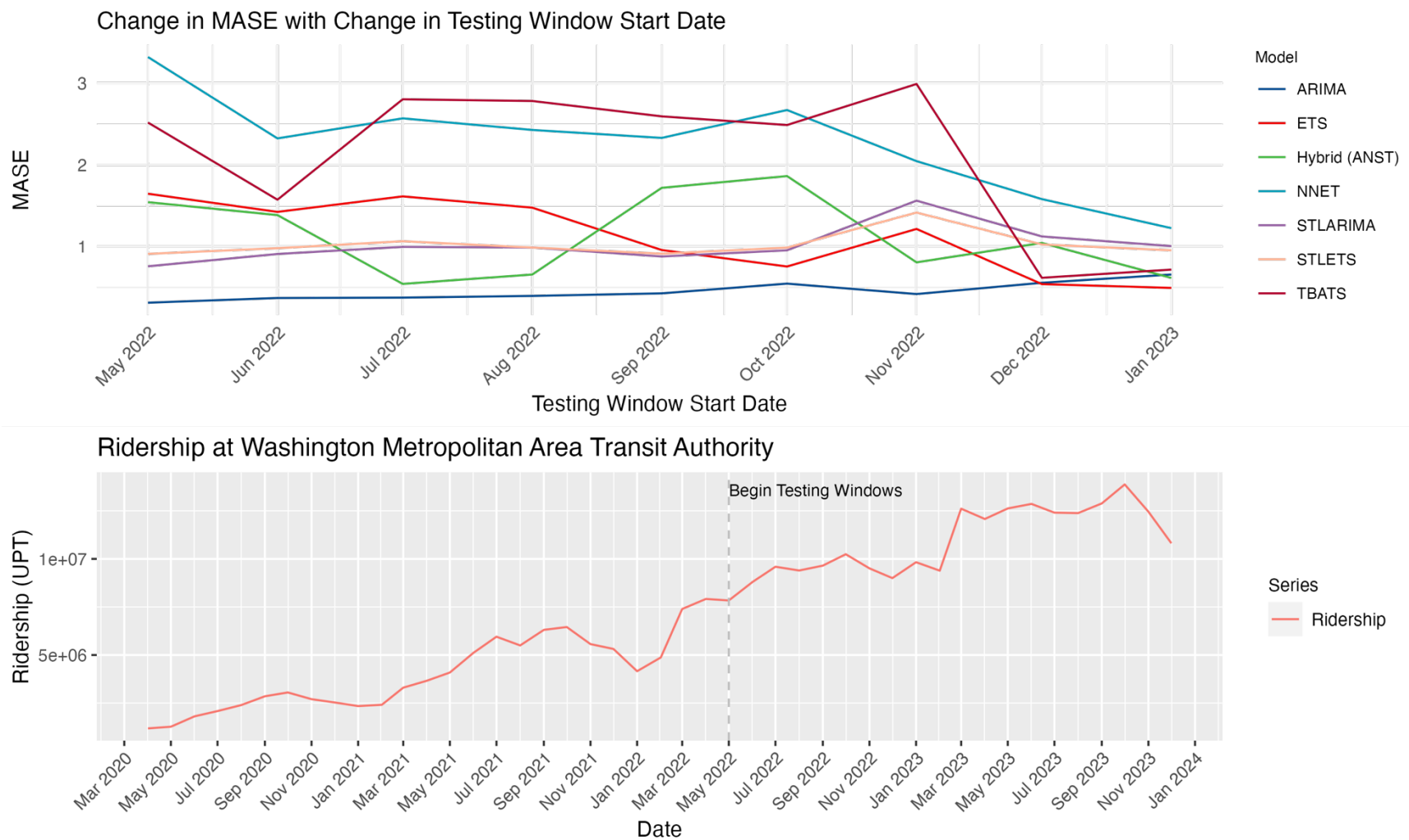


Figure B-35 Full Series Change in MASE at the Washington Metropolitan Area Transit Authority Using the Moving Window

Part C: Post-COVID Moving Window Forecasts

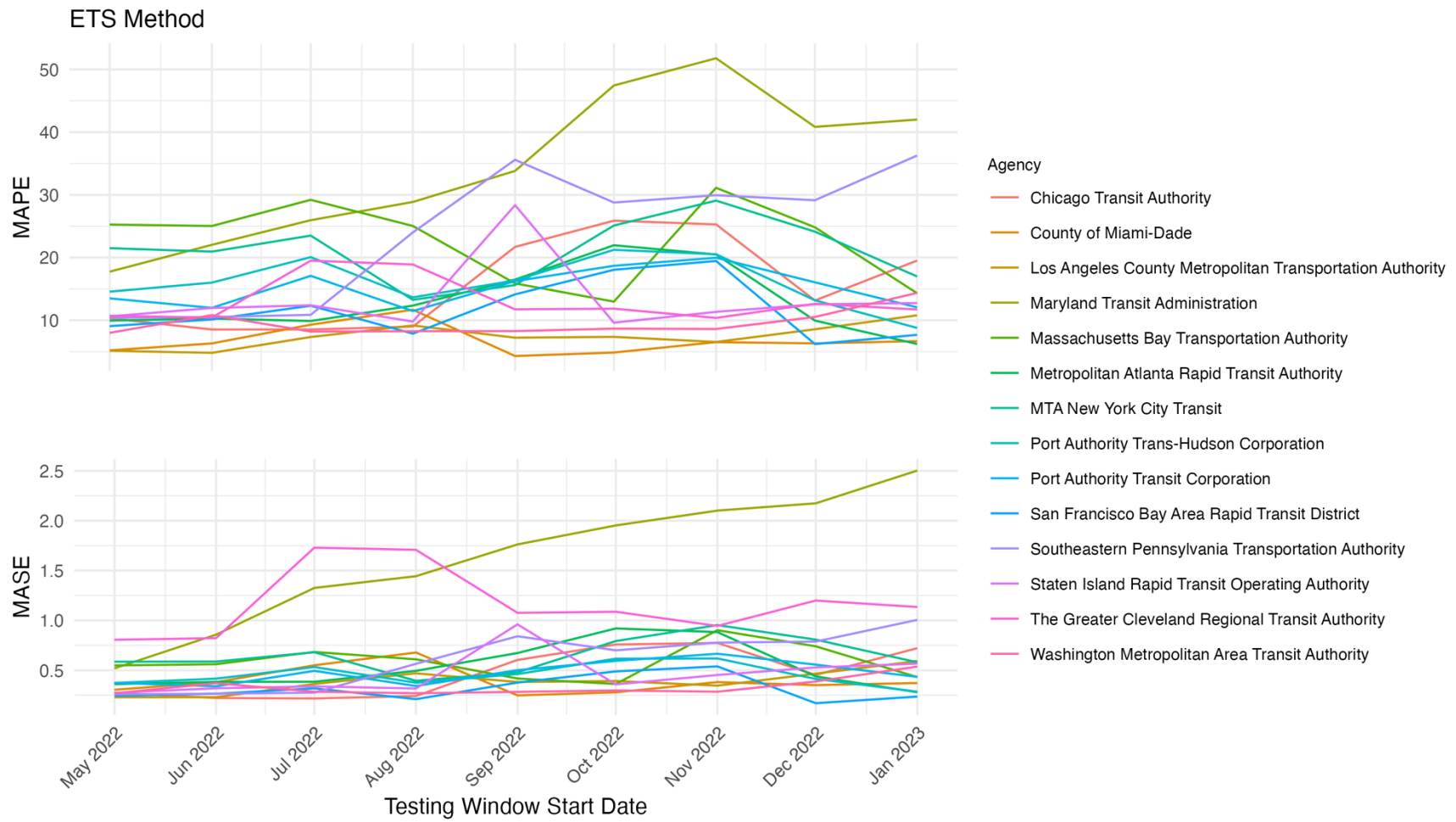


Figure C-1 Post-COVID Performance of the ETS Method

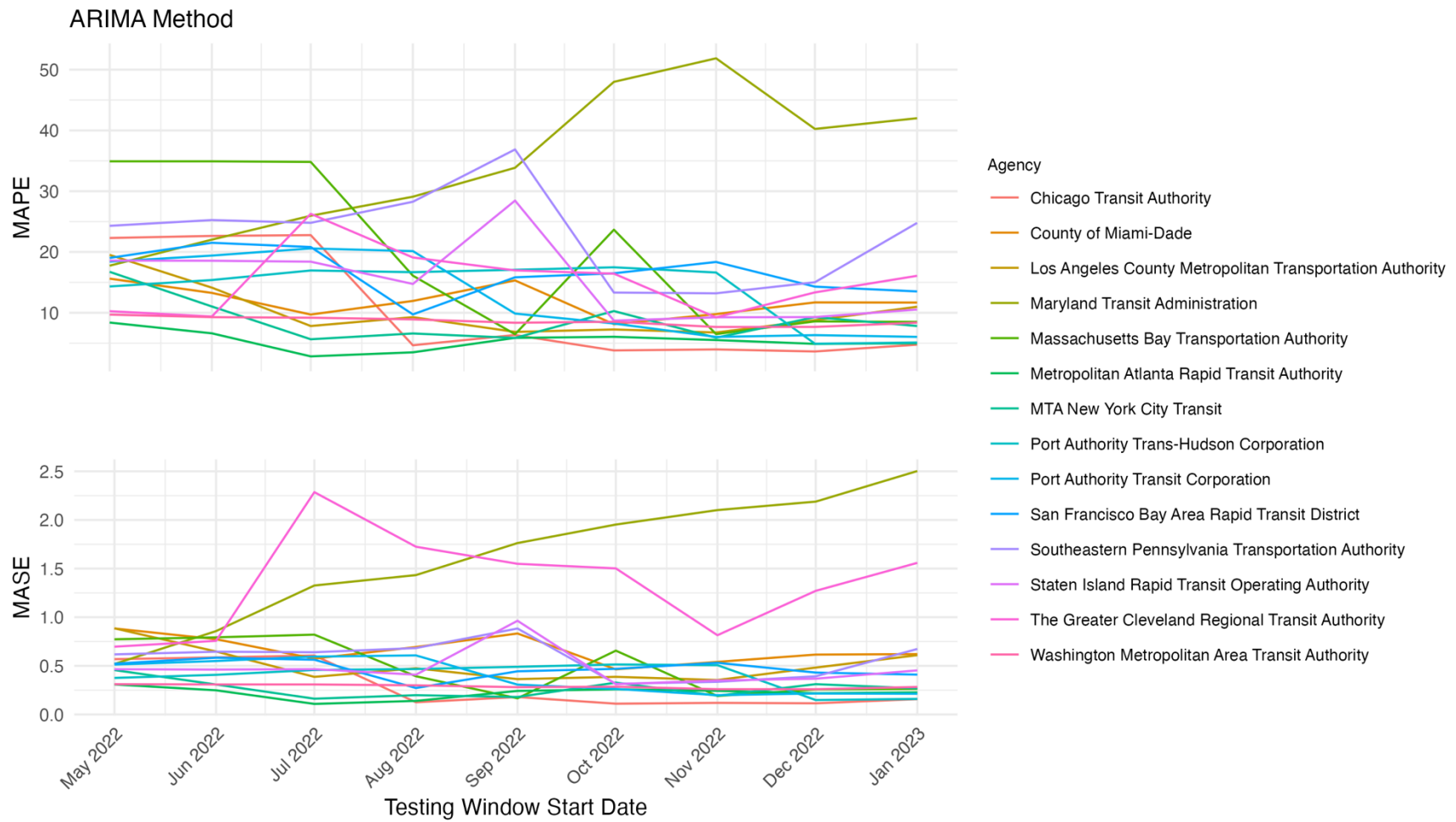


Figure C-2 Post-COVID Performance of the ARIMA Method

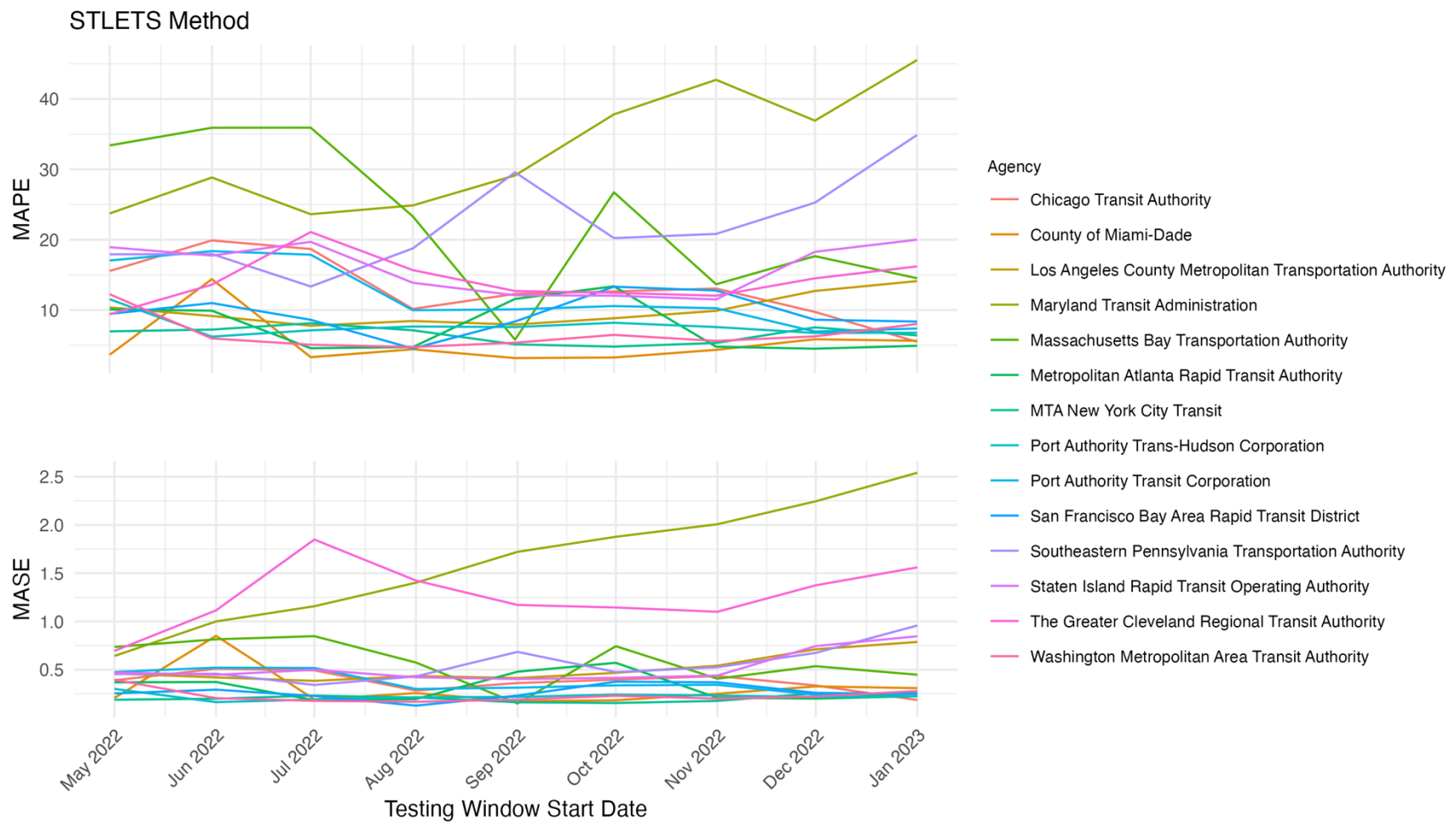


Figure C-3 Post-COVID Performance of the STL-ETS Method

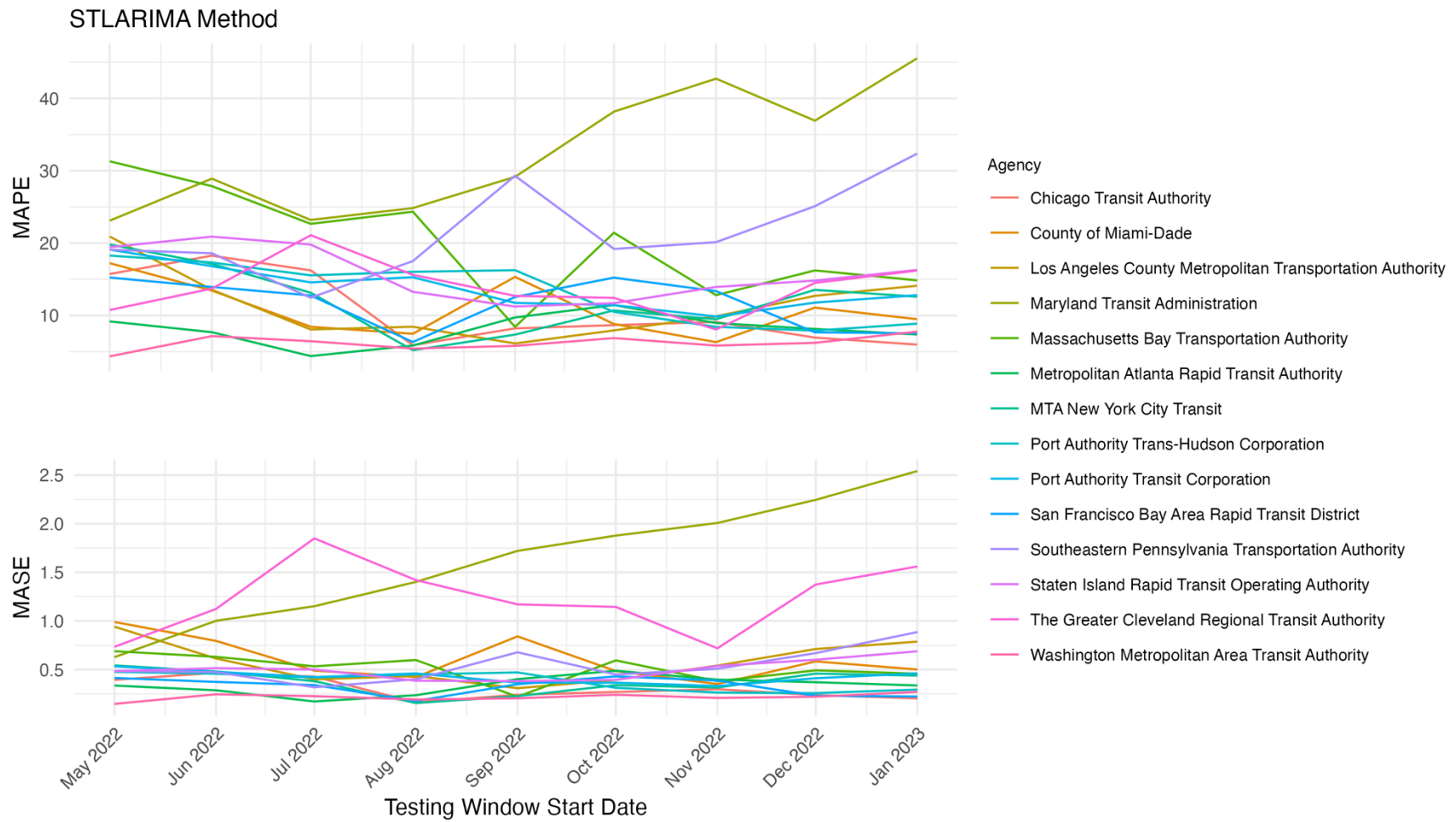


Figure C-4 Post-COVID Performance of the STL-ARIMA Method

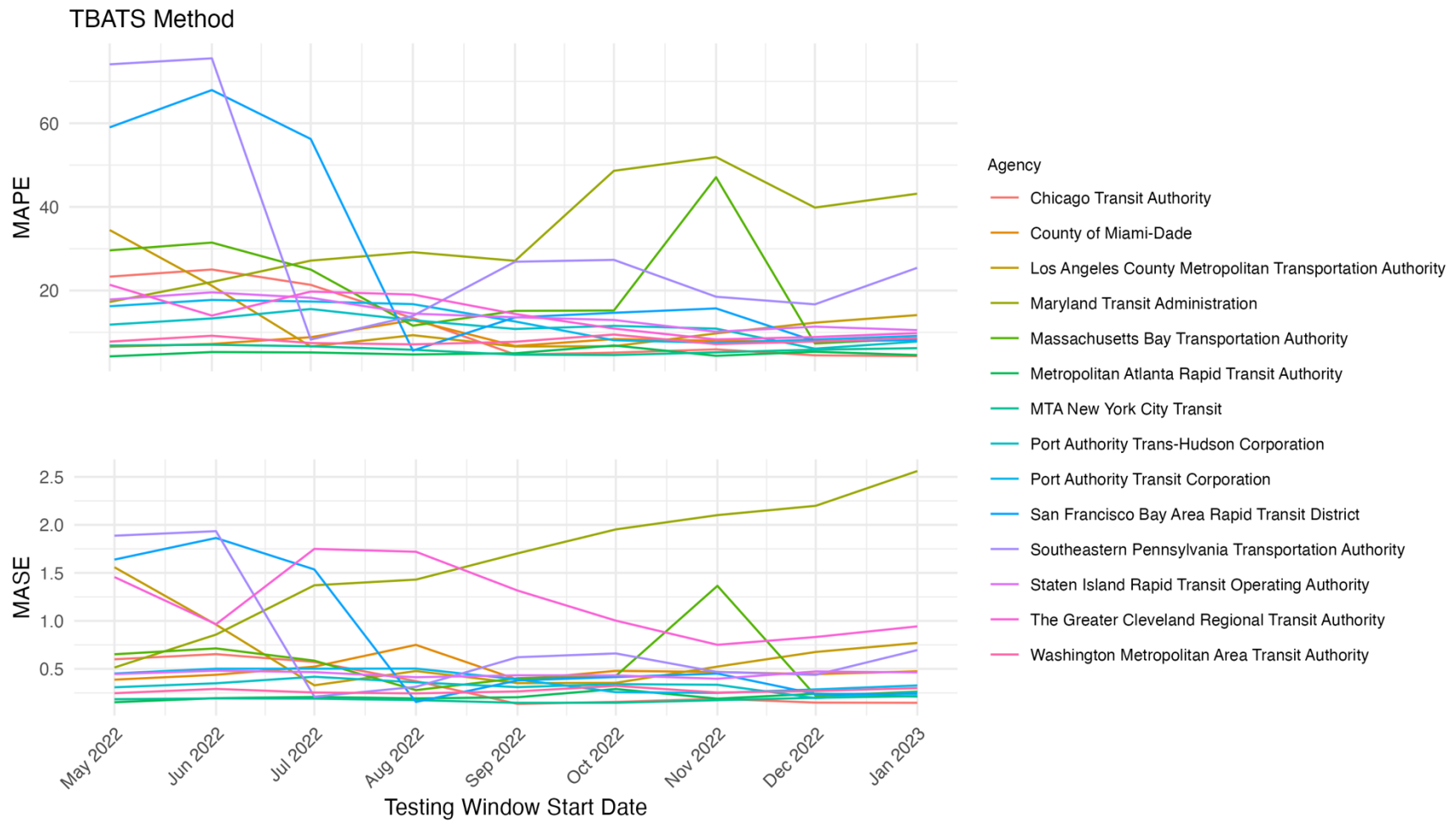


Figure C-5 Post-COVID Performance of the TBATS Method

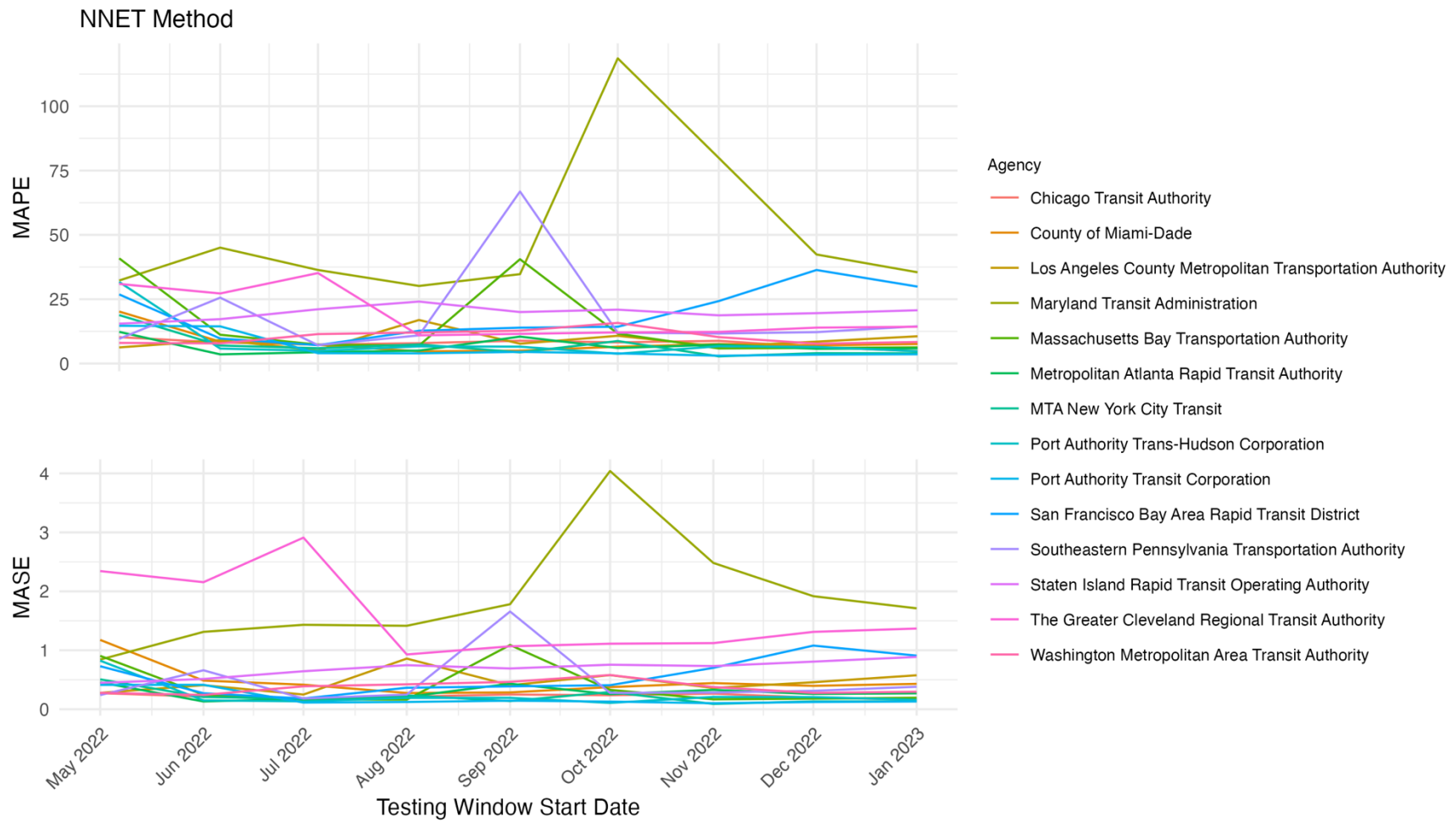


Figure C-6 Post-COVID Performance of the NNET Method

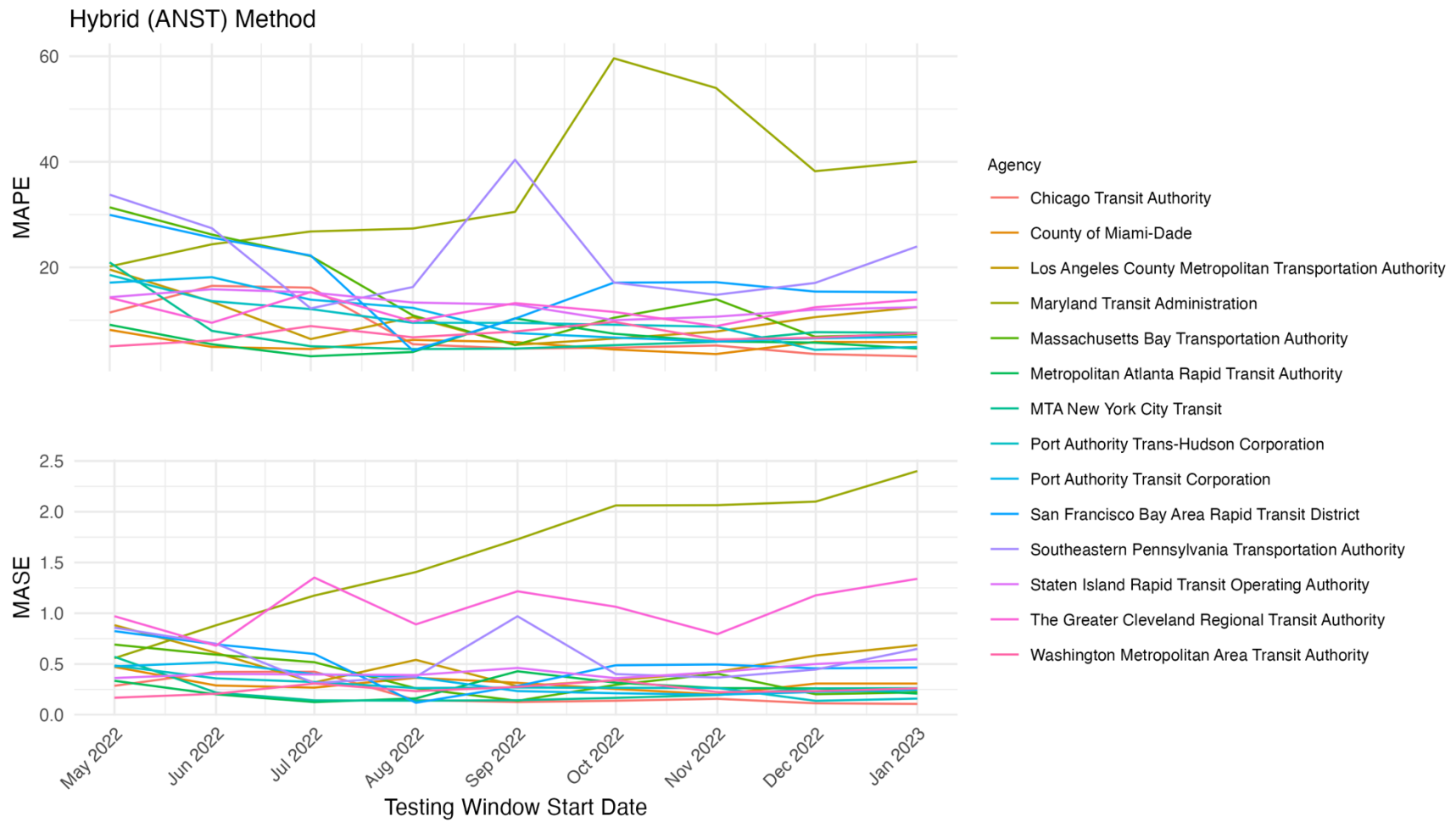


Figure C-7 Post-COVID Performance of the Hybrid Method

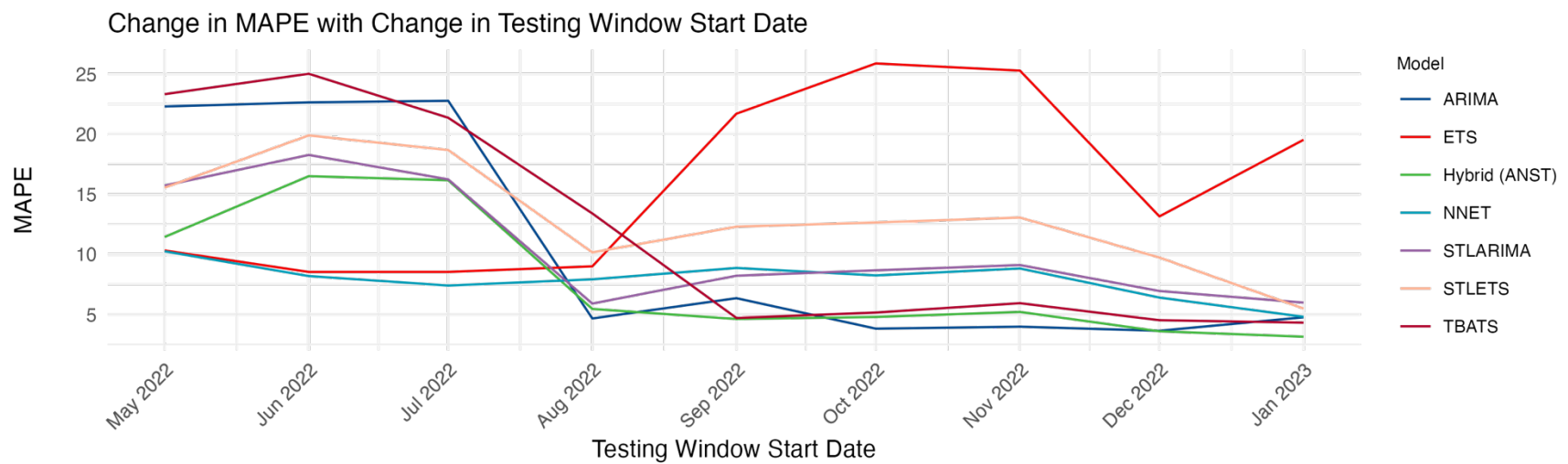
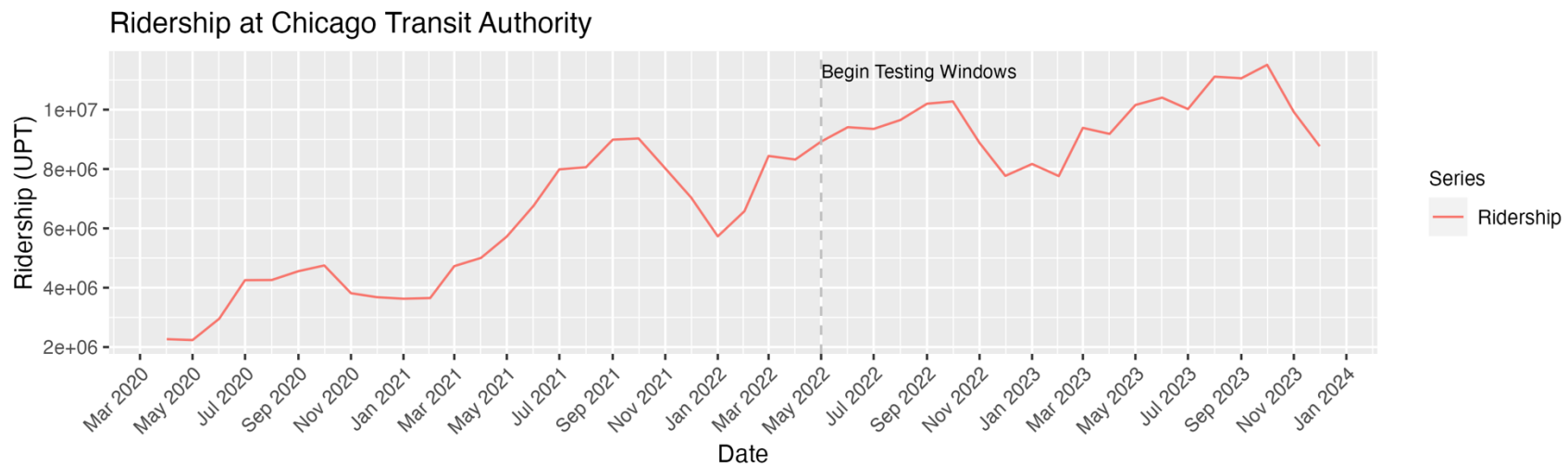


Figure C-8 Post-COVID Change in MAPE at the Chicago Transit Authority Using the Moving Window

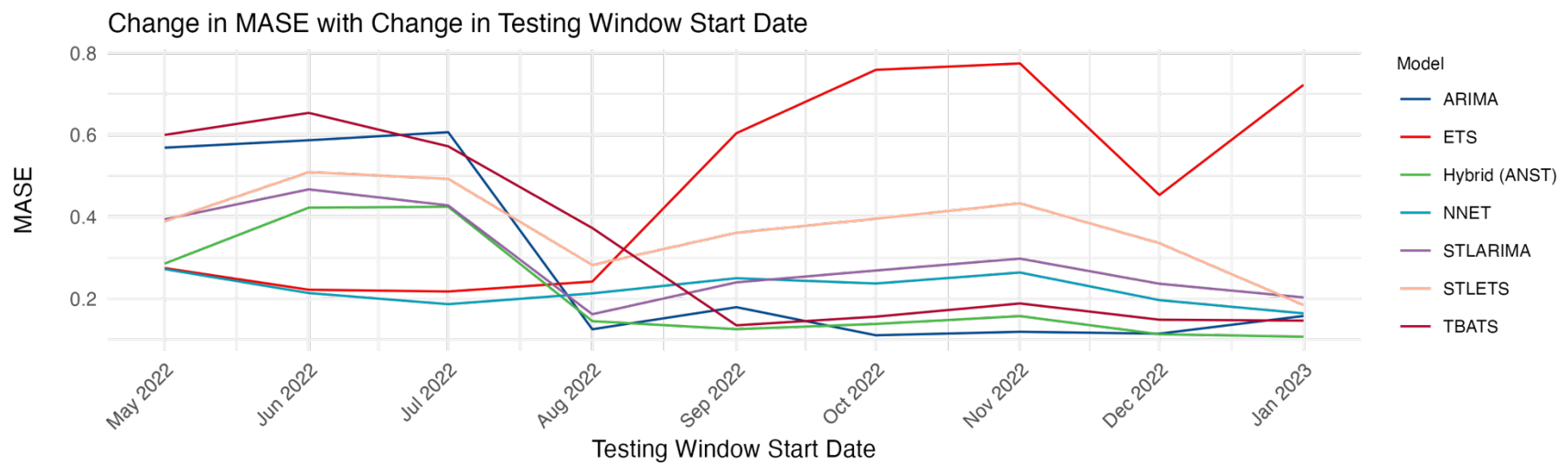
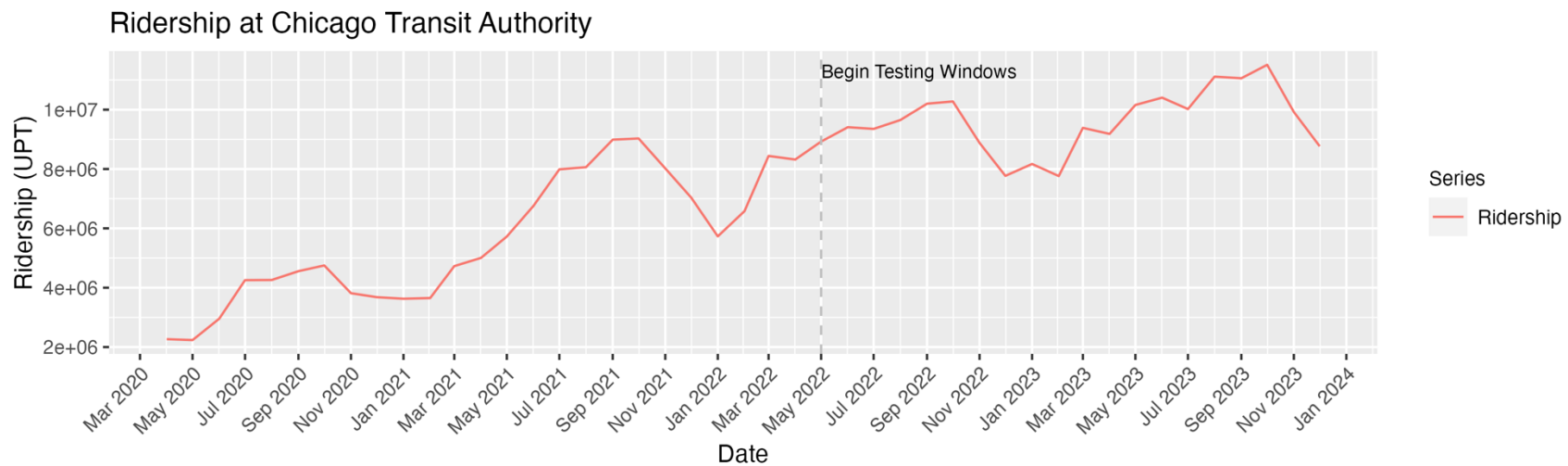


Figure C-9 Post-COVID Change in MASE at the Chicago Transit Authority Using the Moving Window

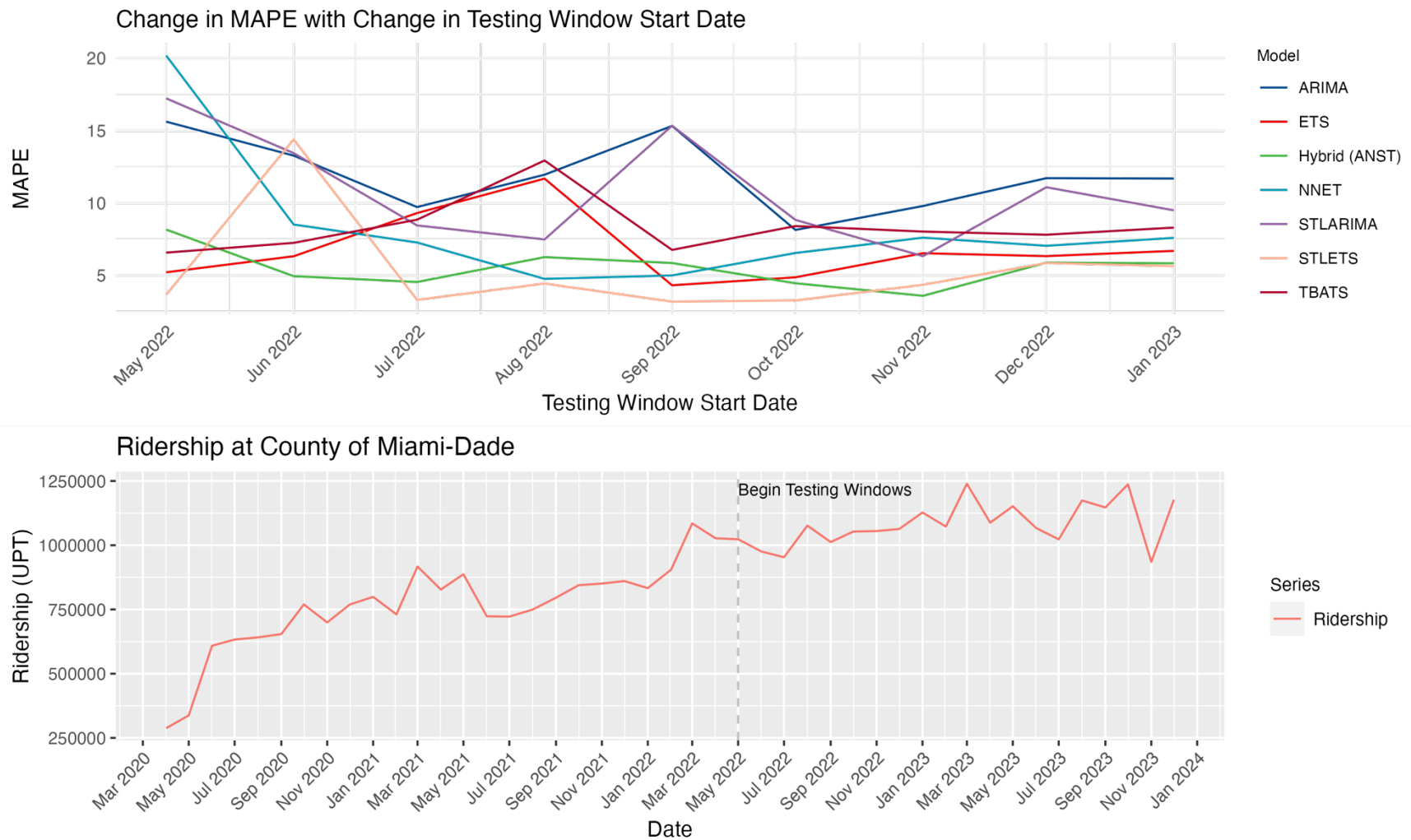


Figure C-10 Post-COVID Change in MAPE at the County of Miami-Dade Using the Moving Window

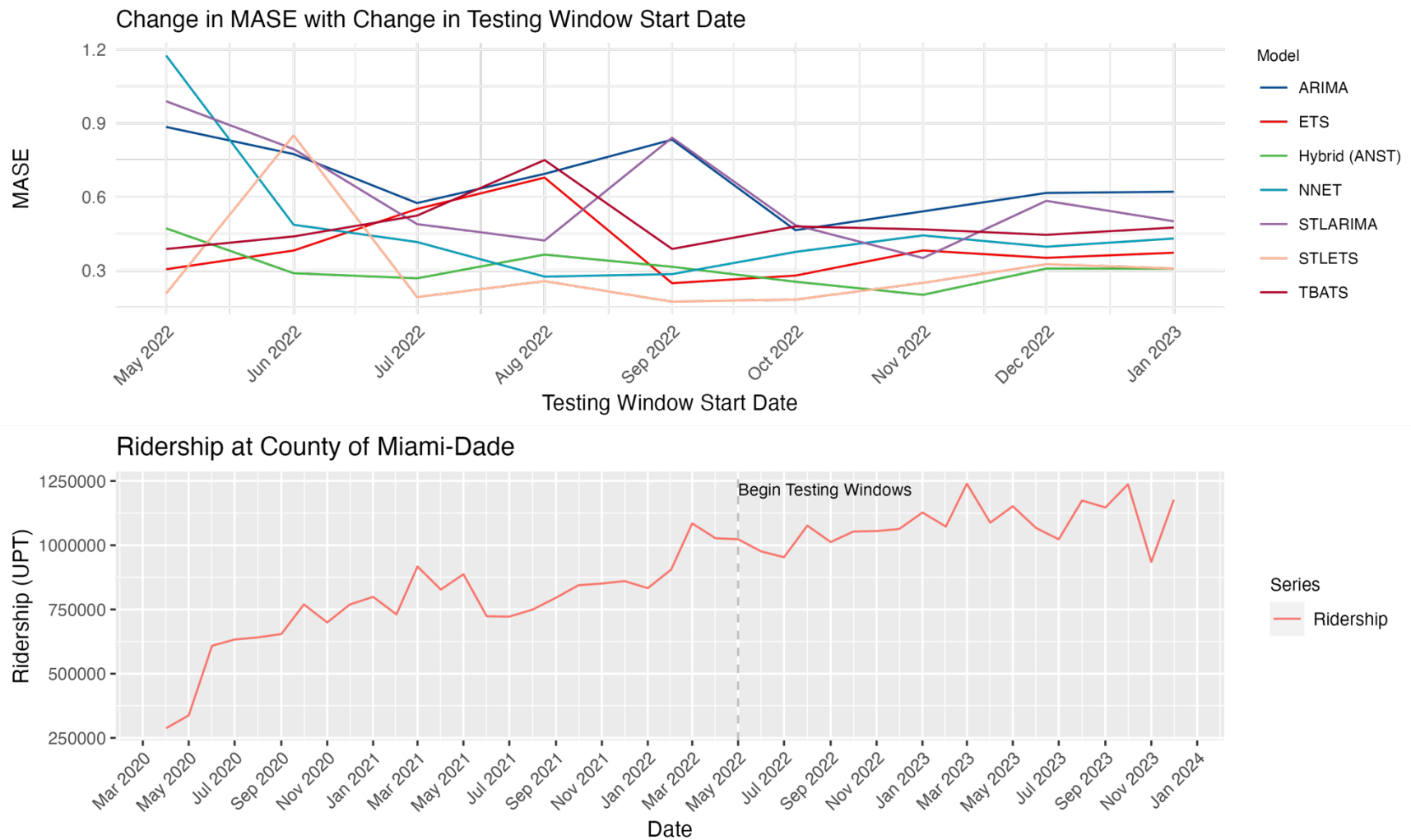


Figure C-11 Post-COVID Change in MASE at the County of Miami-Dade Using the Moving Window

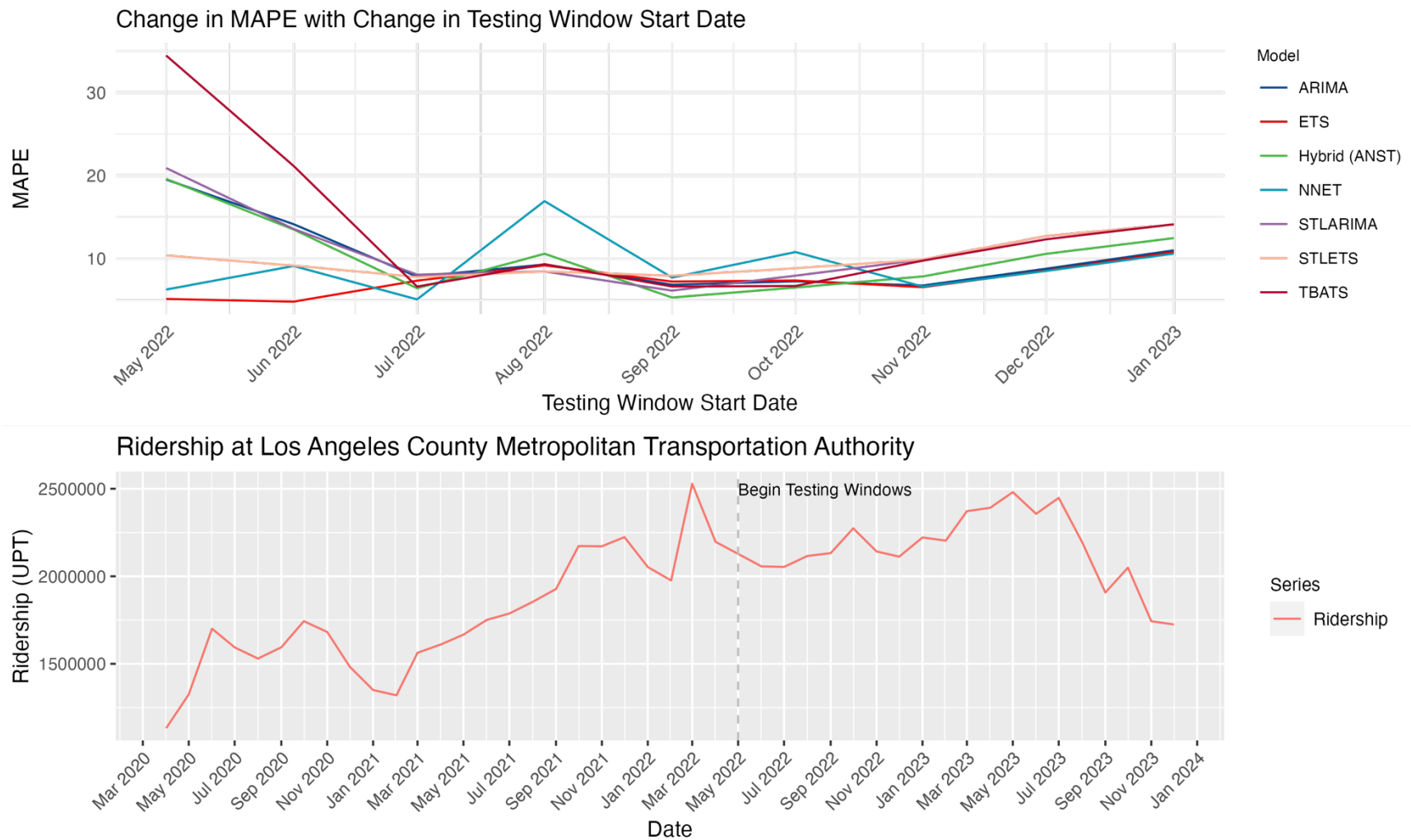


Figure C-12 Post-COVID Change in MAPE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

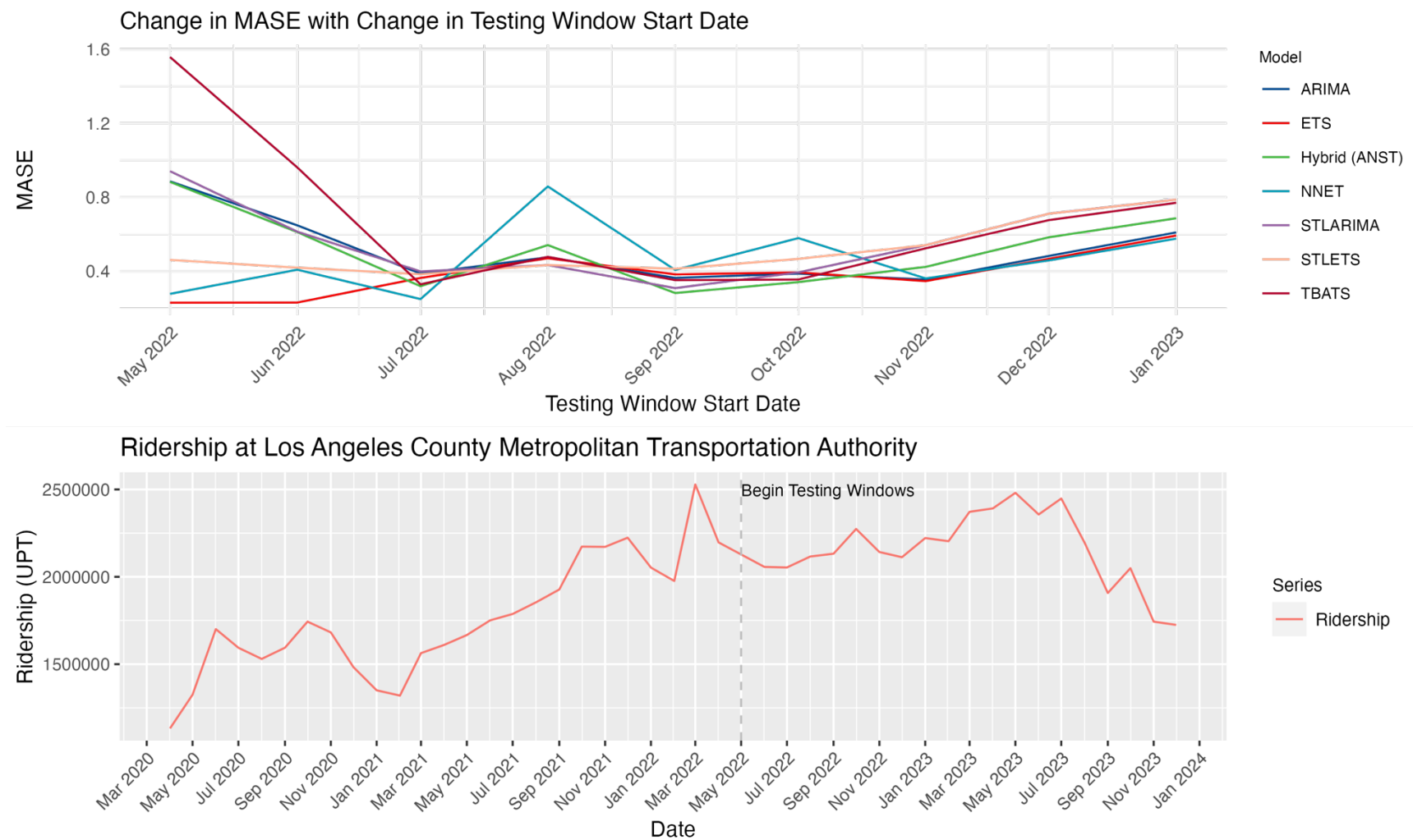


Figure C-13 Change in MASE at the Los Angeles County Metropolitan Transportation Authority Using the Moving Window

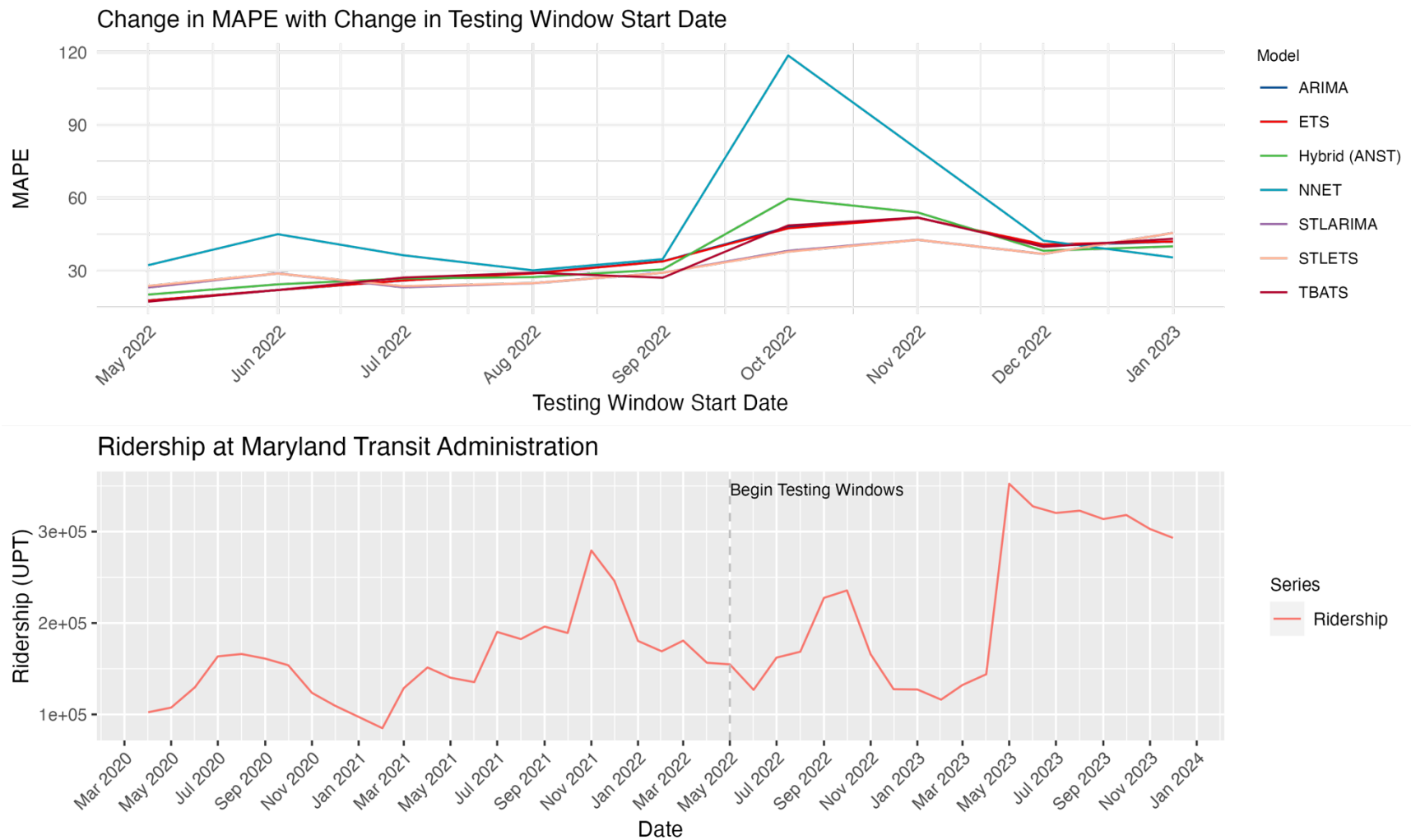


Figure C-14 Post-COVID Change in MAPE at the Maryland Transit Administration Using the Moving Window

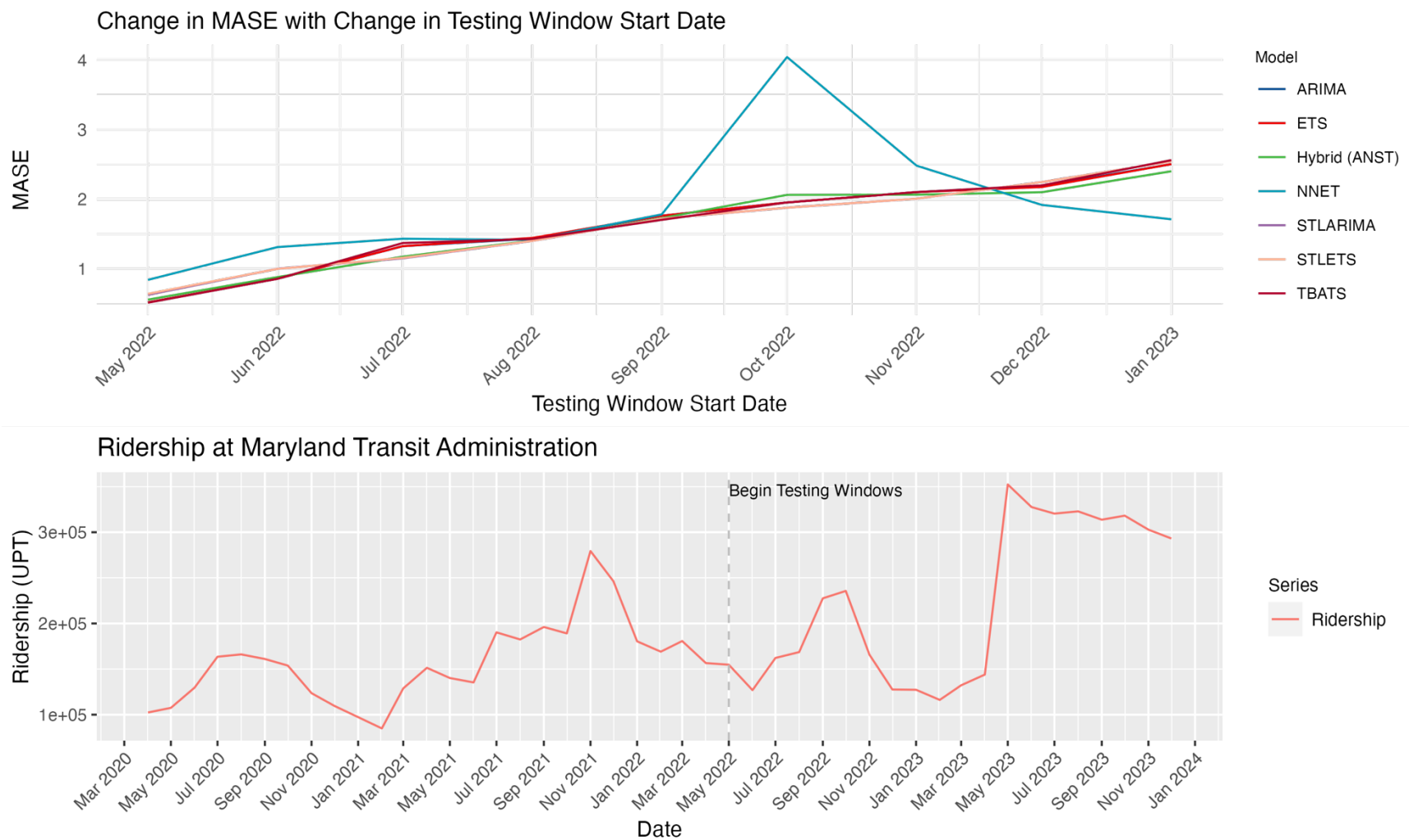


Figure C-15 Post-COVID Change in MASE at the Maryland Transit Administration Using the Moving Window

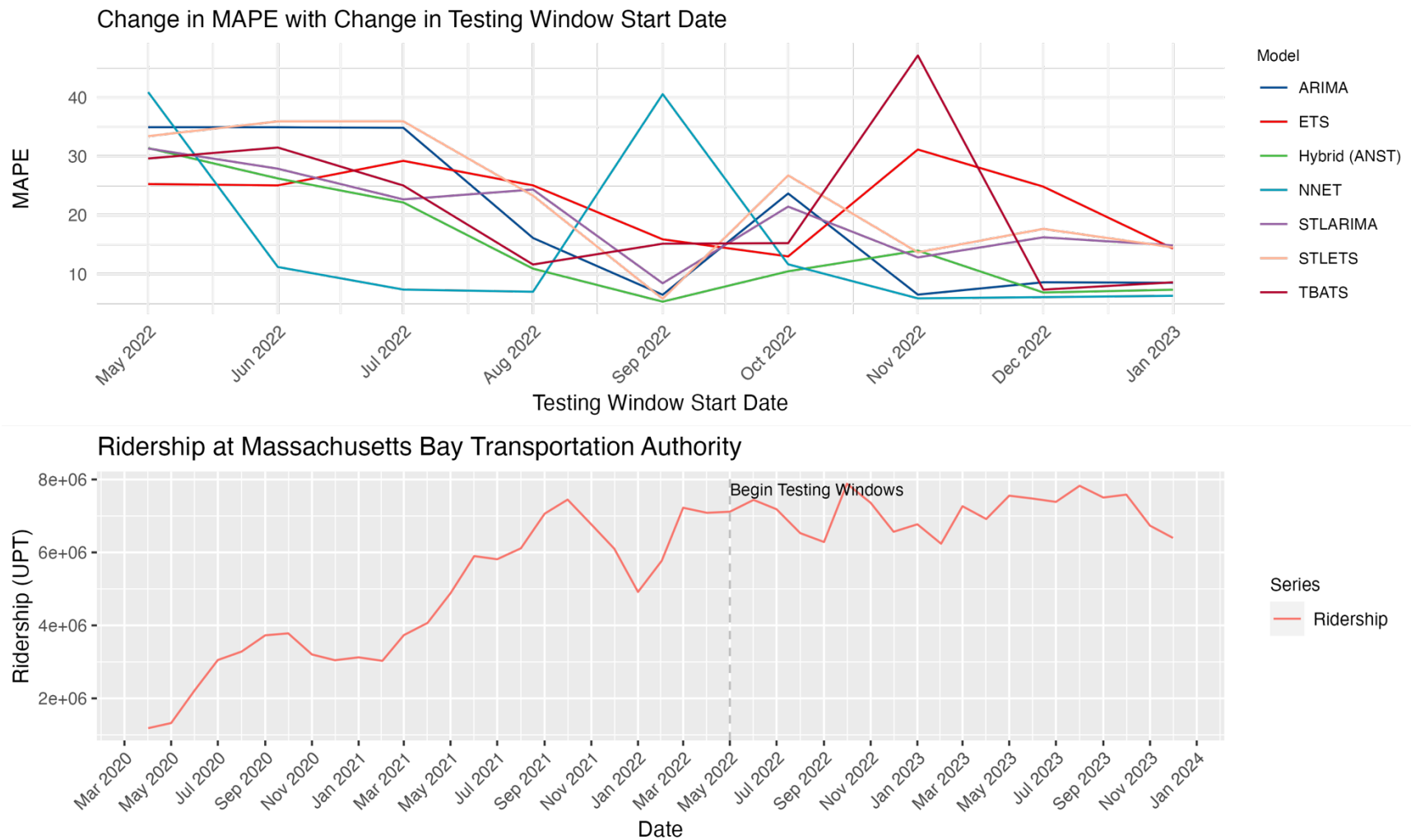


Figure C-16 Post-COVID Change in MAPE at the Massachusetts Bay Transportation Authority Using the Moving Window

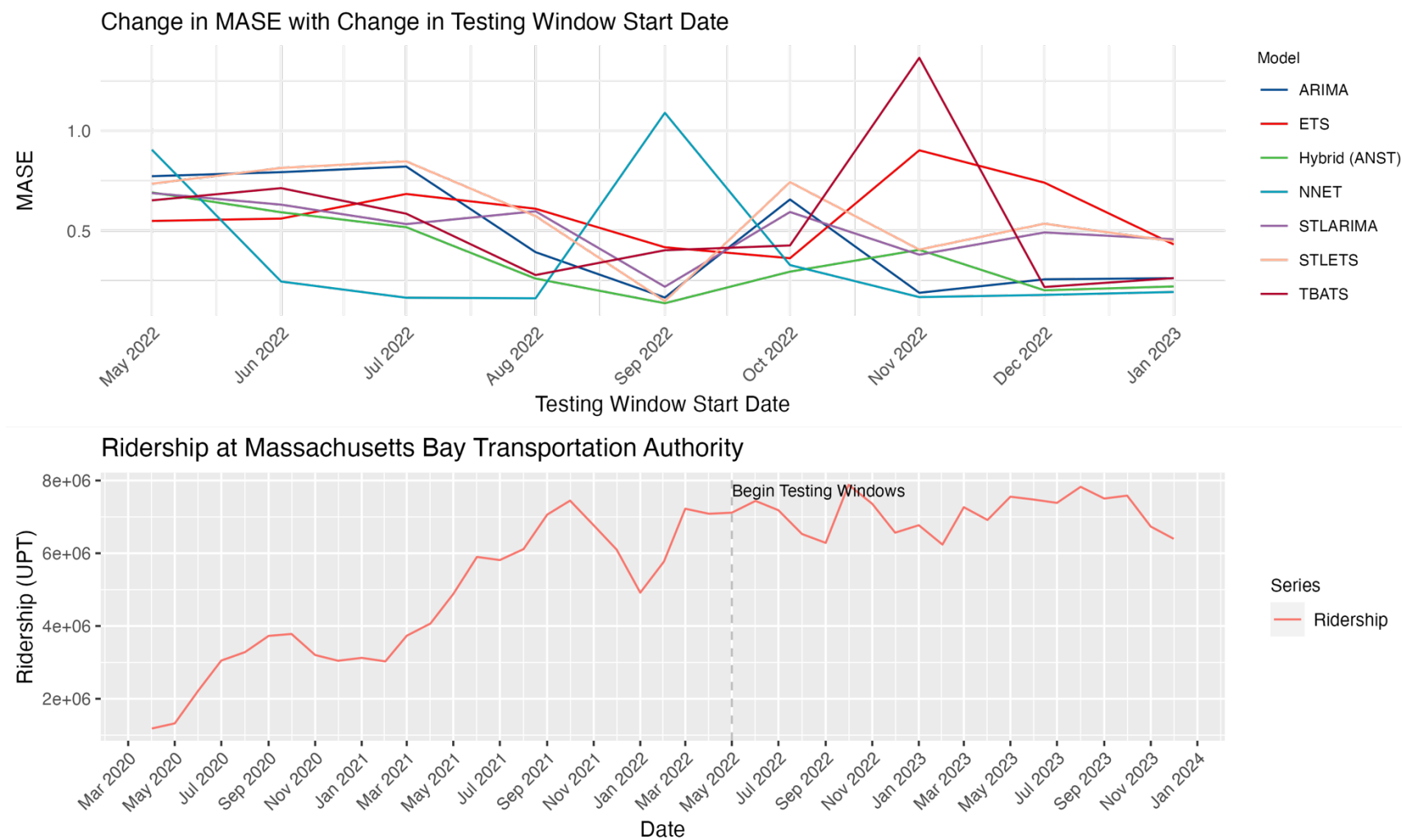


Figure C-17 Post-COVID Change in MASE at the Massachusetts Bay Transportation Authority Using the Moving Window

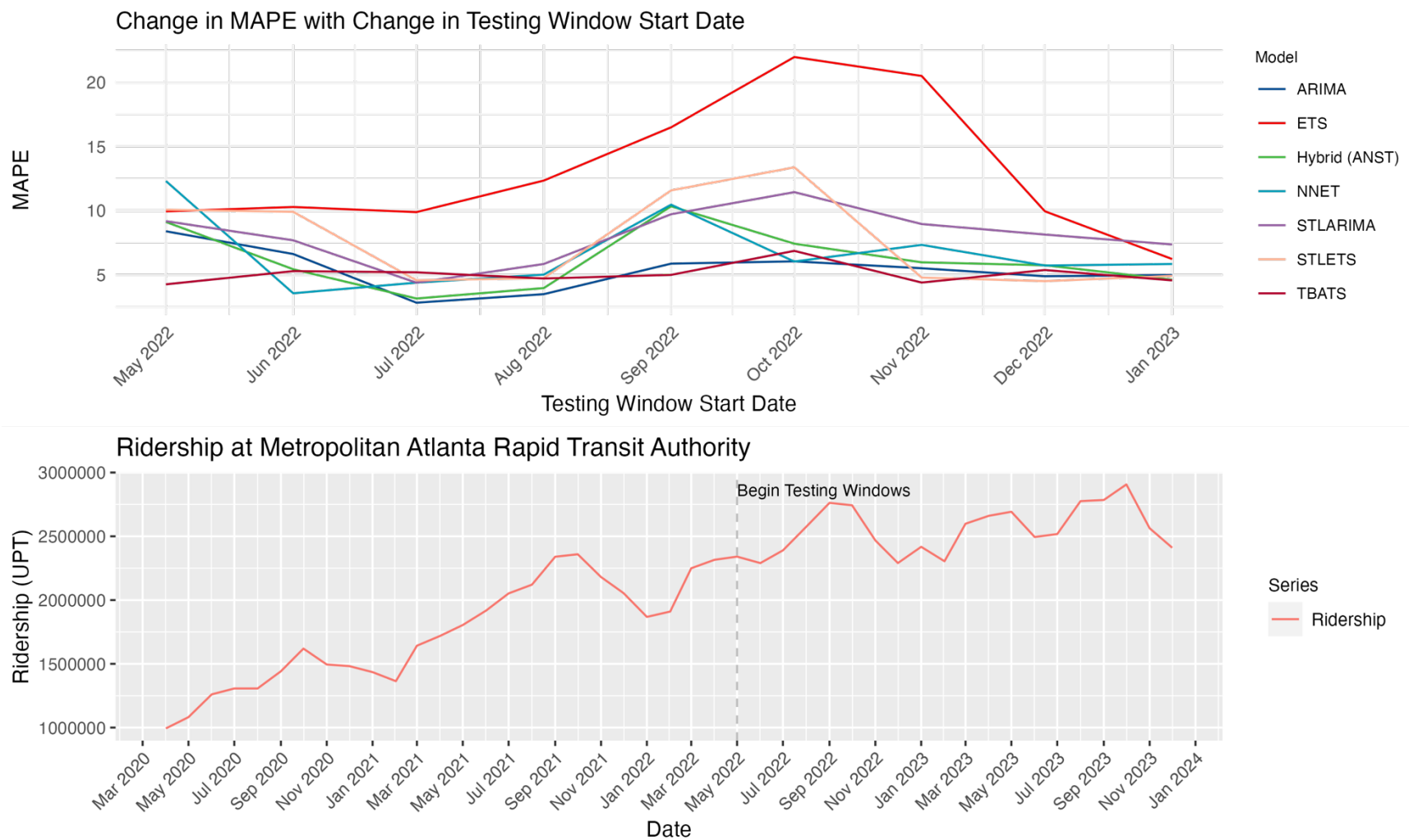


Figure C-18 Post-COVID Change in MAPE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

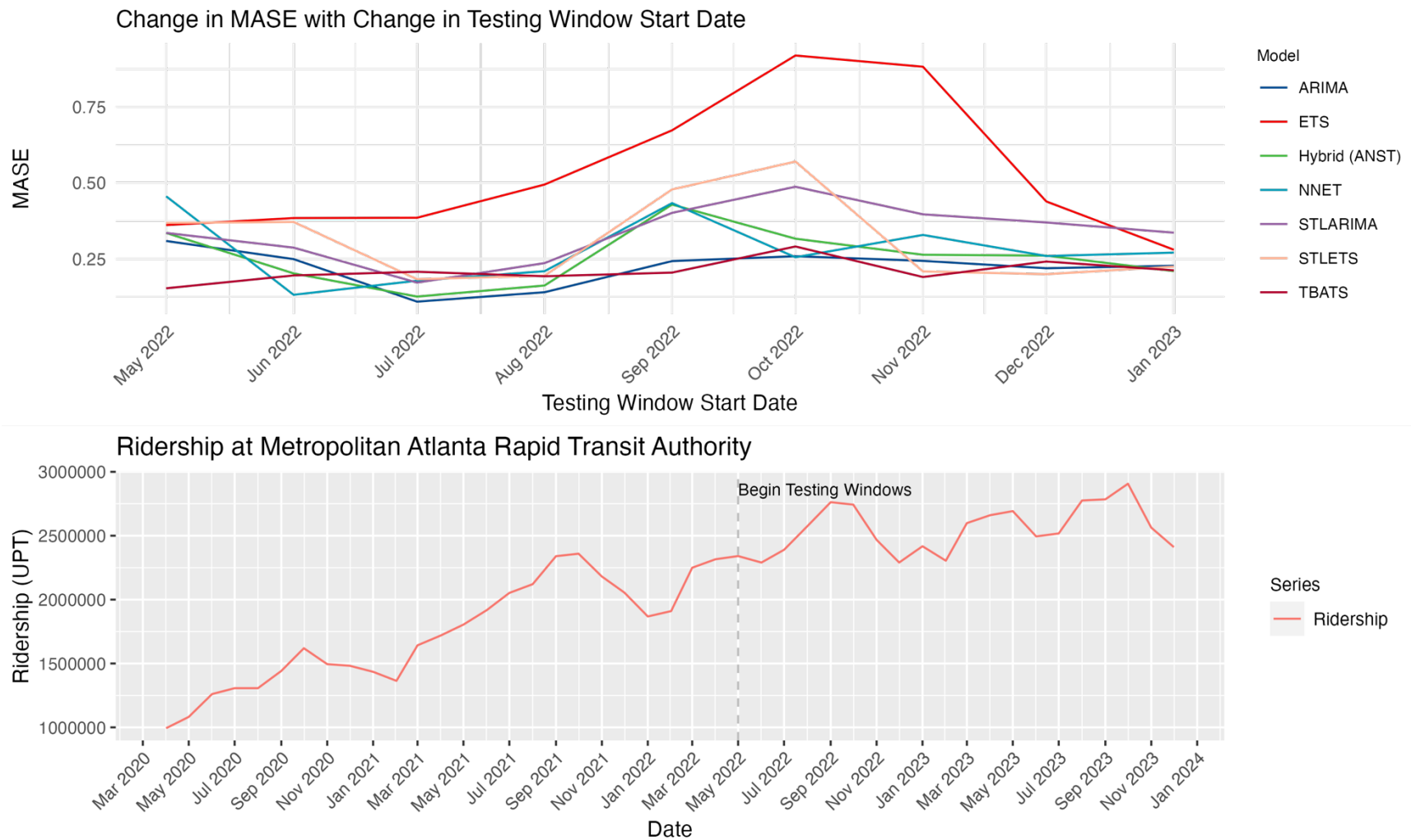


Figure C-19 Post-COVID Change in MASE at the Metropolitan Atlanta Rapid Transit Authority Using the Moving Window

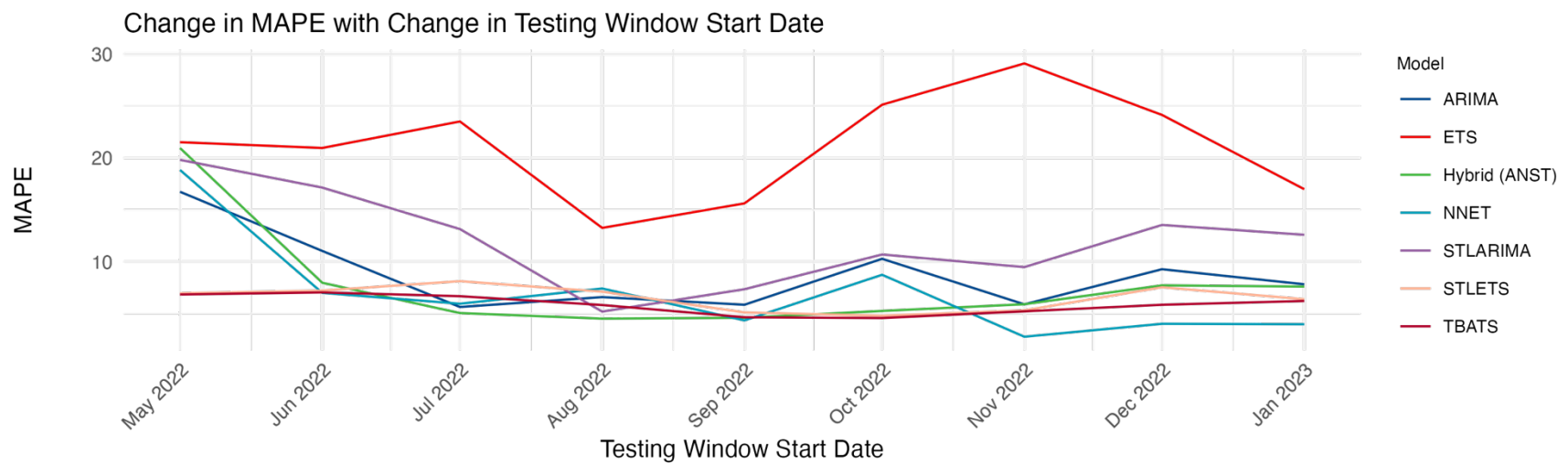
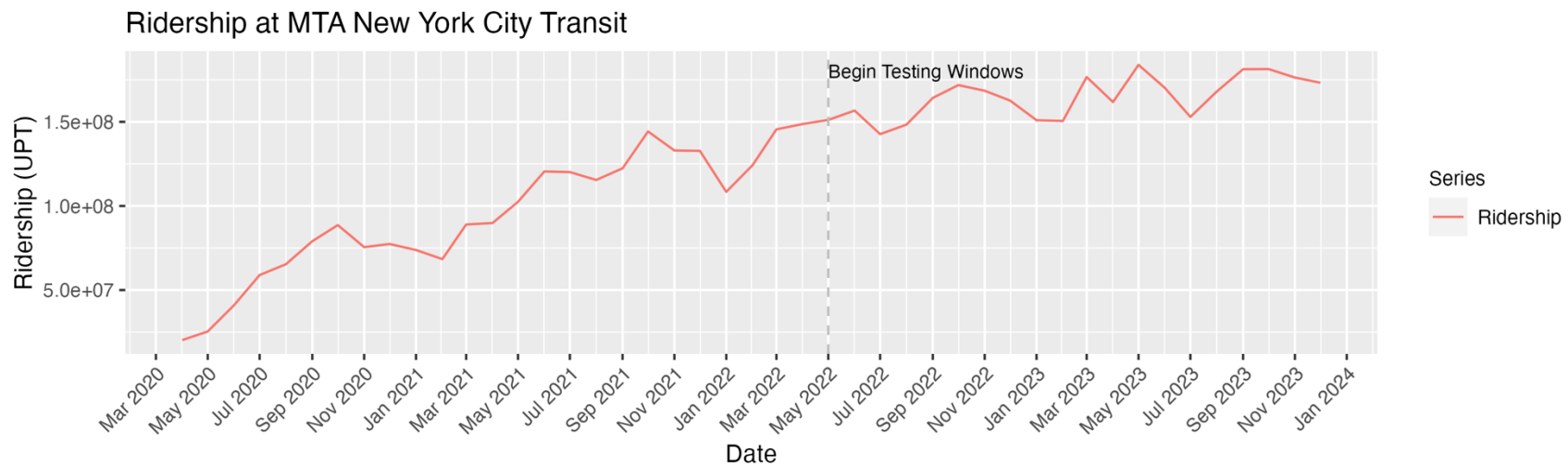


Figure C-20 Post-COVID Change in MAPE at MTA New York City Transit Using the Moving Window

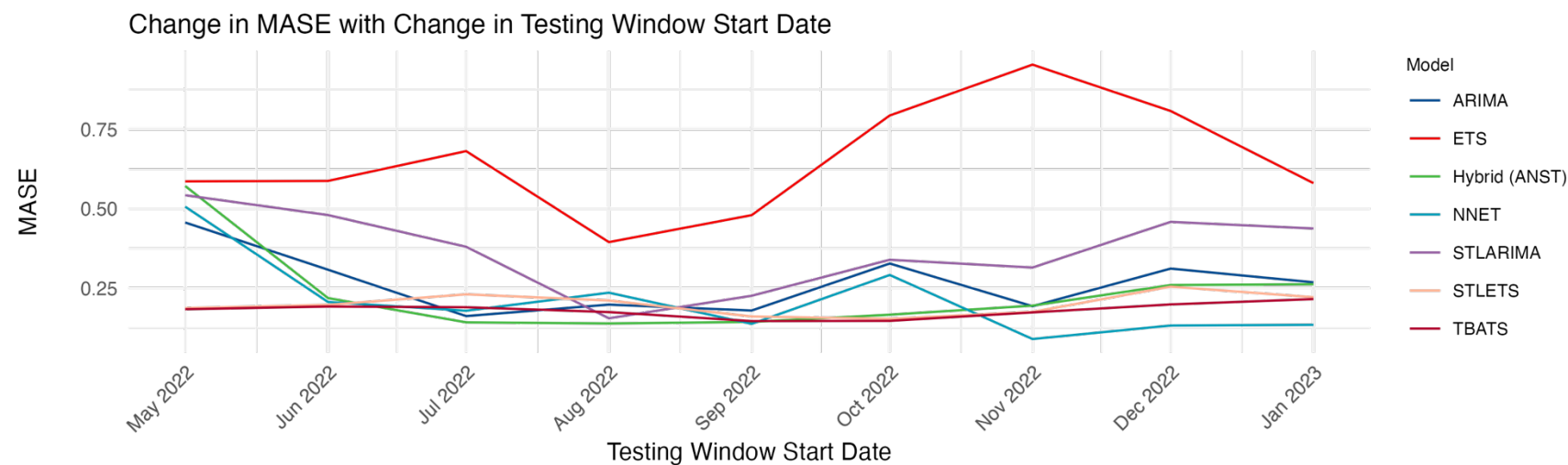
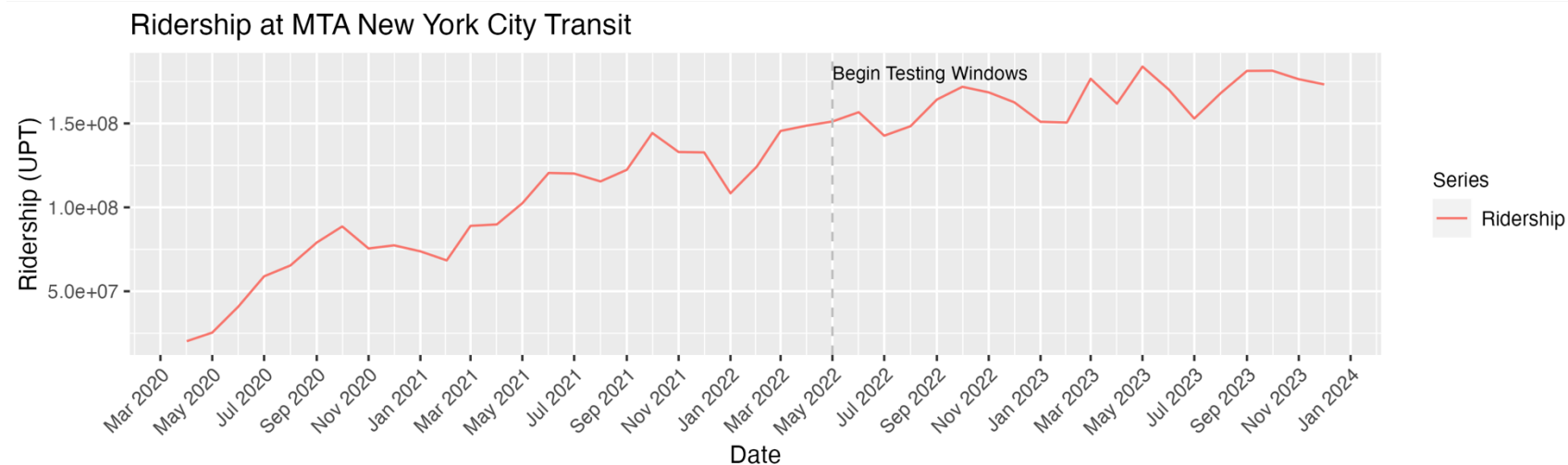


Figure C-21 Post-COVID Change in MASE at MTA New York City Transit Using the Moving Window

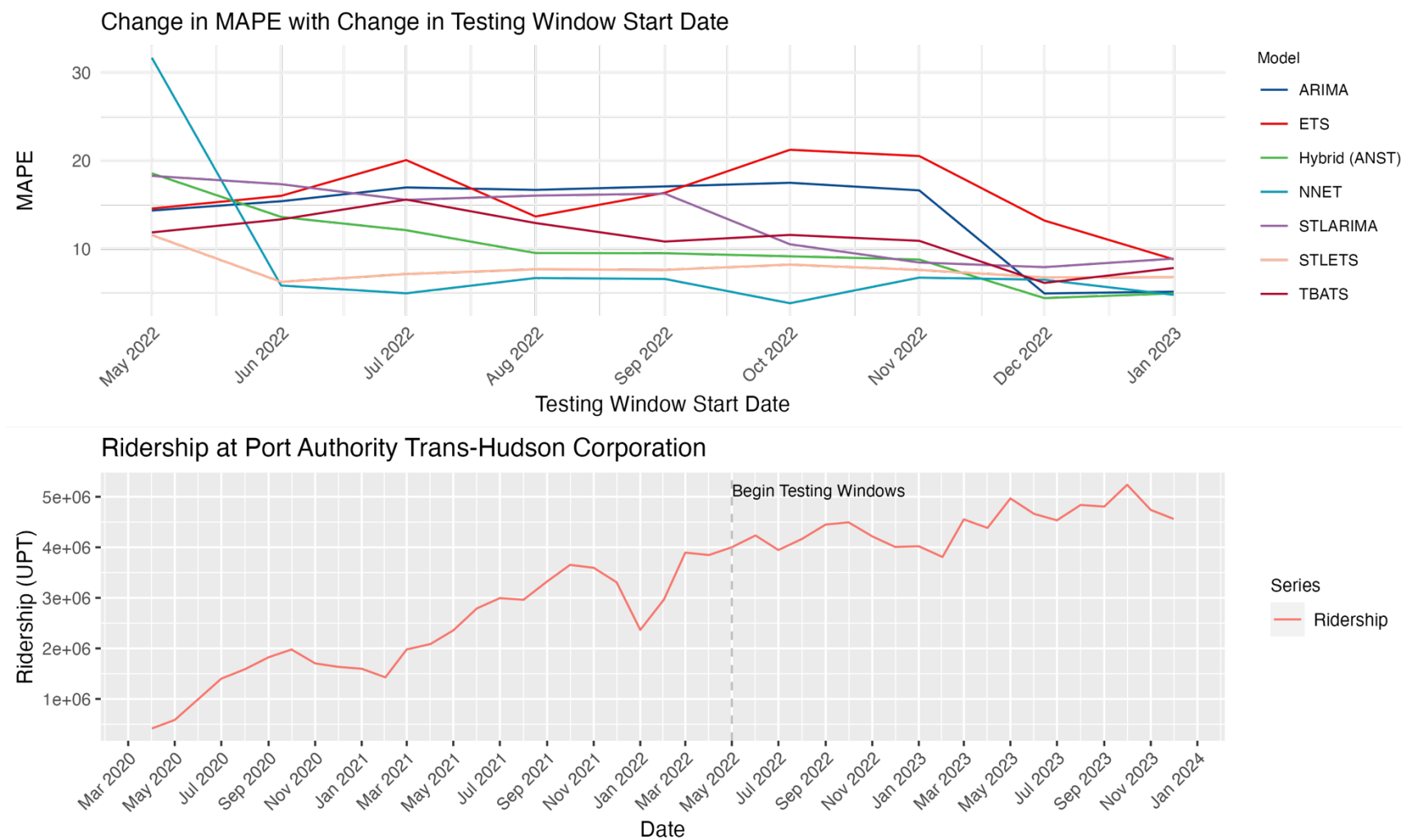


Figure C-22 Post-COVID Change in MAPE at the Port Authority Trans-Hudson Corporation Using the Moving Window

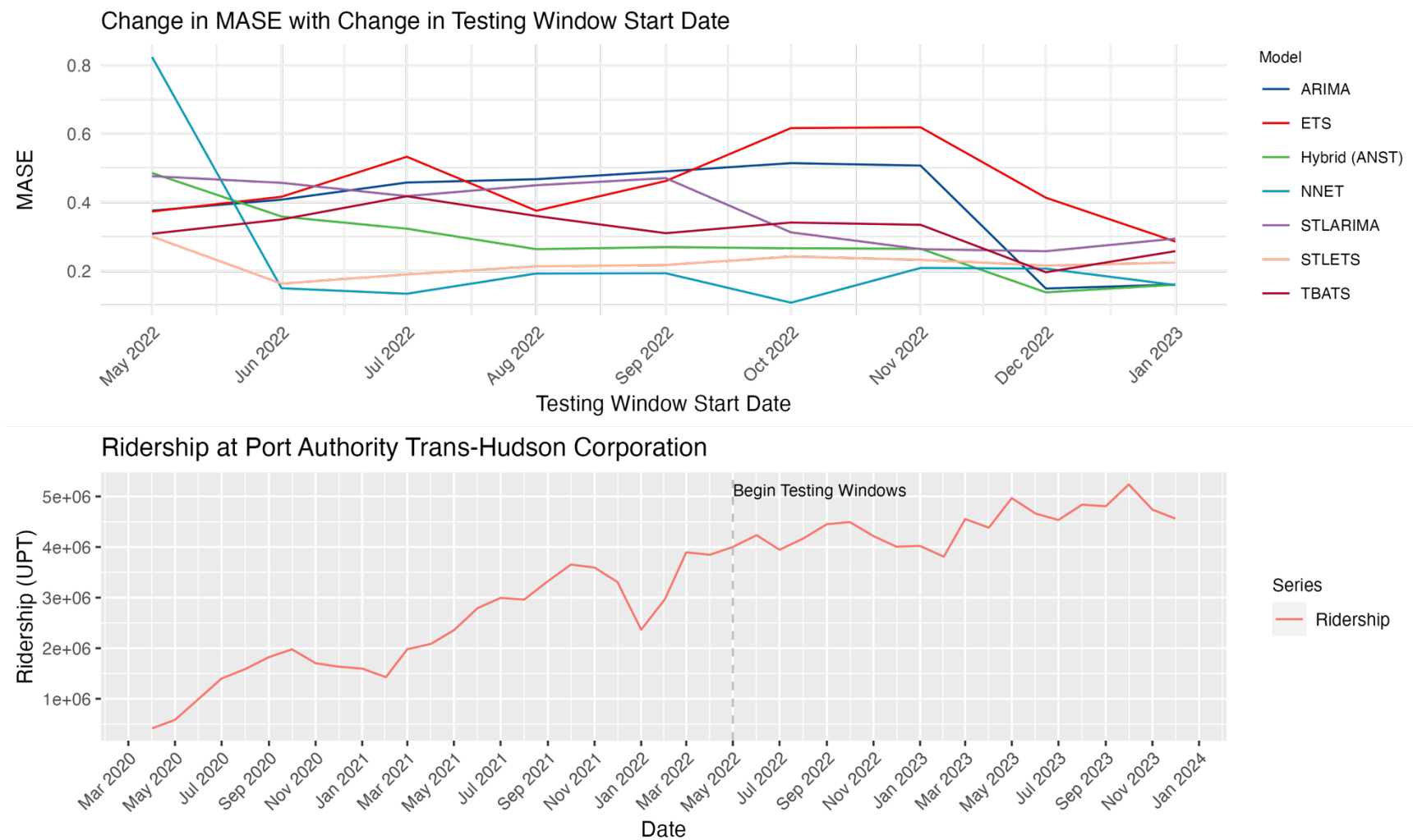


Figure C-23 Post-COVID Change in MASE at the Port Authority Trans-Hudson Corporation Using the Moving Window

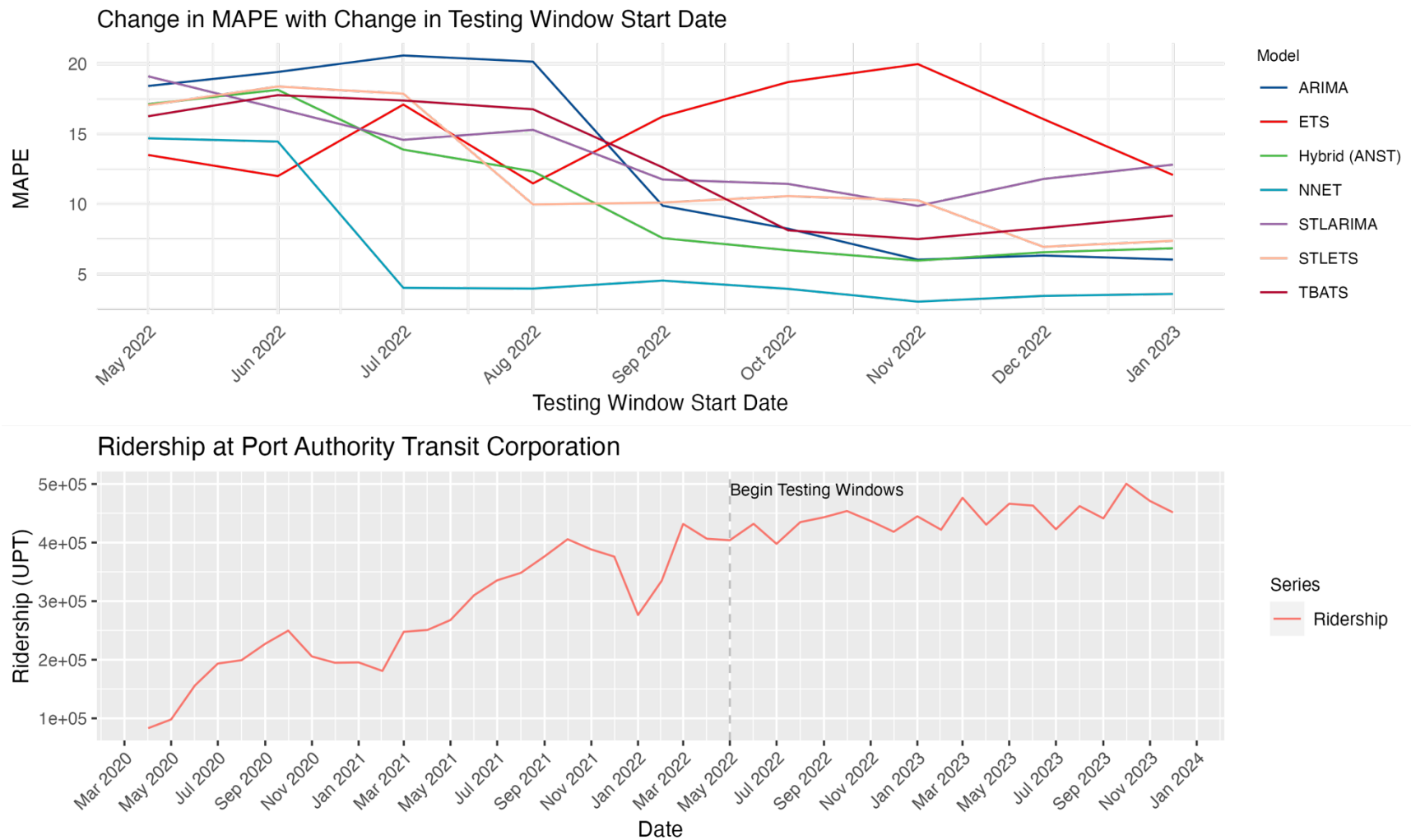


Figure C-24 Post-COVID Change in MAPE at the Port Authority Transit Corporation Using the Moving Window

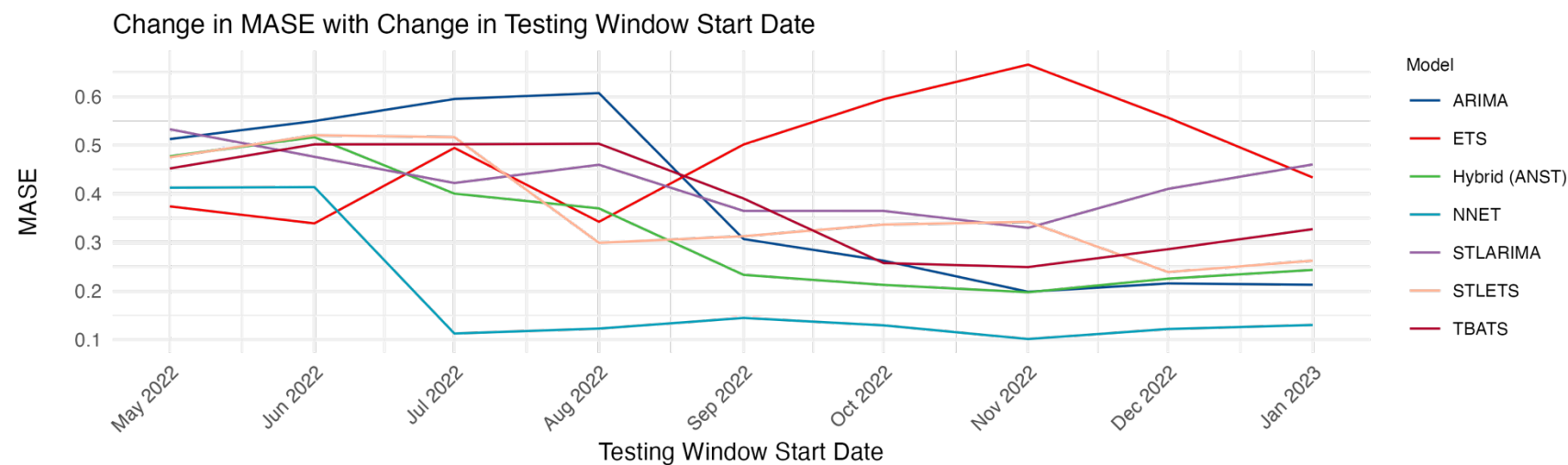
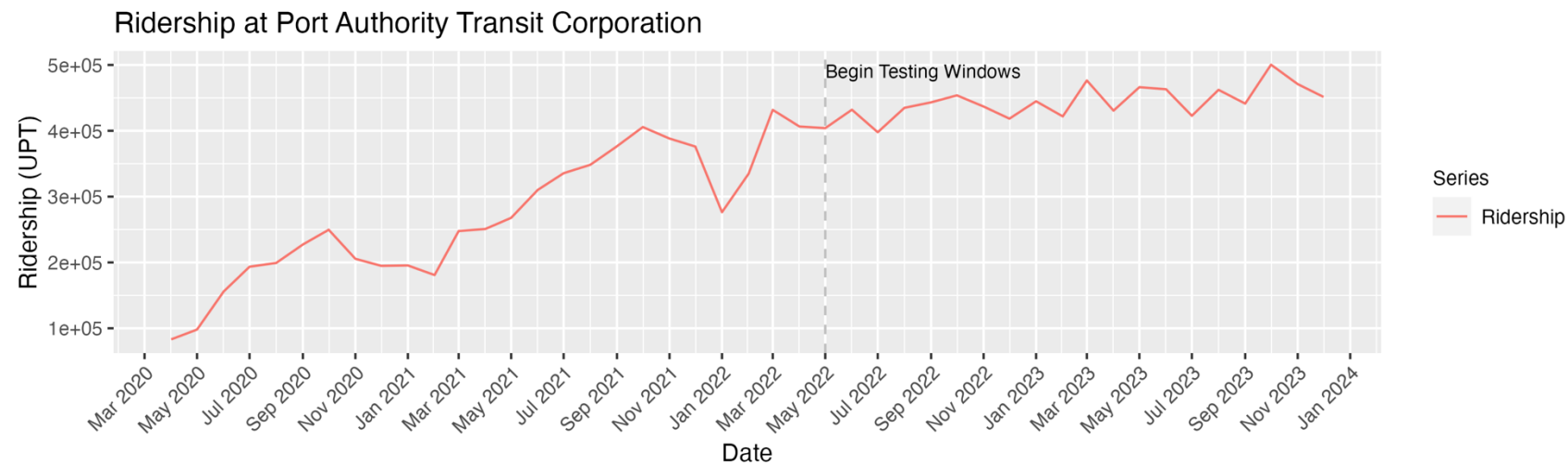


Figure C-25 Post-COVID Change in MASE at the Port Authority Transit Corporation Using the Moving Window

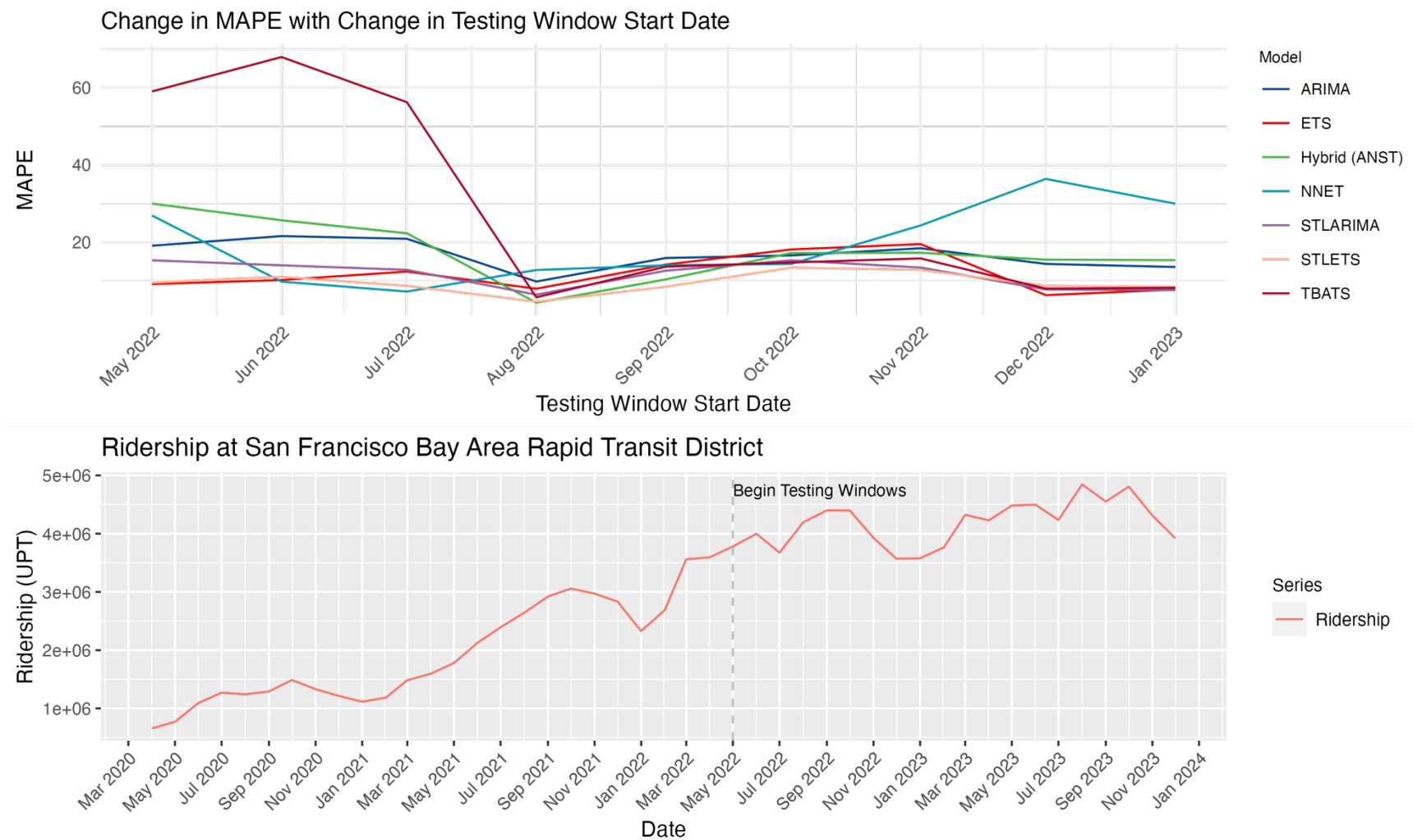


Figure C-26 Post-COVID Change in MAPE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

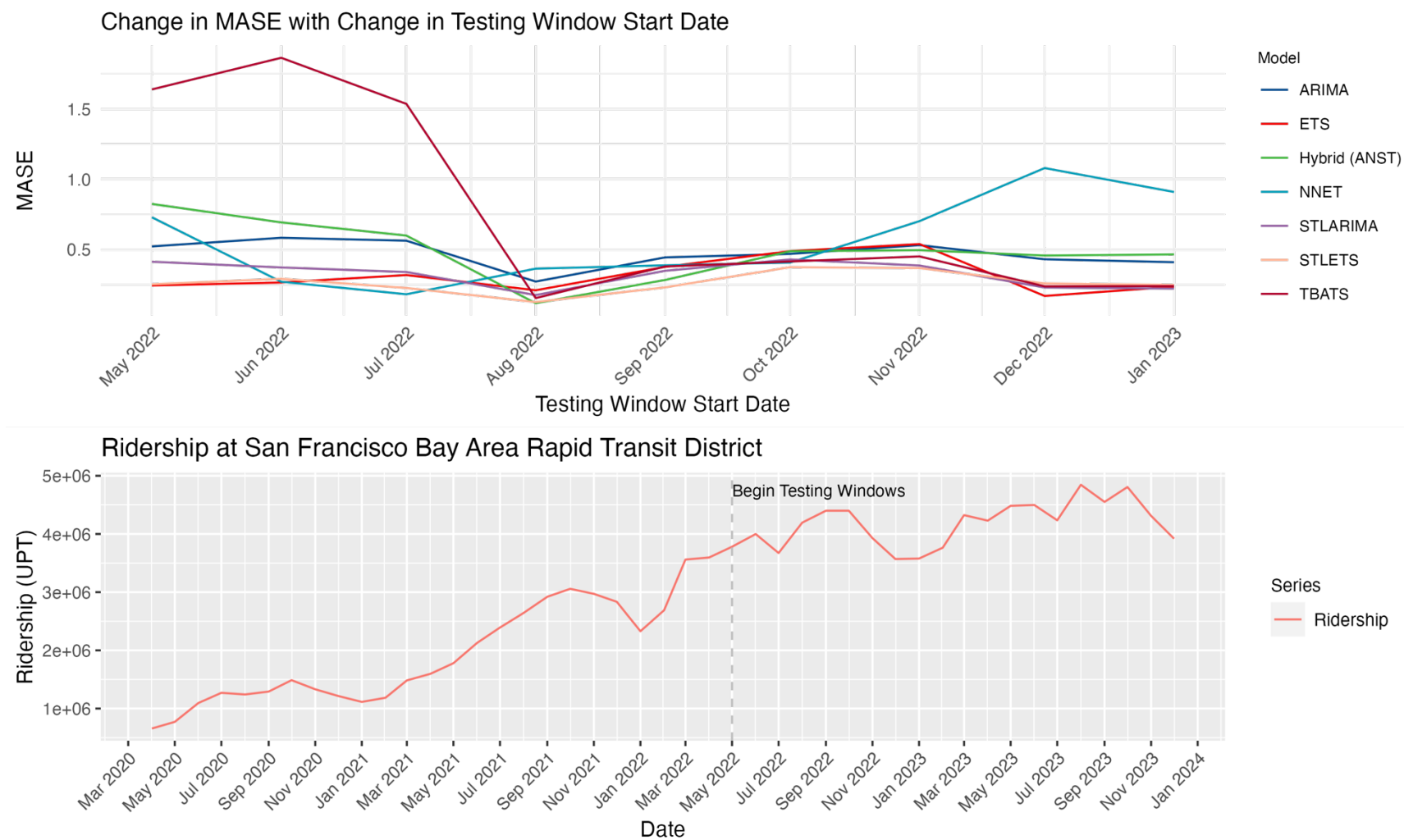


Figure C-27 Post-COVID Change in MASE at the San Francisco Bay Area Rapid Transit District Using the Moving Window

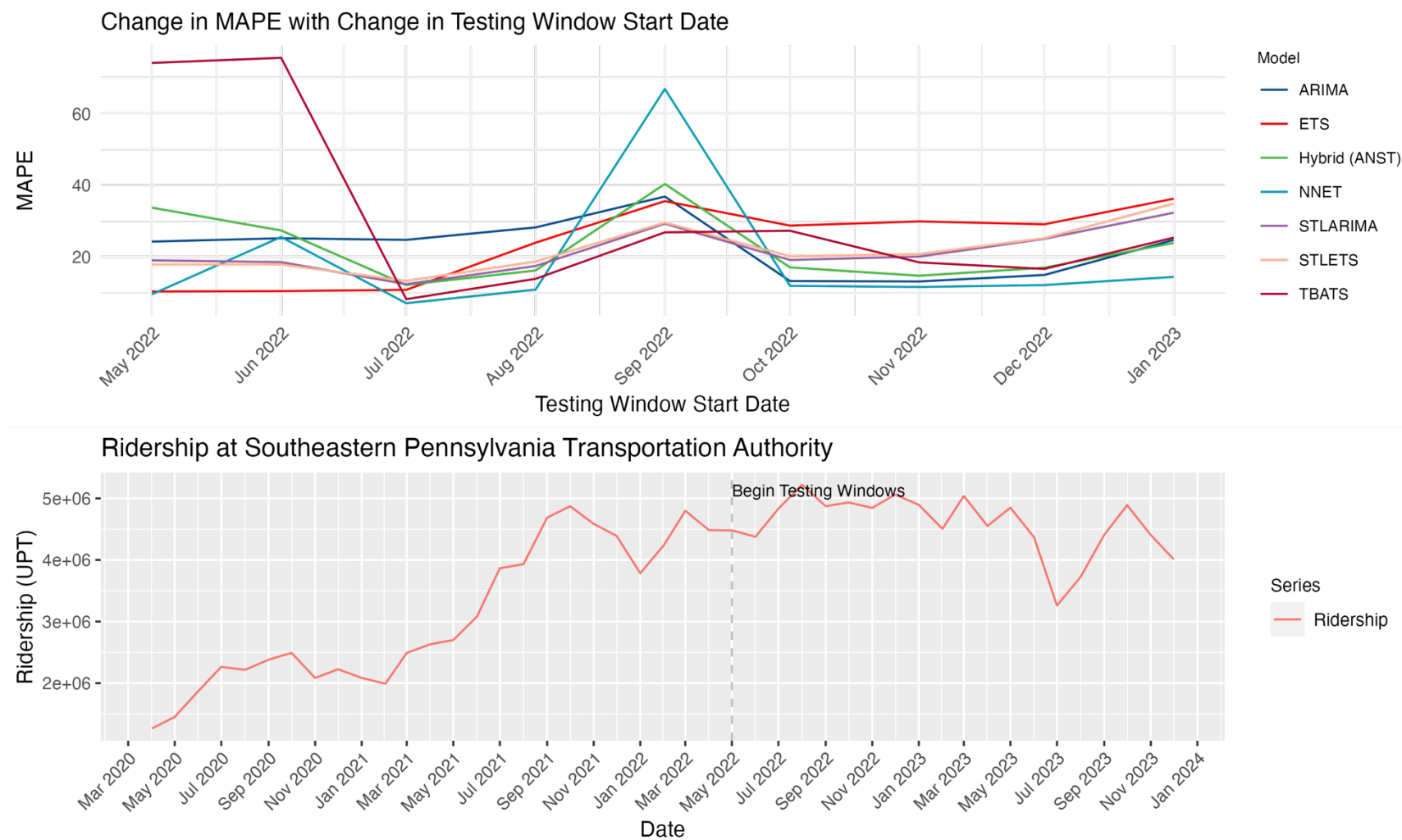


Figure C-28 Post-COVID Change in MAPE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

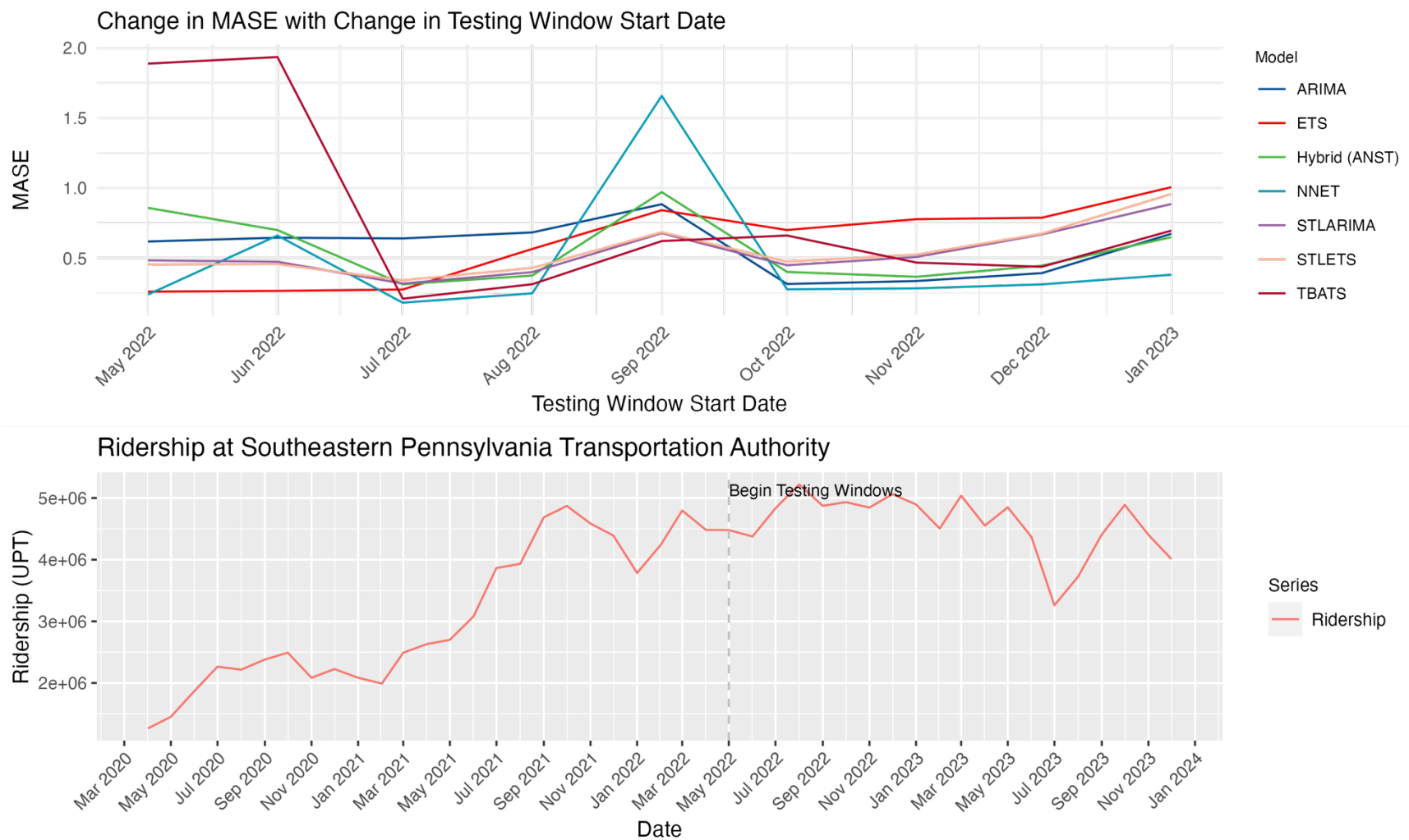


Figure C-29 Post-COVID Change in MASE at the Southeastern Pennsylvania Transportation Authority Using the Moving Window

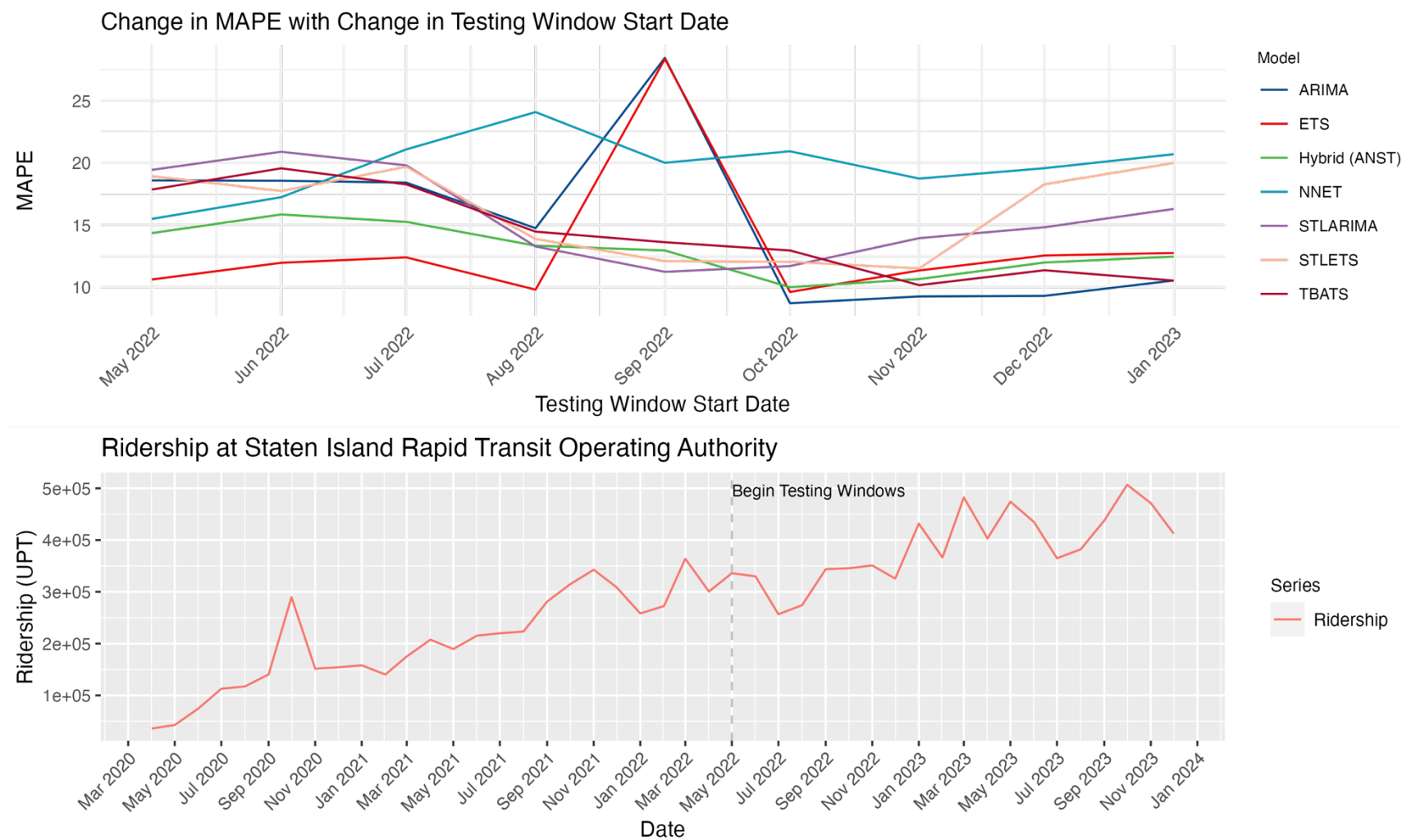


Figure C-30 Post-COVID Change in MAPE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

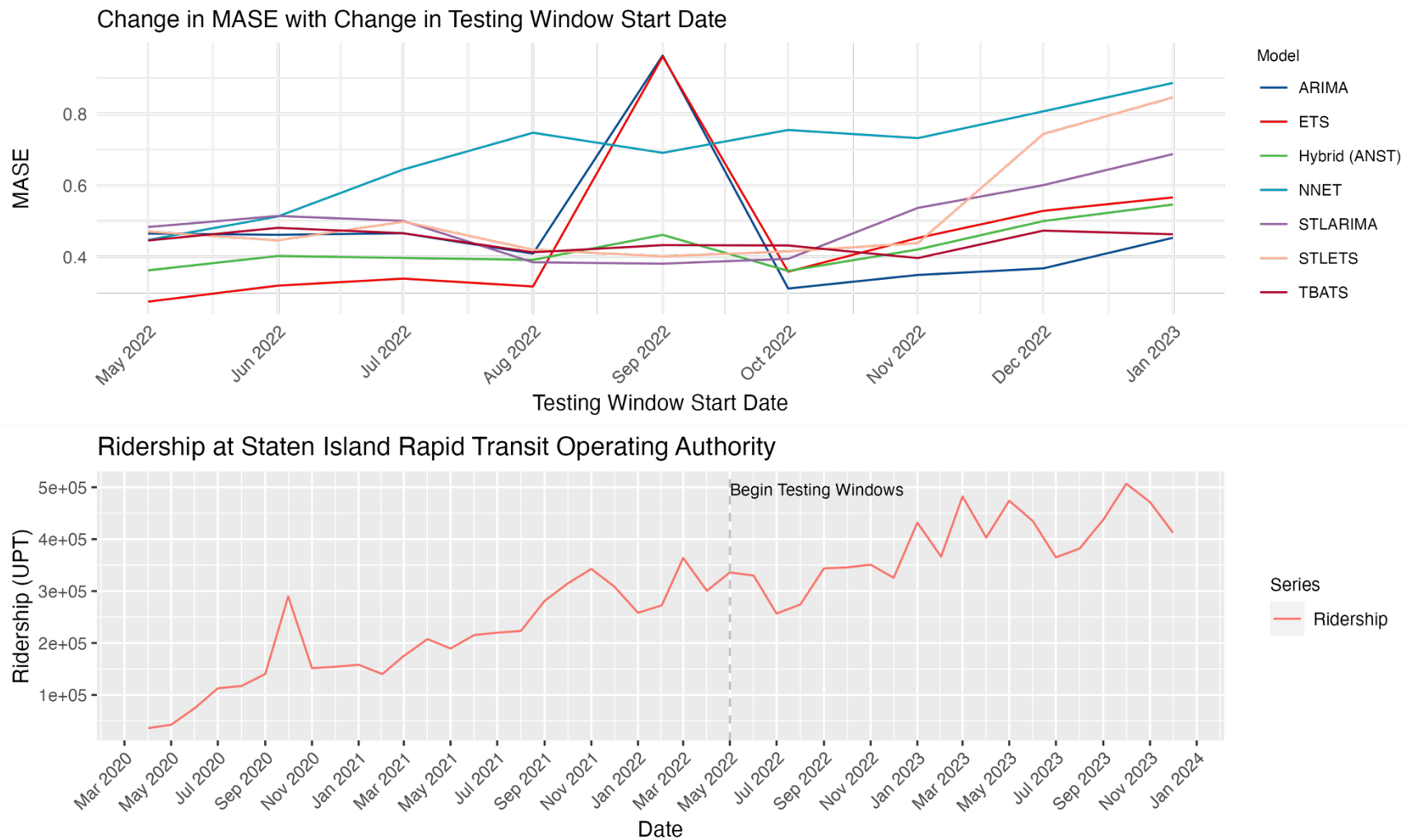


Figure C-31 Post-COVID Change in MASE at the Staten Island Rapid Transit Operating Authority Using the Moving Window

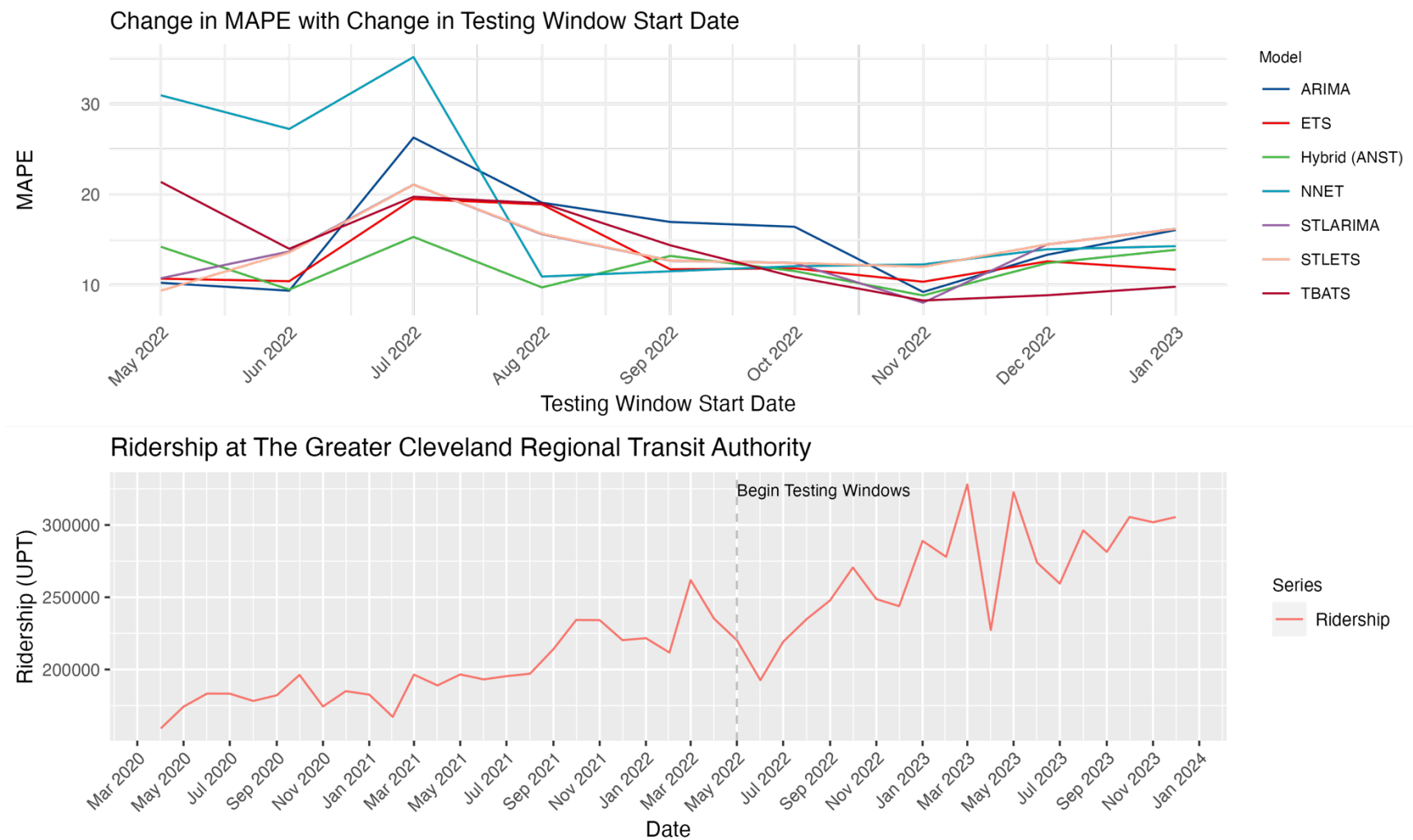


Figure C-32 Post-COVID Change in MAPE at the Greater Cleveland Regional Transit Authority Using the Moving Window

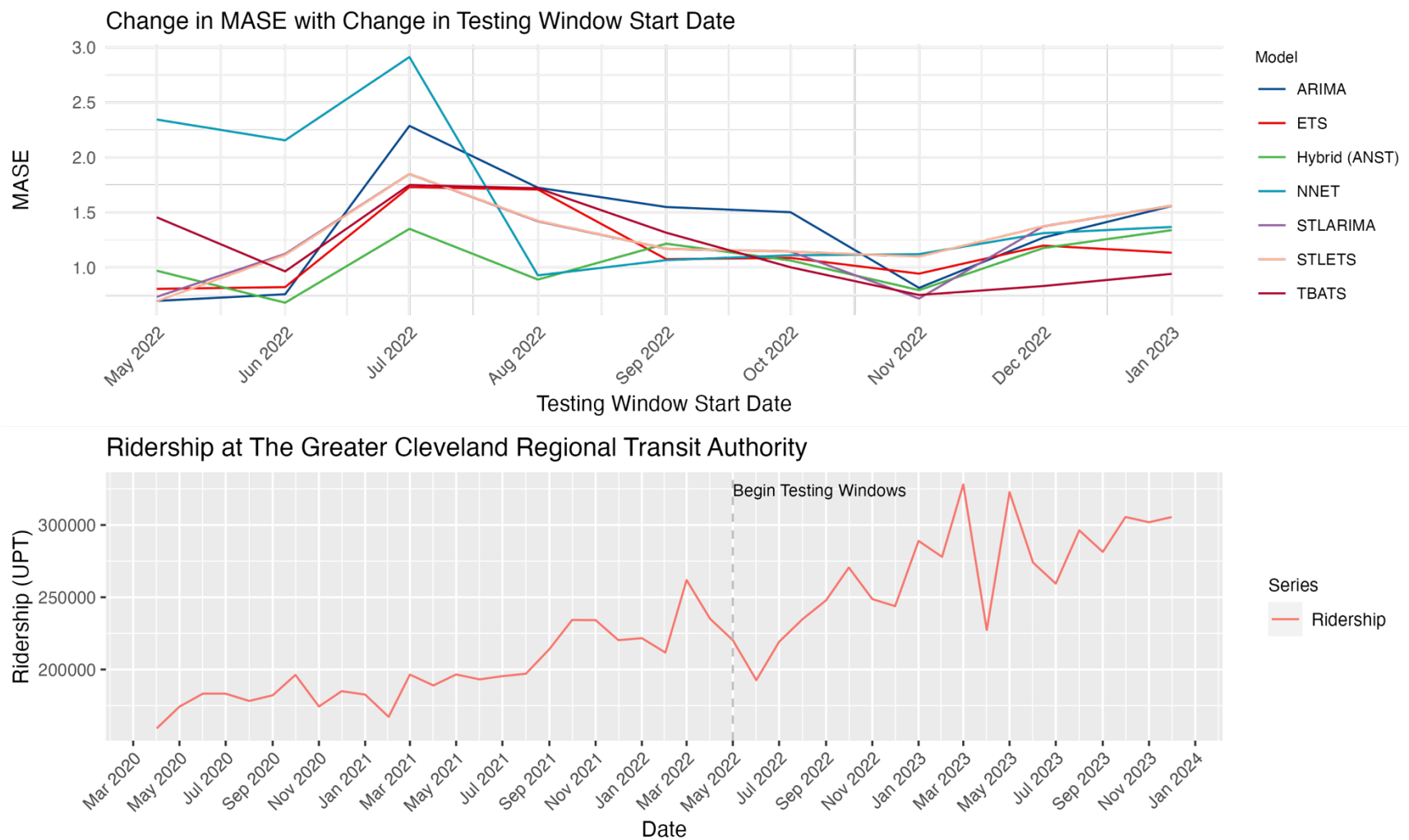


Figure C-33 Post-COVID Change in MASE at the Greater Cleveland Regional Transit Authority Using the Moving Window

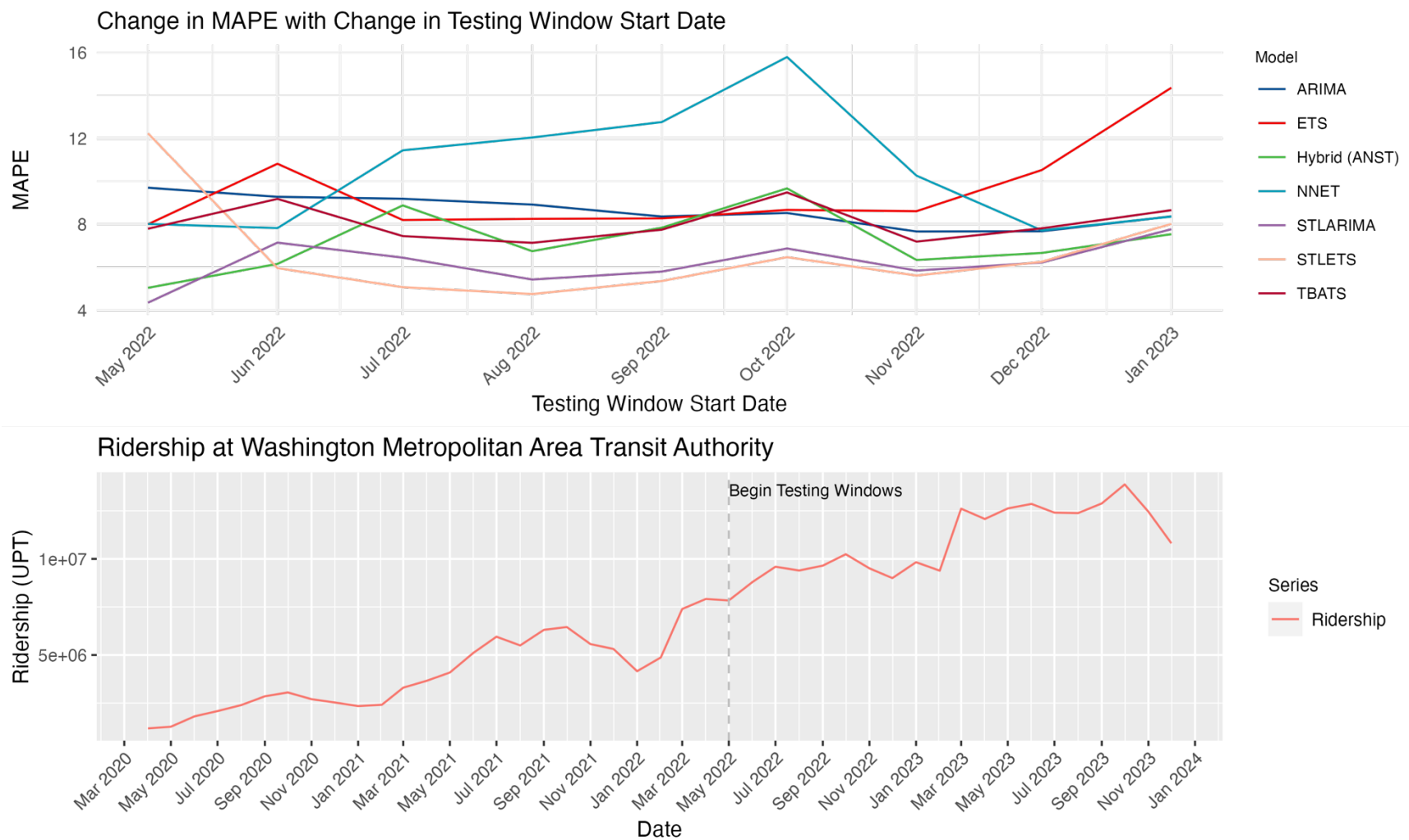


Figure C-34 Post-COVID Change in MAPE at the Washington Metropolitan Area Transit Authority Using the Moving Window

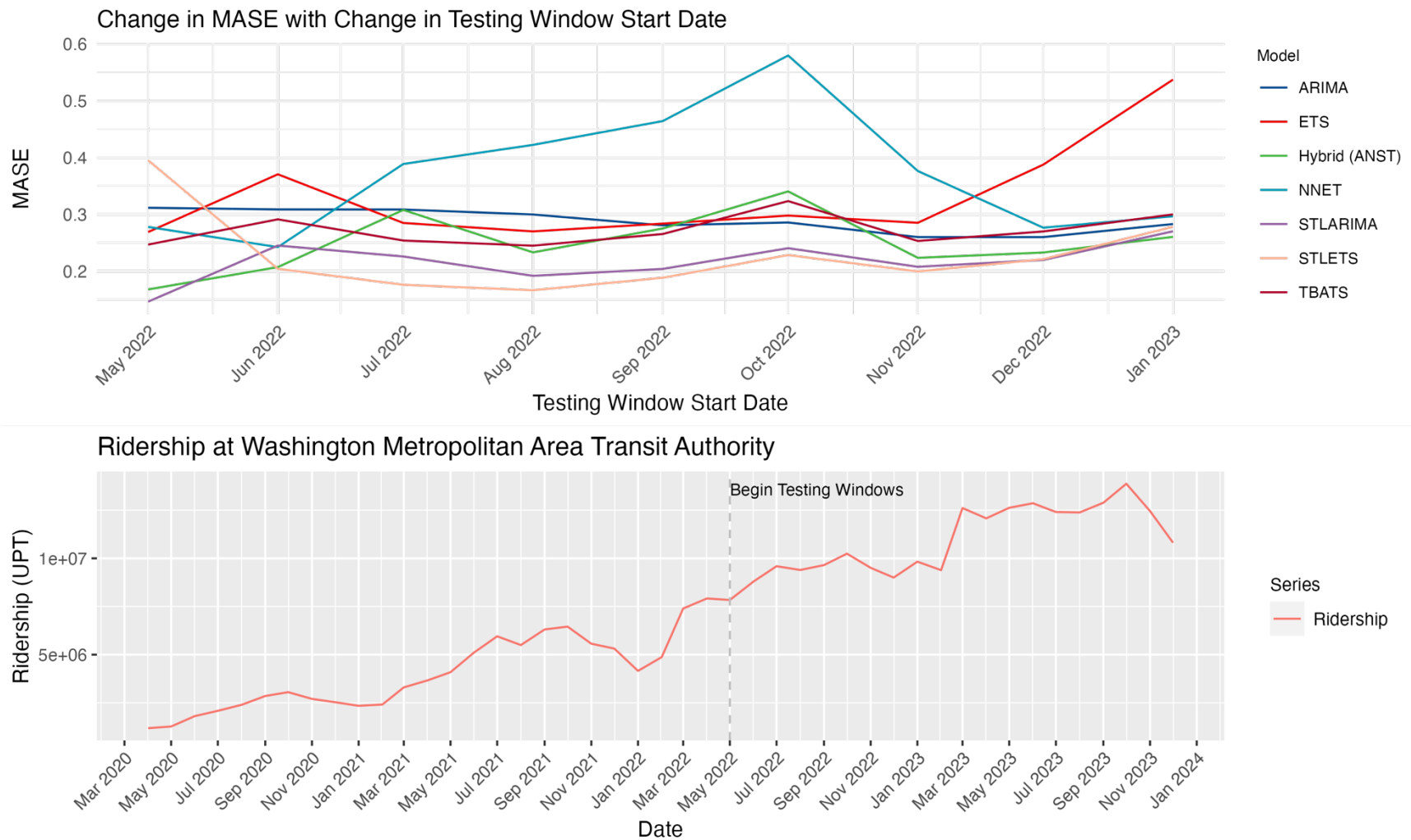


Figure C-35 Post-COVID Change in MASE at the Washington Metropolitan Area Transit Authority Using the Moving Window

Part D: Pre-COVID Forecasts for March 2019 to February 2020

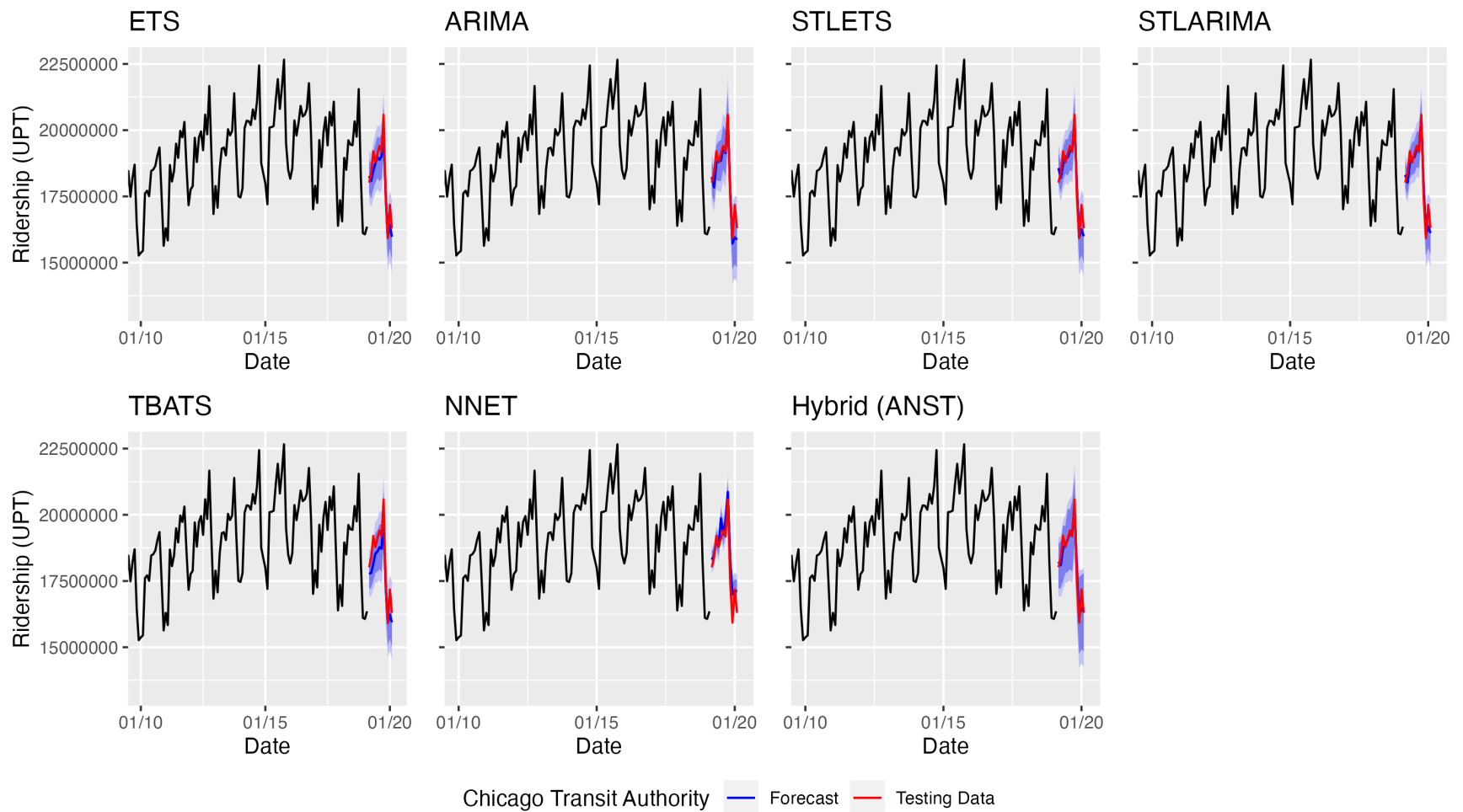


Figure D-1 Pre-COVID Forecasts of Ridership at the Chicago Transit Authority from March 2019 to February 2020

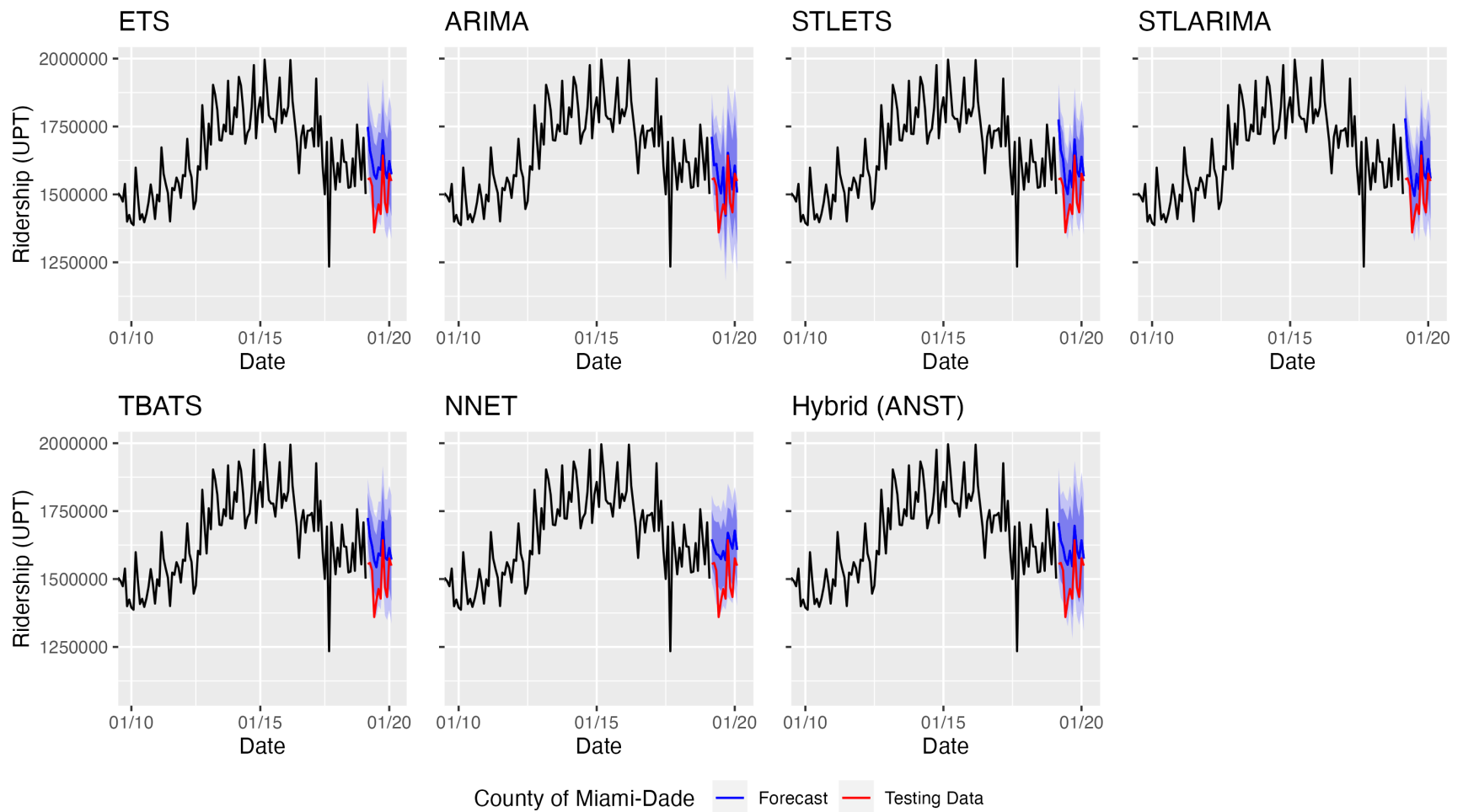


Figure D-2 Pre-COVID Forecasts of Ridership at the County of Miami-Dade from March 2019 to February 2020

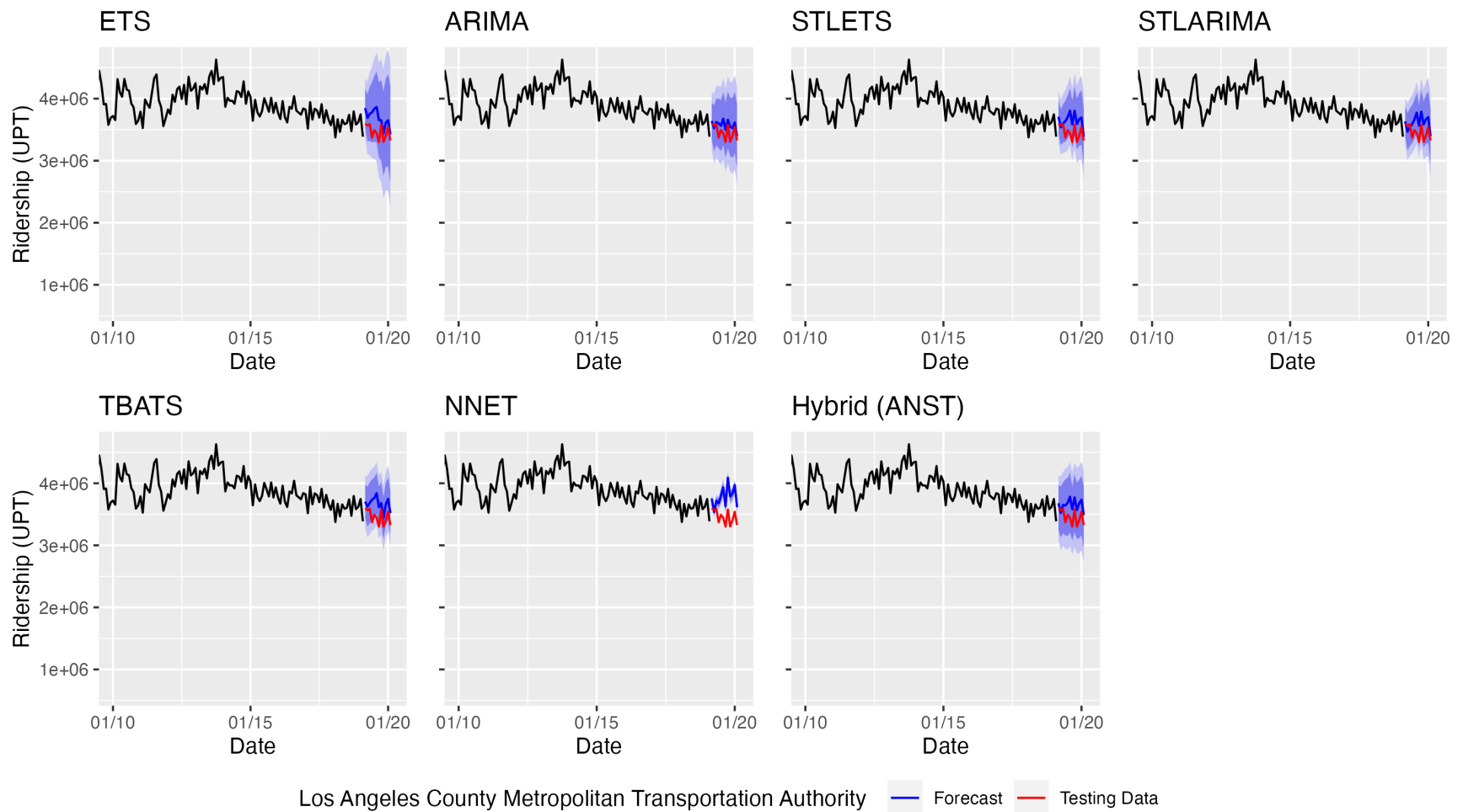


Figure D-3 Pre-COVID Forecasts of Ridership at the Los Angeles County Metropolitan Transportation Authority from March 2019 to February 2020

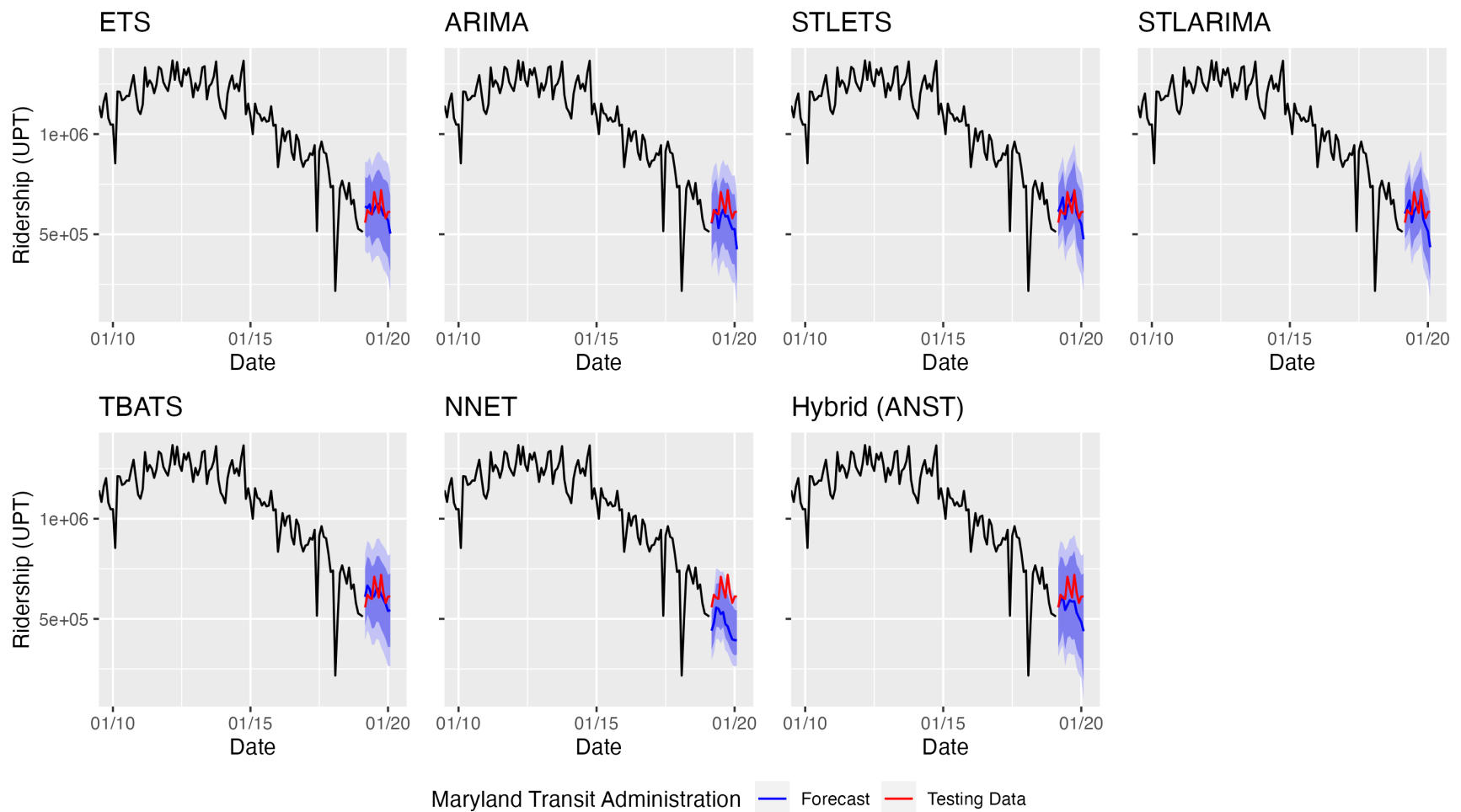


Figure D-4 Pre-COVID Forecasts of Ridership at the Maryland Transit Administration from March 2019 to February 2020

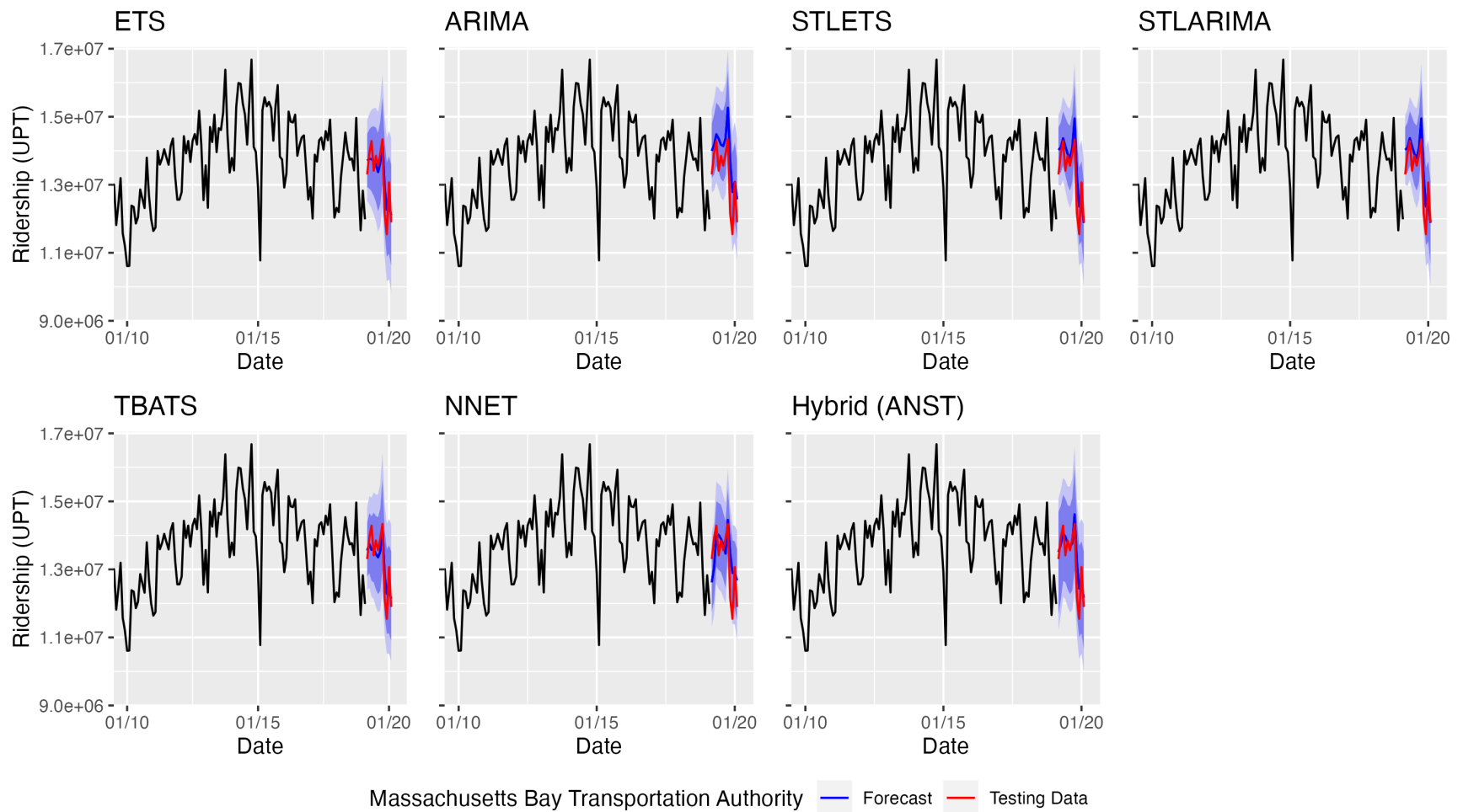


Figure D-5 Pre-COVID Forecasts of Ridership at the Massachusetts Bay Transportation Authority from March 2019 to February 2020

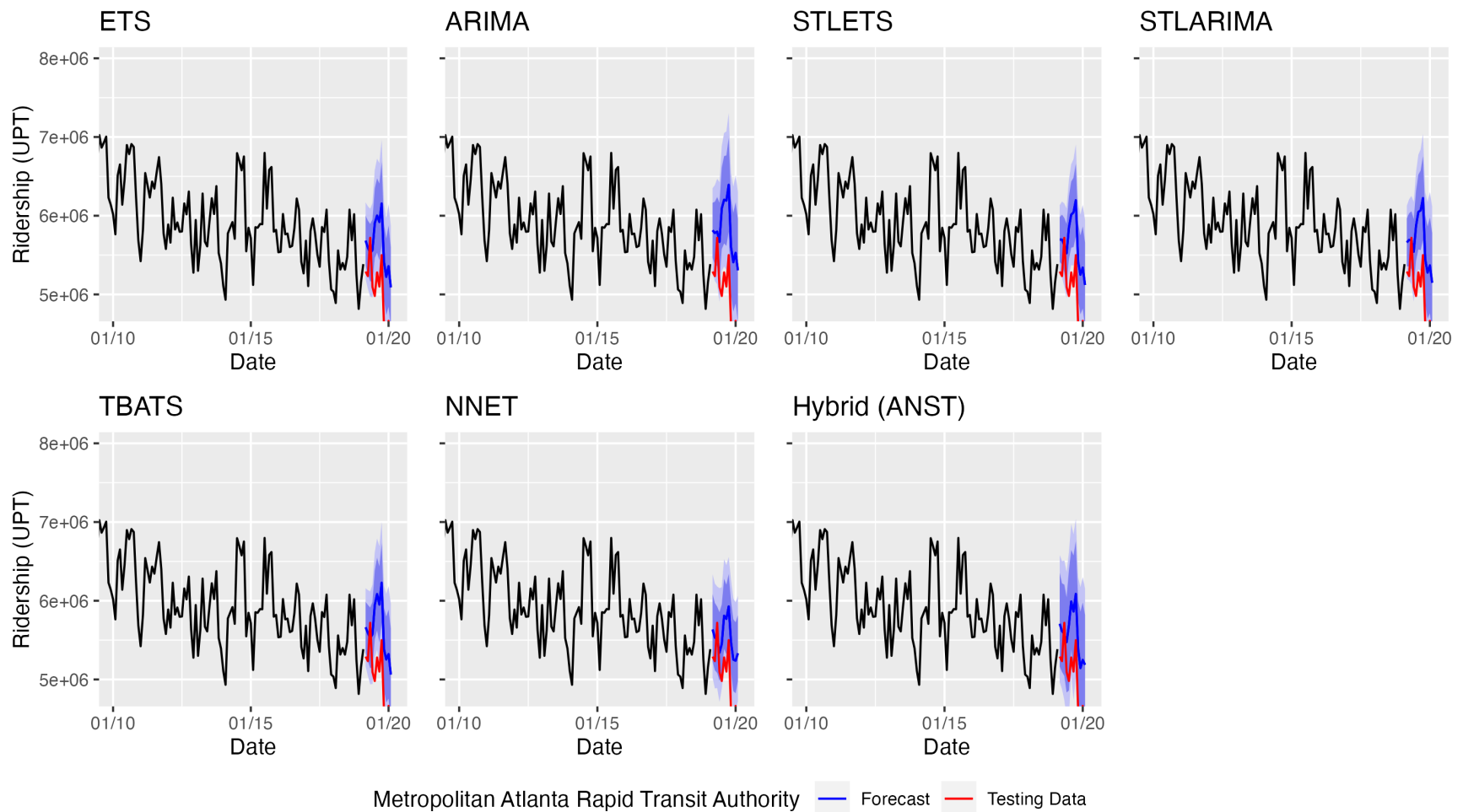


Figure D-6 Pre-COVID Forecasts of Ridership at the Metropolitan Atlanta Rapid Transit Authority from March 2019 to February 2020

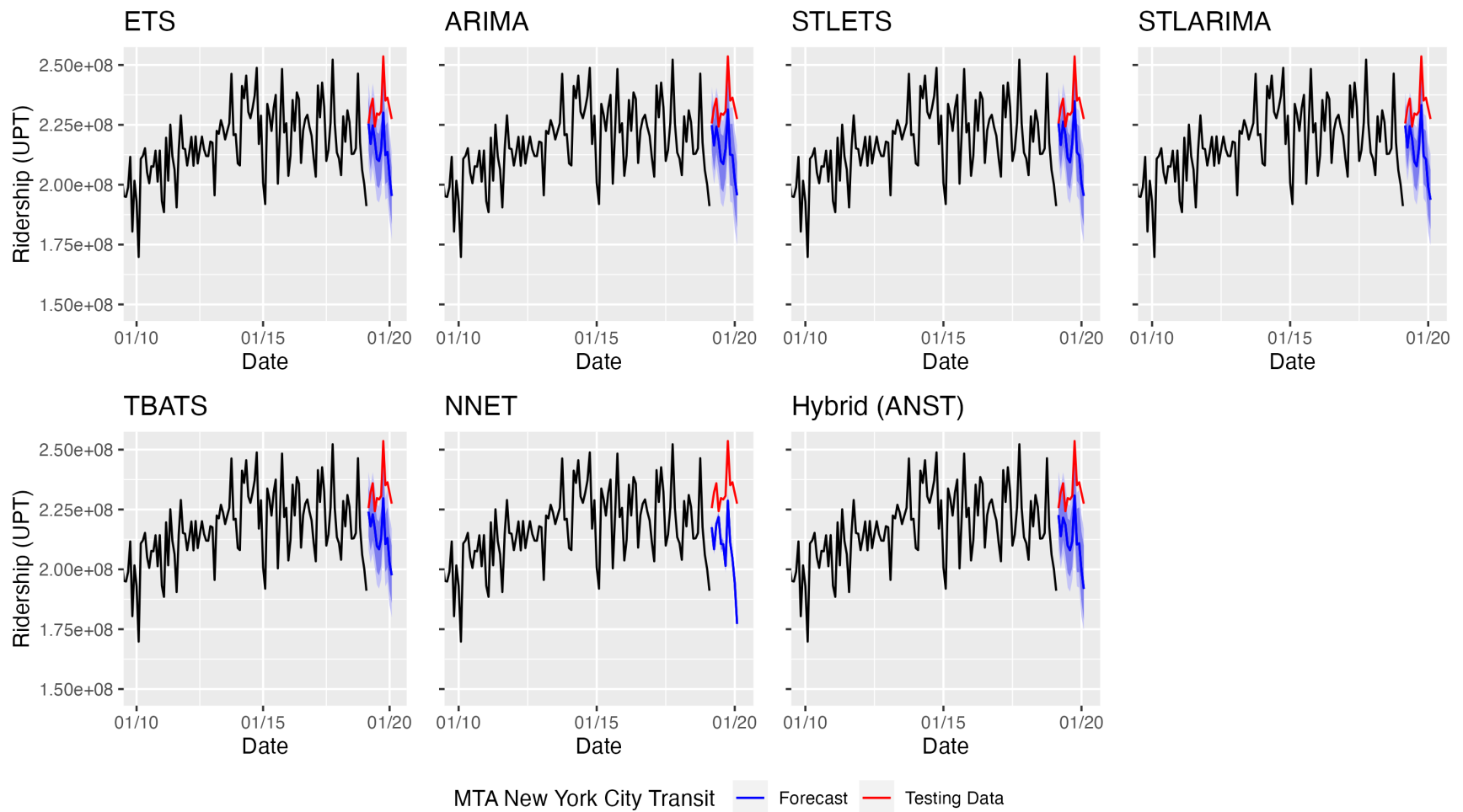


Figure D-7 Pre-COVID Forecasts of Ridership at MTA New York City Transit from March 2019 to February 2020

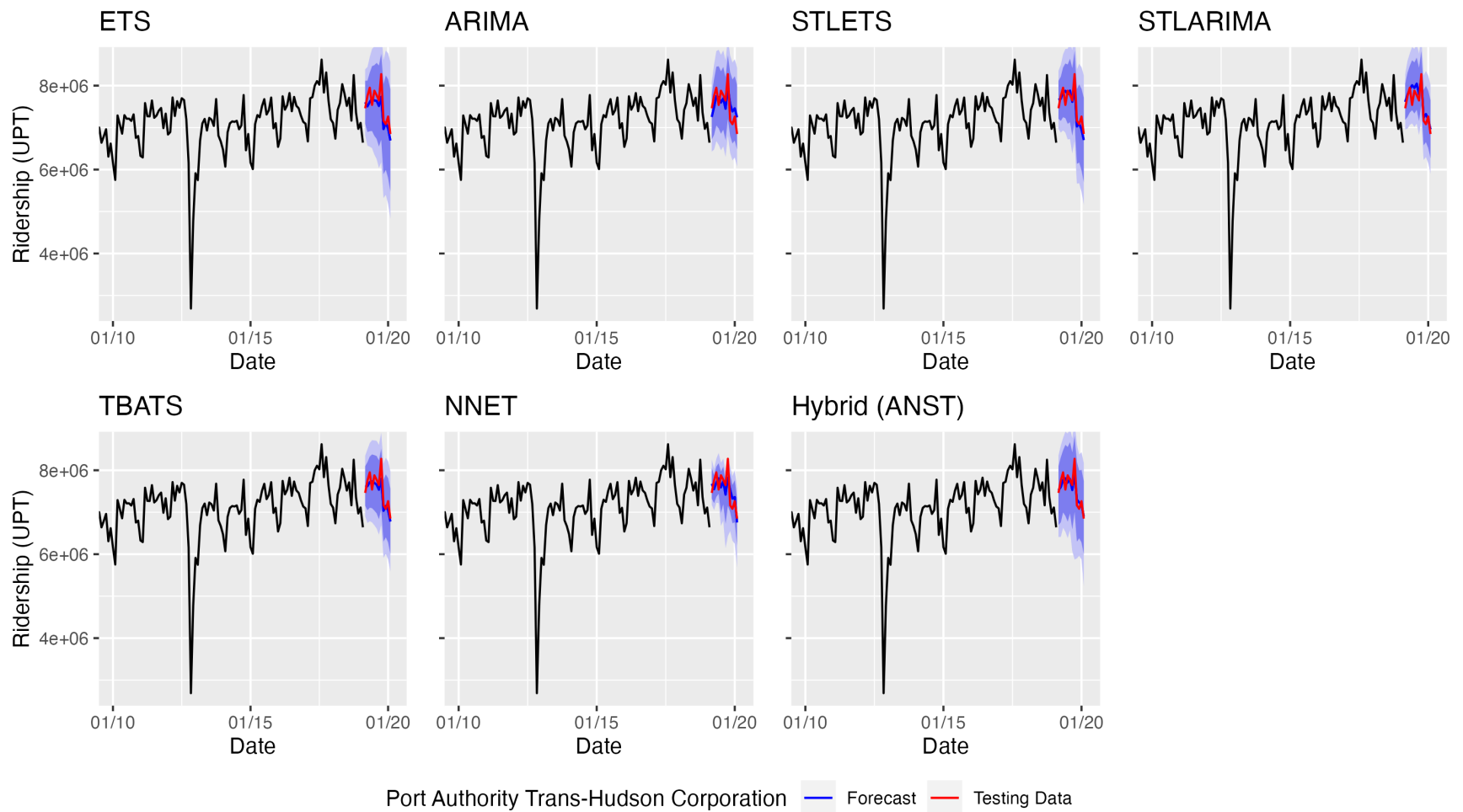


Figure D-8 Pre-COVID Forecasts of Ridership at the Port Authority Trans-Hudson Corporation from March 2019 to February 2020

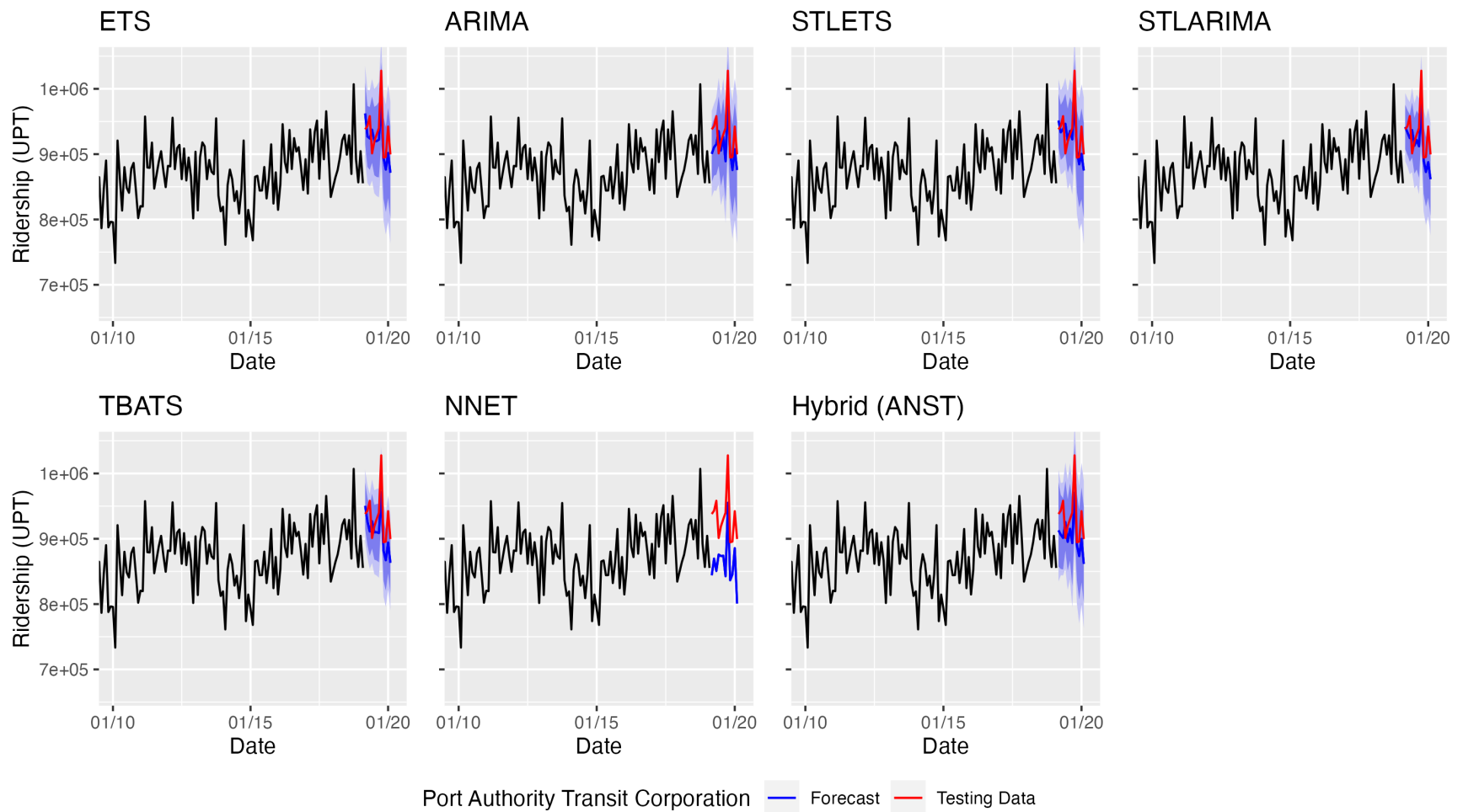


Figure D-9 Pre-COVID Forecasts of Ridership at the Port Authority Transit Corporation from March 2019 to February 2020

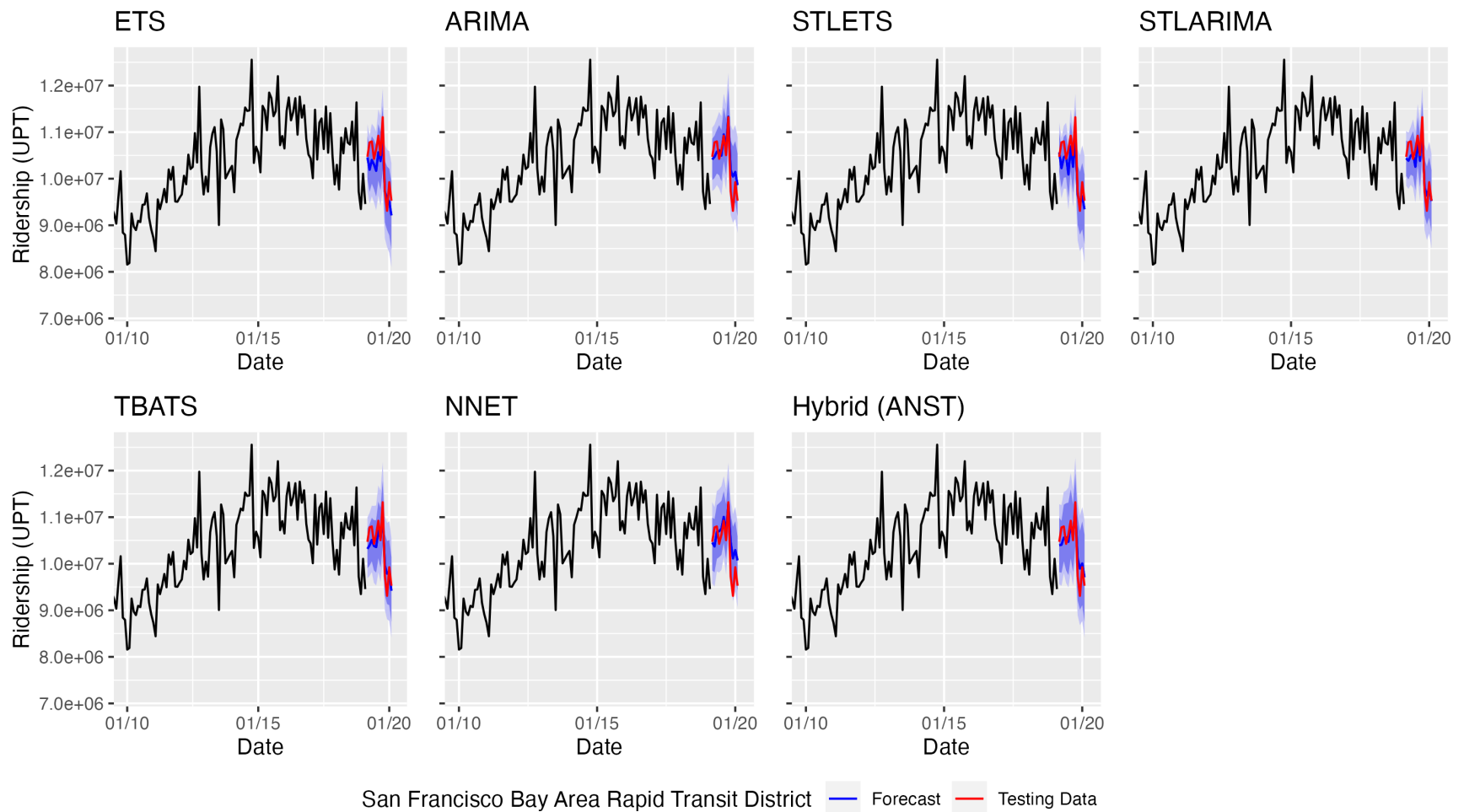


Figure D-10 Pre-COVID Forecasts of Ridership at the San Francisco Bay Area Rapid Transit District from March 2019 to February 2020

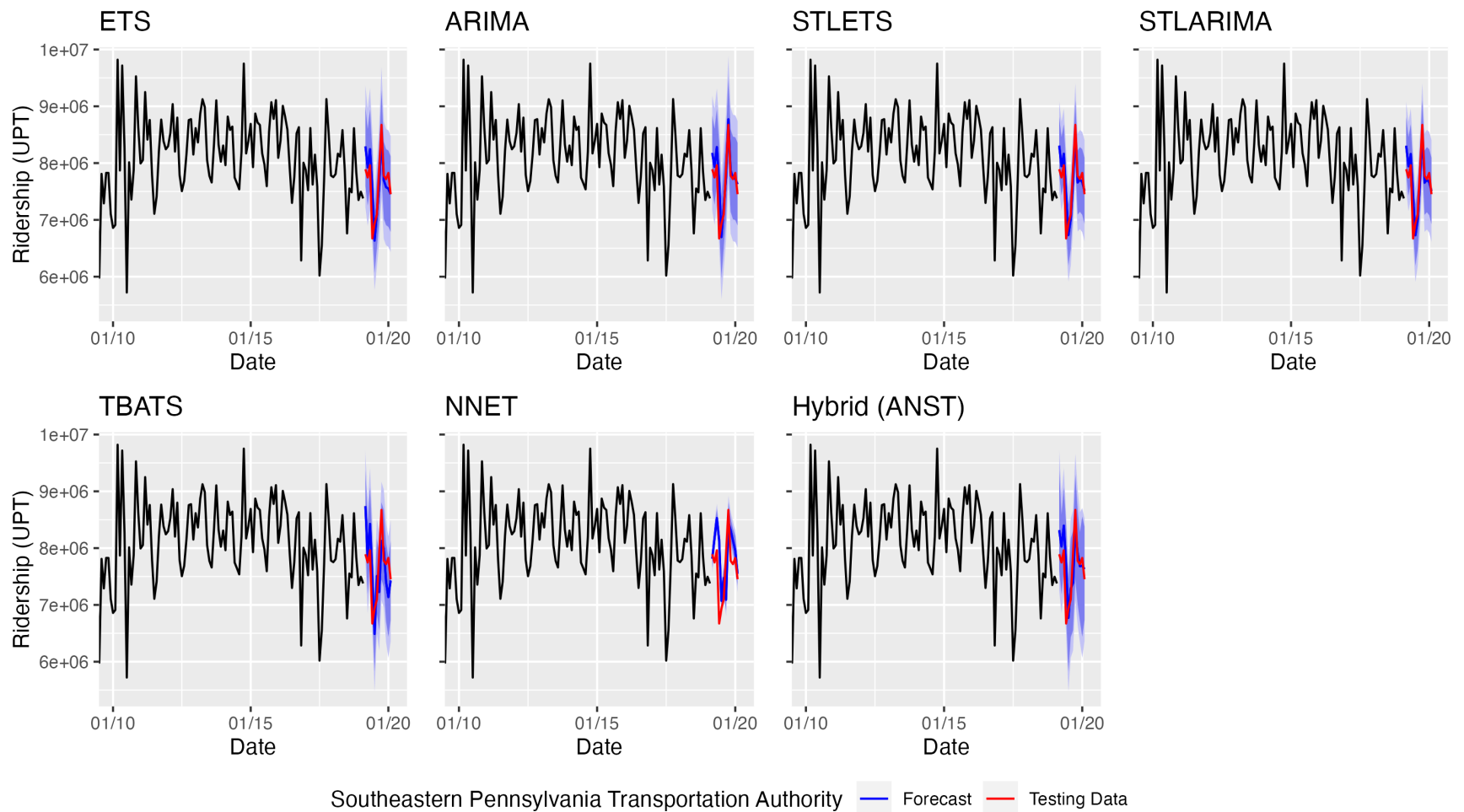


Figure D-11 Pre-COVID Forecasts of Ridership at the Southeastern Pennsylvania Transportation Authority from March 2019 to February 2020

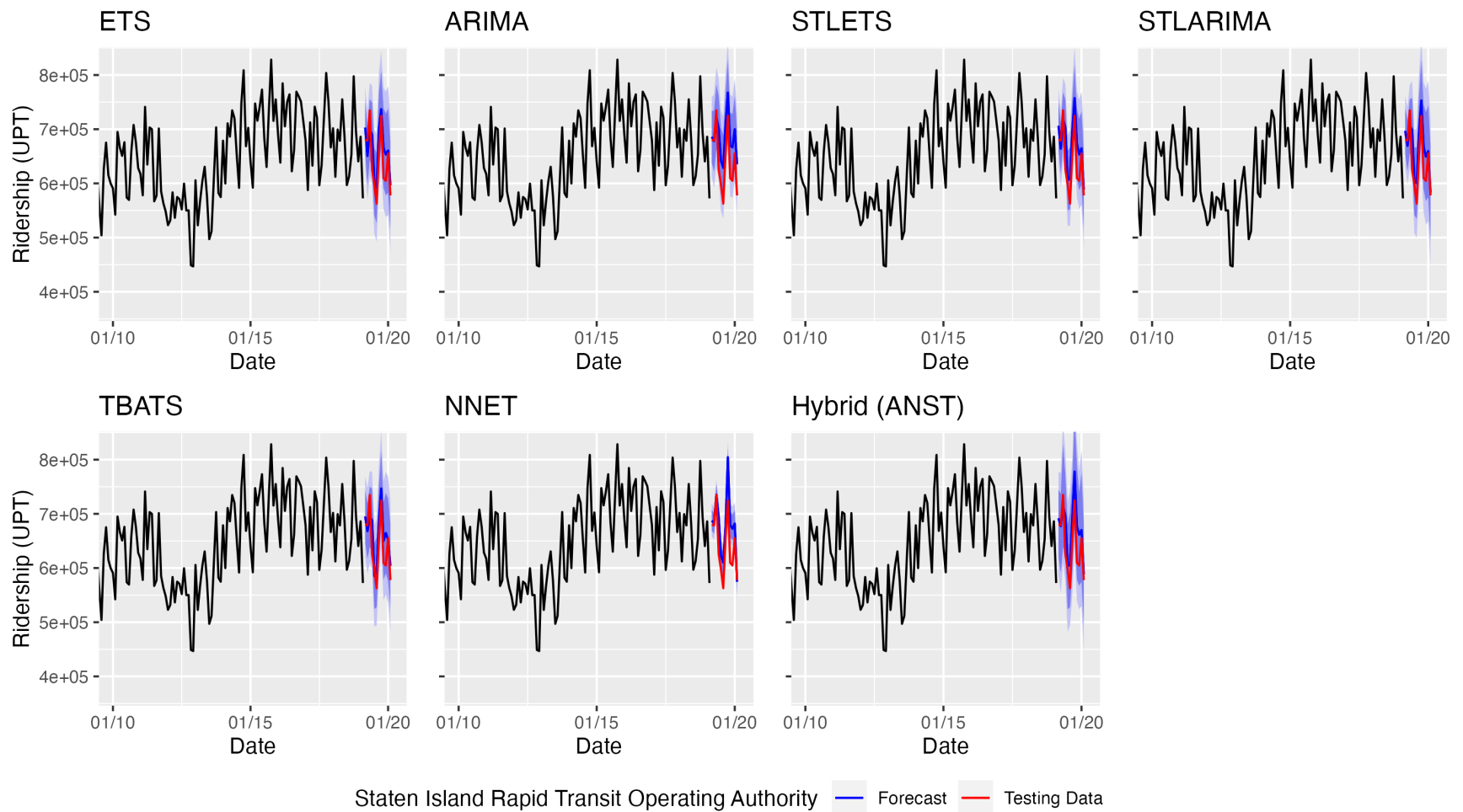


Figure D-12 Pre-COVID Forecasts of Ridership at the Staten Island Rapid Transit Operating Authority from March 2019 to February 2020

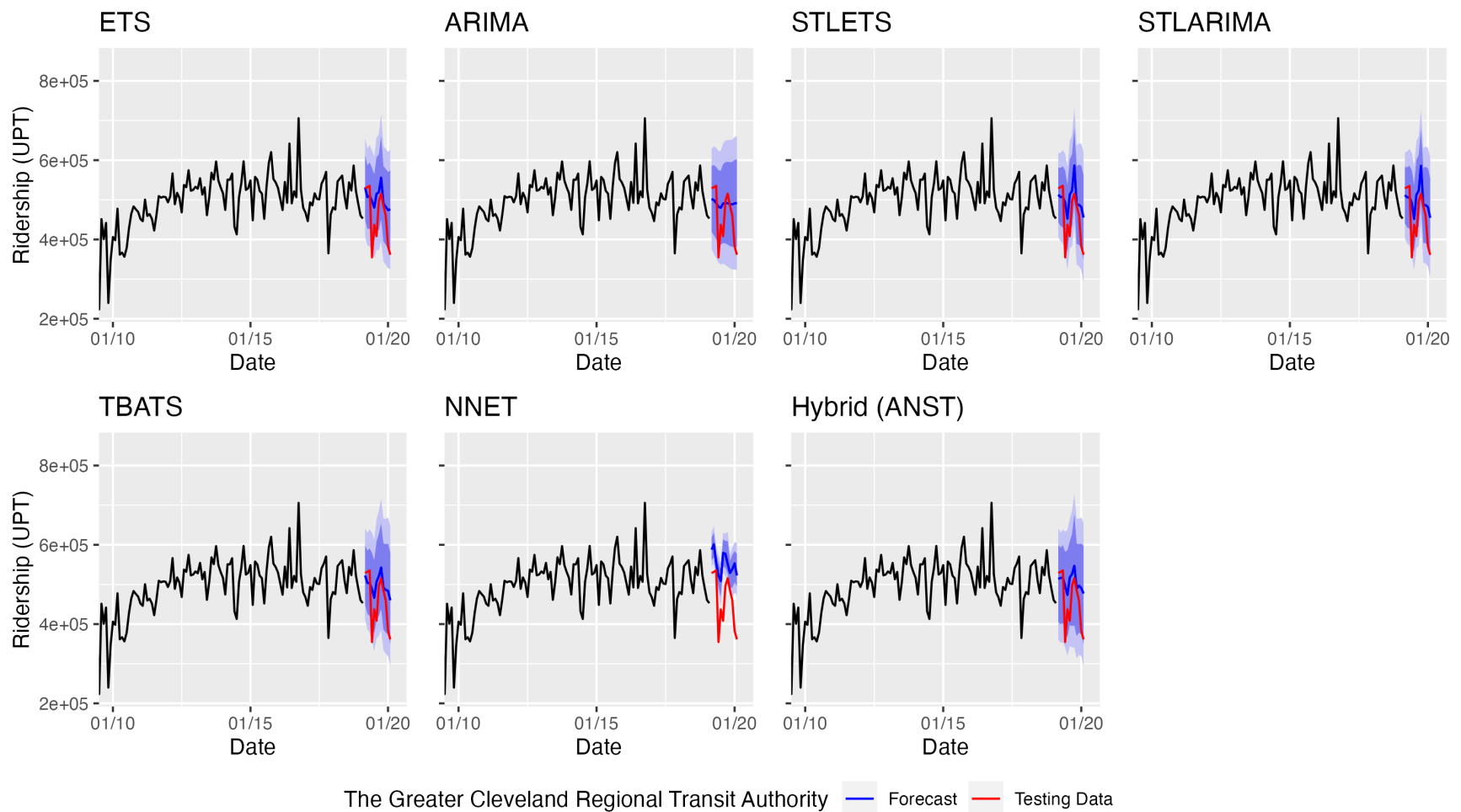


Figure D-13 Pre-COVID Forecasts of Ridership at the Greater Cleveland Regional Transit Authority from March 2019 to February 2020

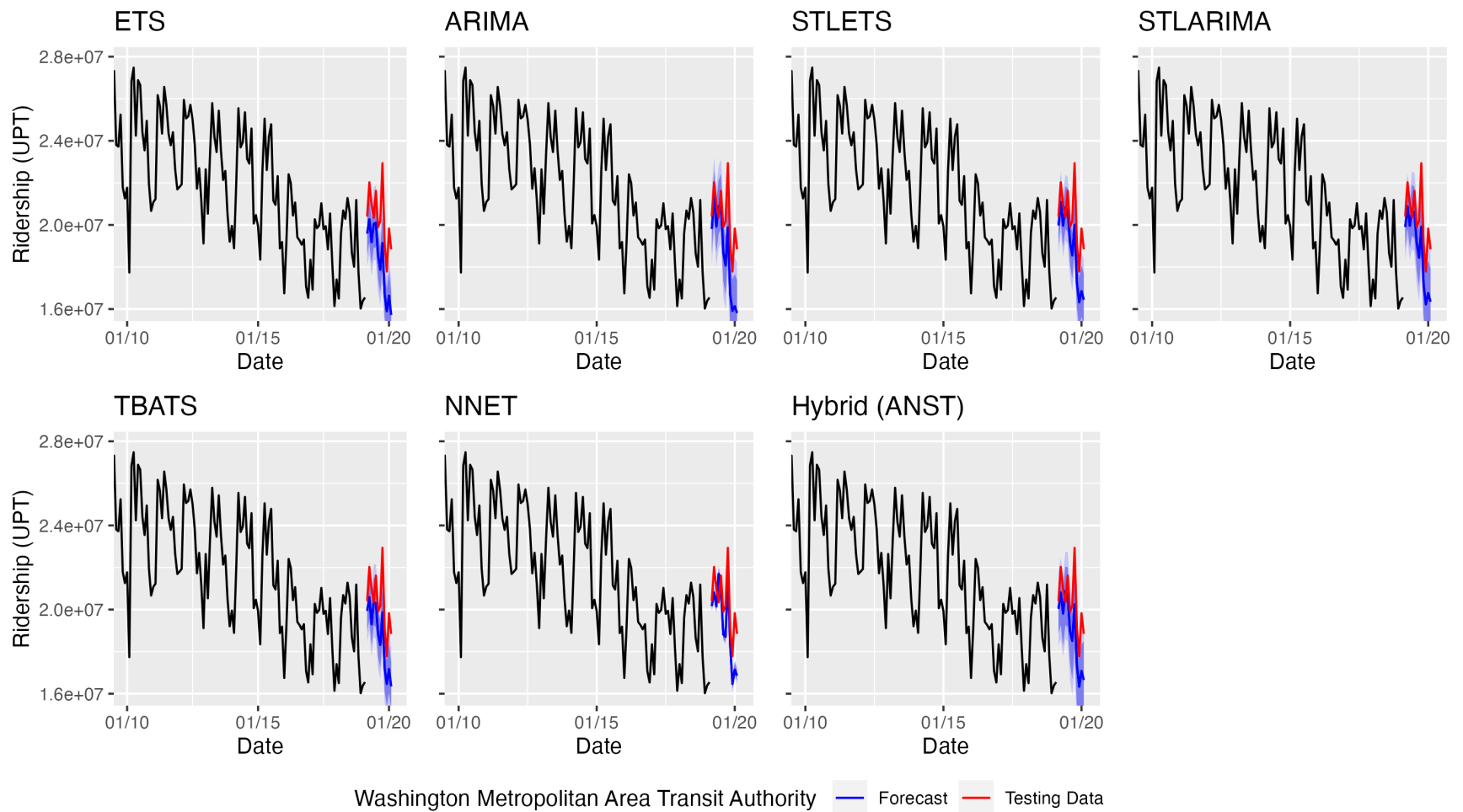


Figure D-14 Pre-COVID Forecasts of Ridership at the Washington Metropolitan Area Transit Authority from March 2019 to February 2020

Part E: Full Series Forecasts for 2023

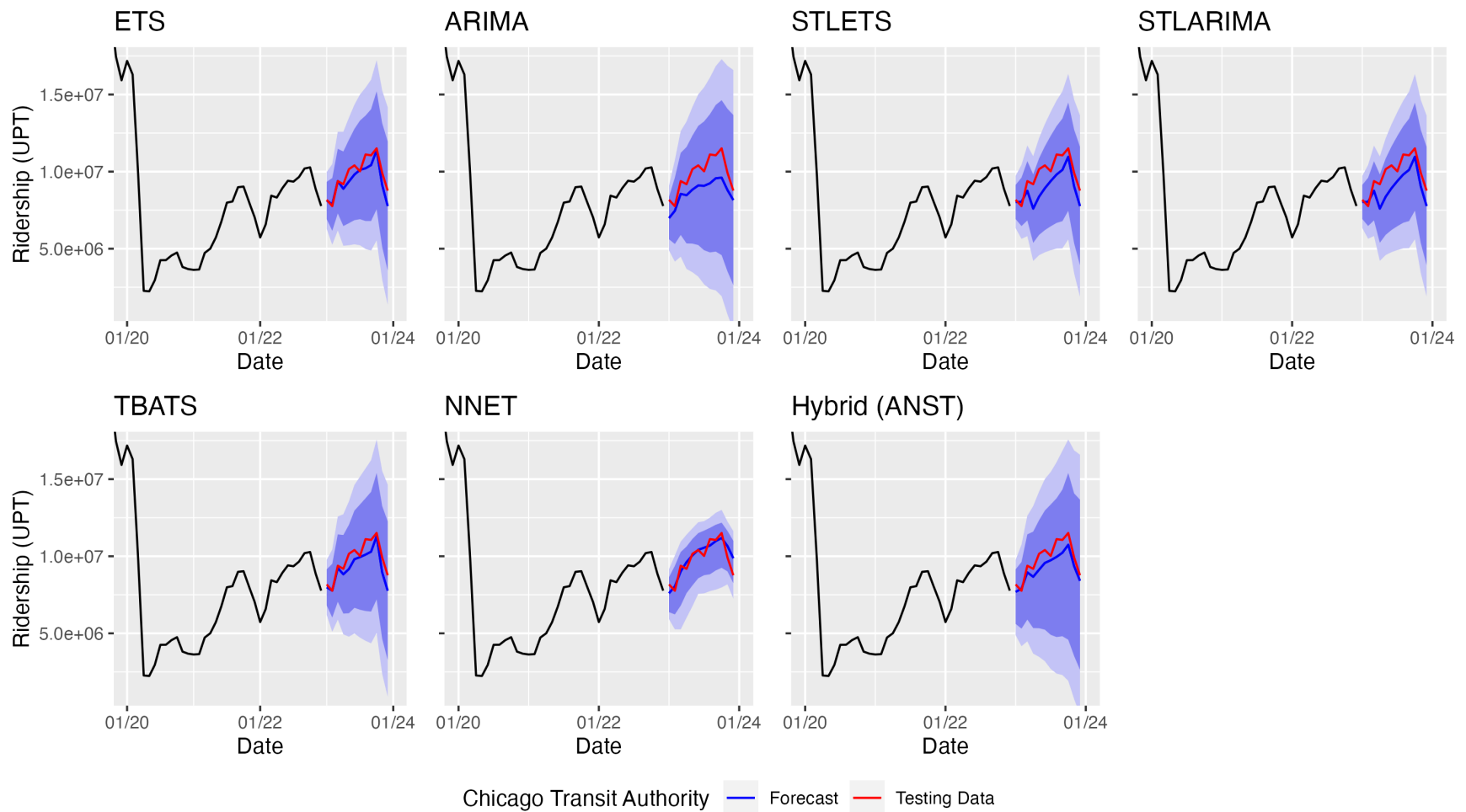


Figure E-1 Full Series Forecasts of Ridership at the Chicago Transit Authority for 2023

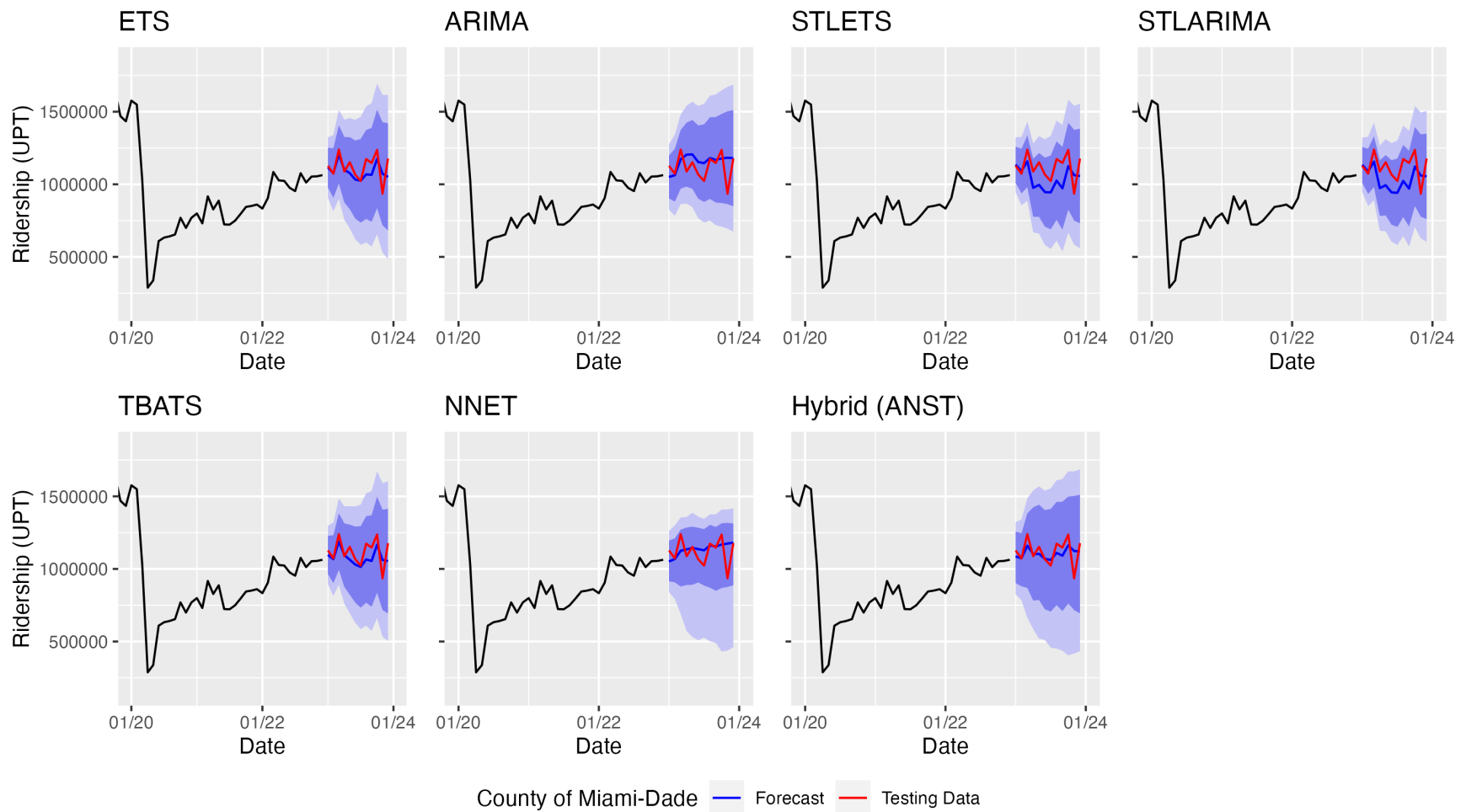


Figure E-2 Full Series Forecasts of Ridership at the County of Miami-Dade for 2023

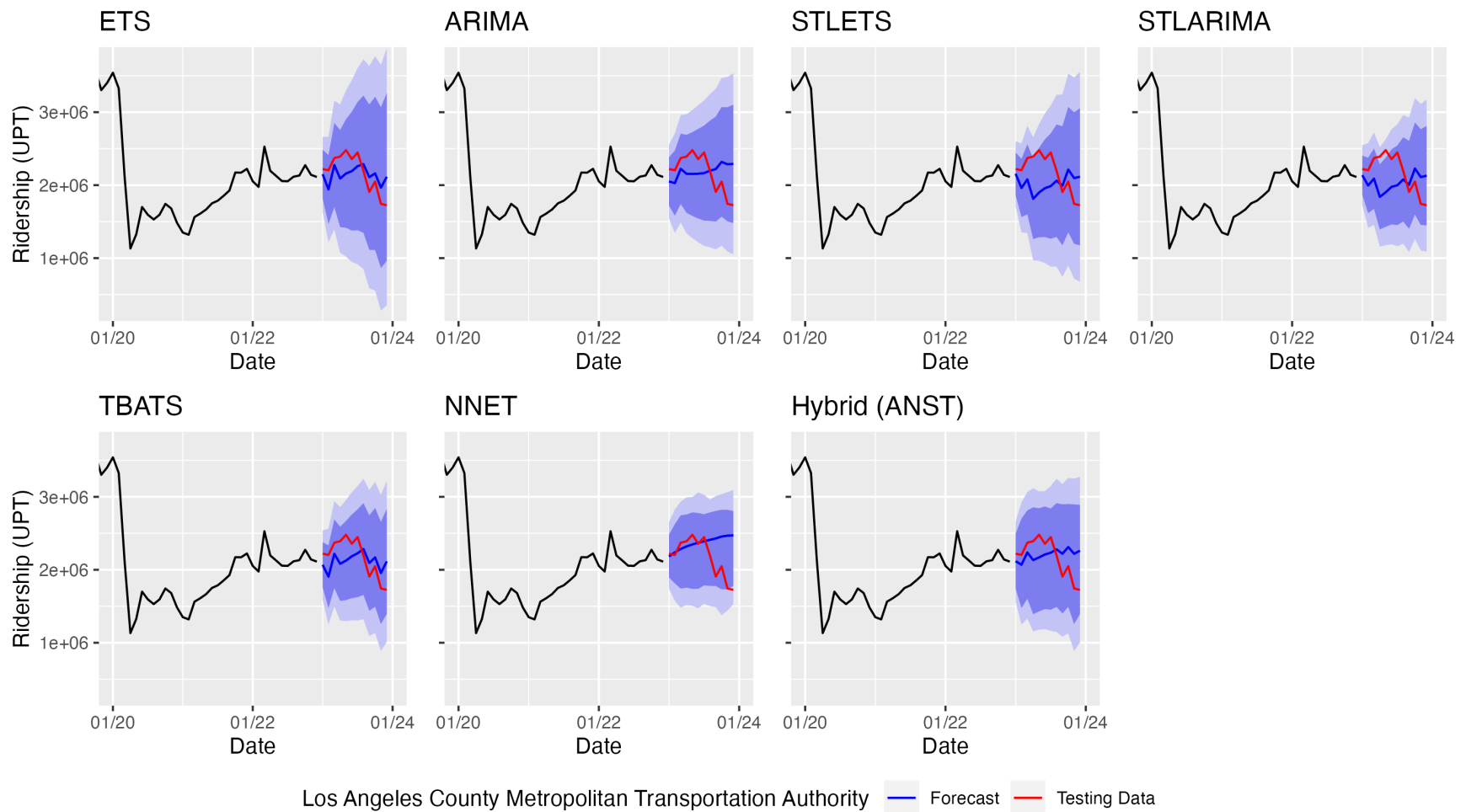


Figure E-3 Full Series Forecasts of Ridership at the Los Angeles County Metropolitan Transportation Authority for 2023

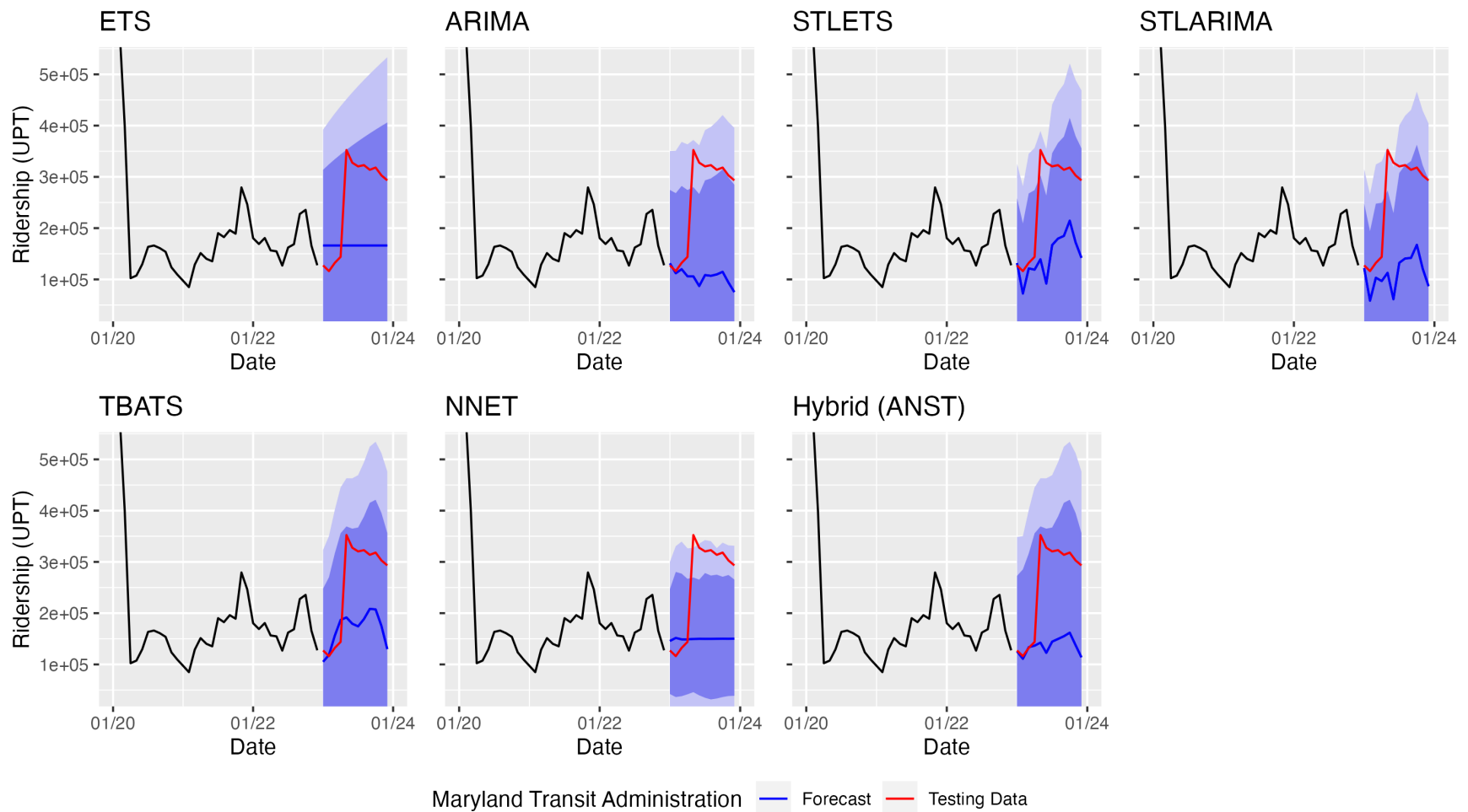


Figure E-4 Full Series Forecasts of Ridership at the Maryland Transit Administration for 2023

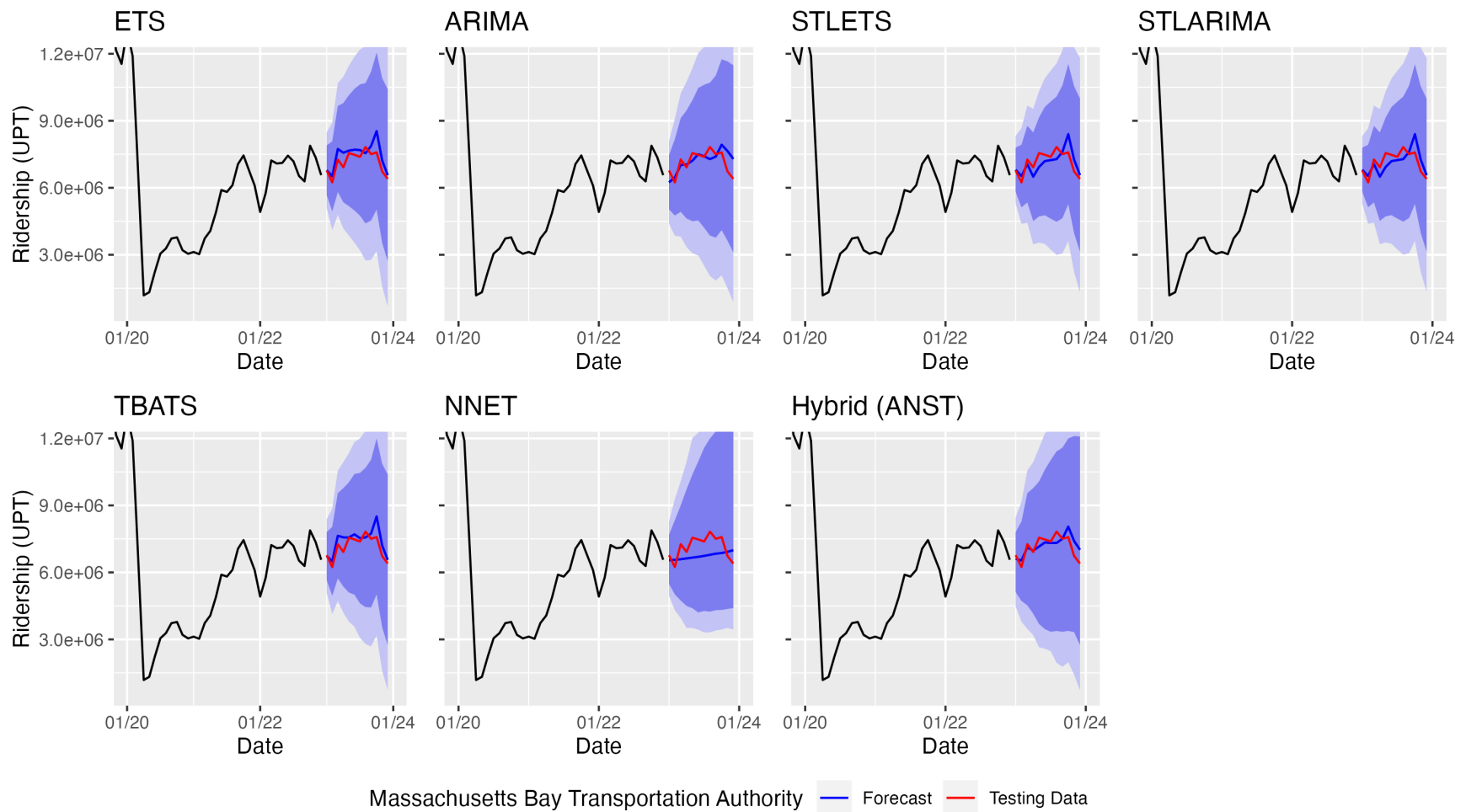


Figure E-5 Full Series Forecasts of Ridership at the Massachusetts Bay Transportation Authority for 2023

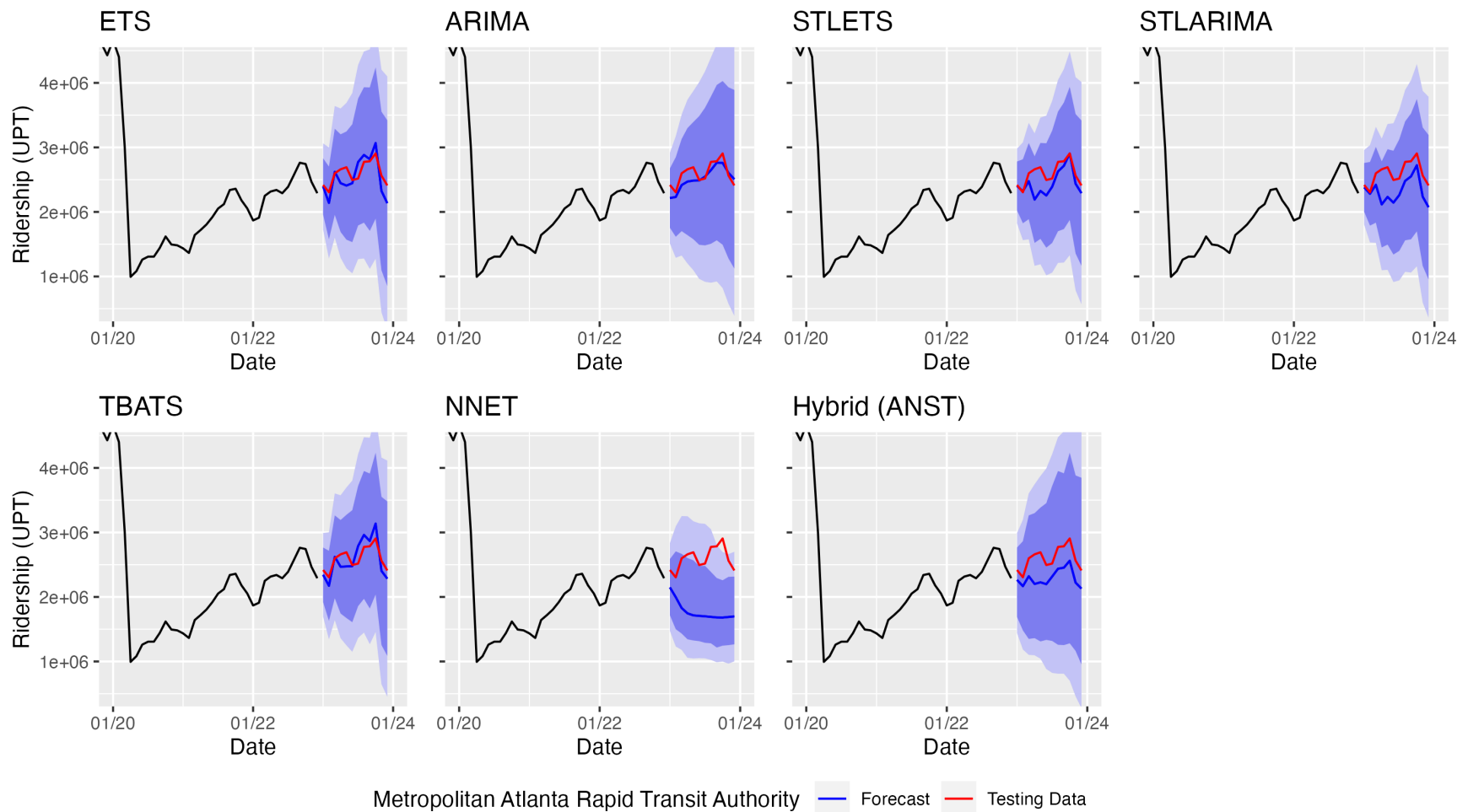


Figure E-6 Full Series Forecasts of Ridership at the Metropolitan Atlanta Rapid Transit Authority for 2023

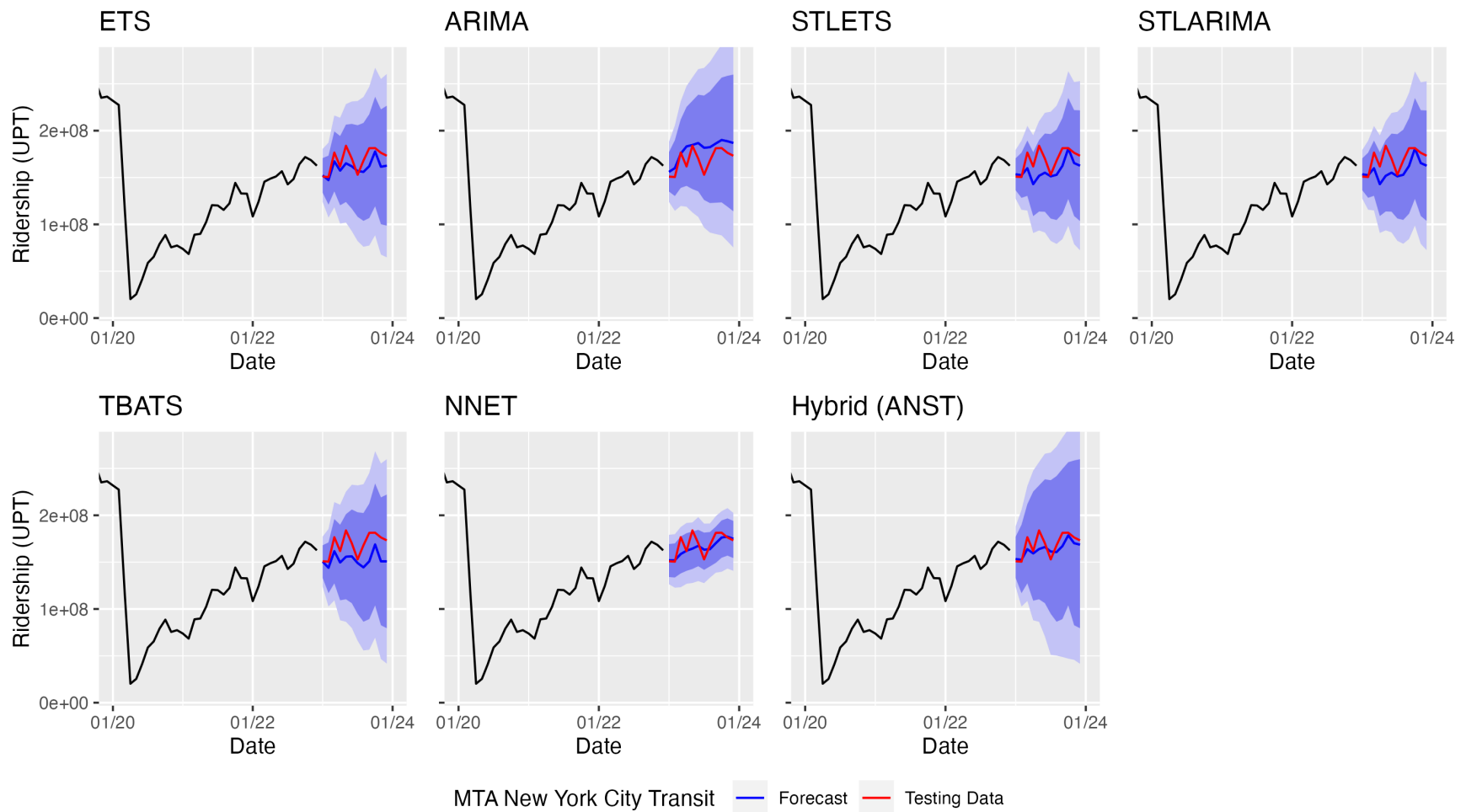


Figure E-7 Full Series Forecasts of Ridership at MTA New York City Transit for 2023

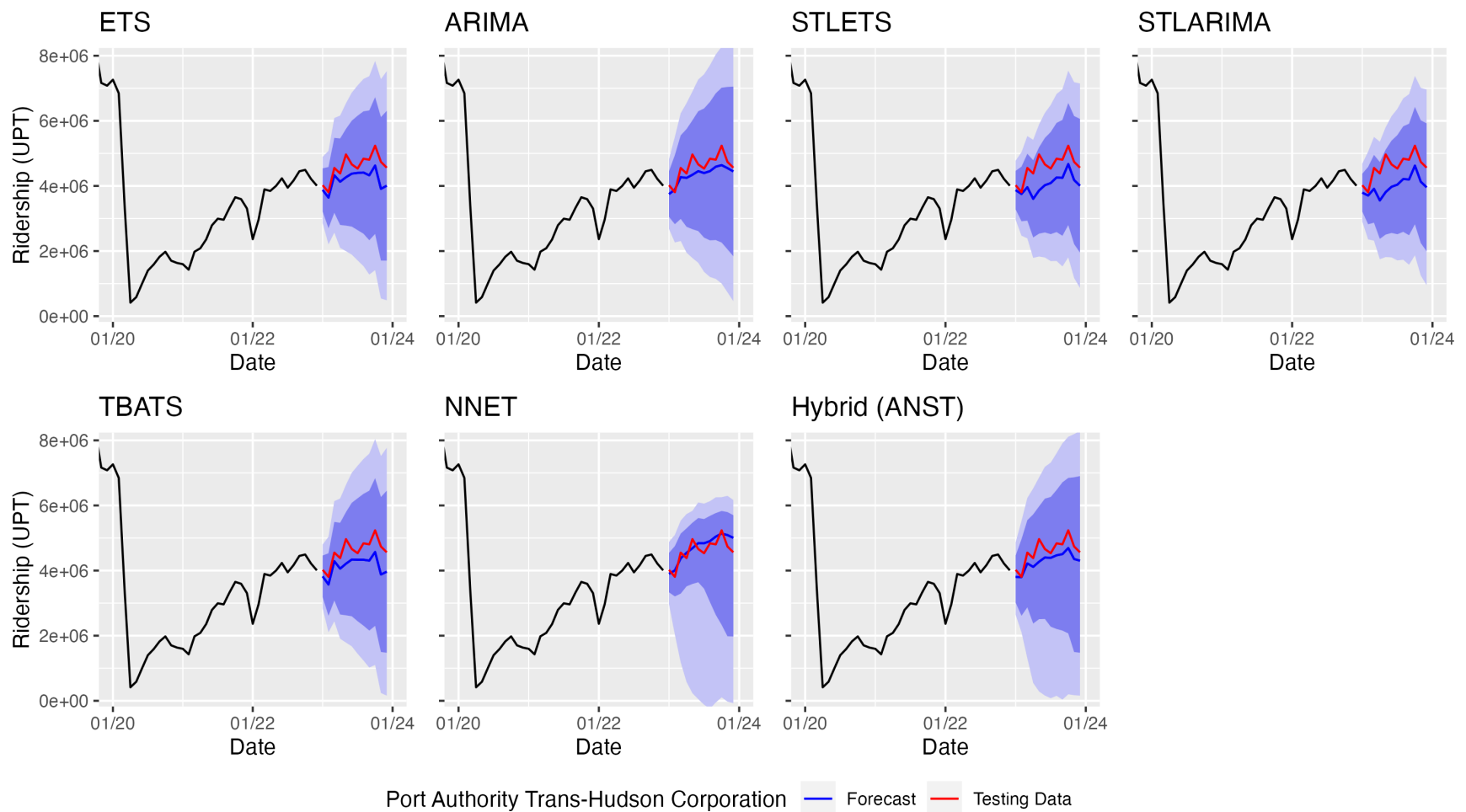


Figure E-8 Full Series Forecasts of Ridership at the Port Authority Trans-Hudson Corporation for 2023

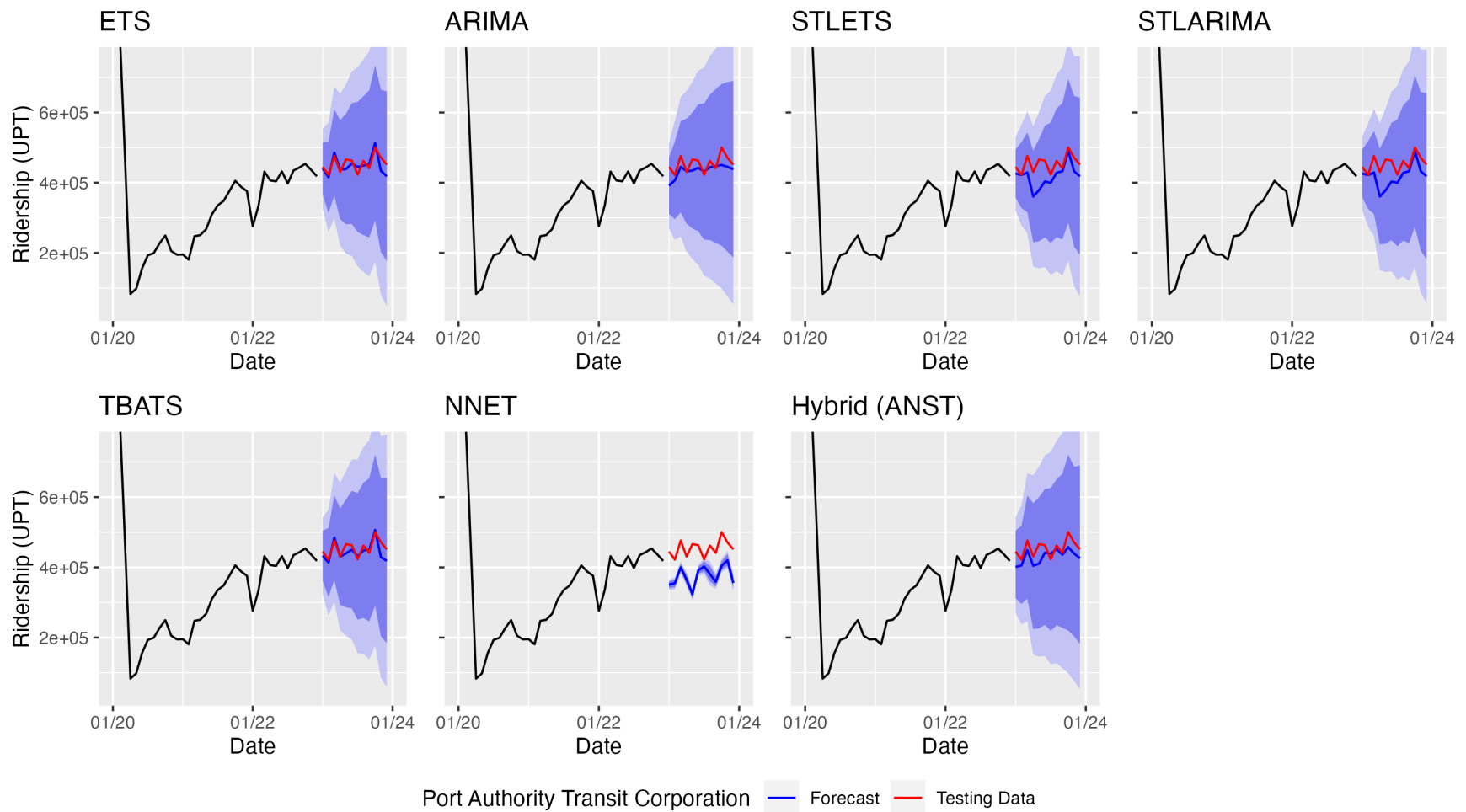


Figure E-9 Full Series Forecasts of Ridership at the Port Authority Transit Corporation for 2023

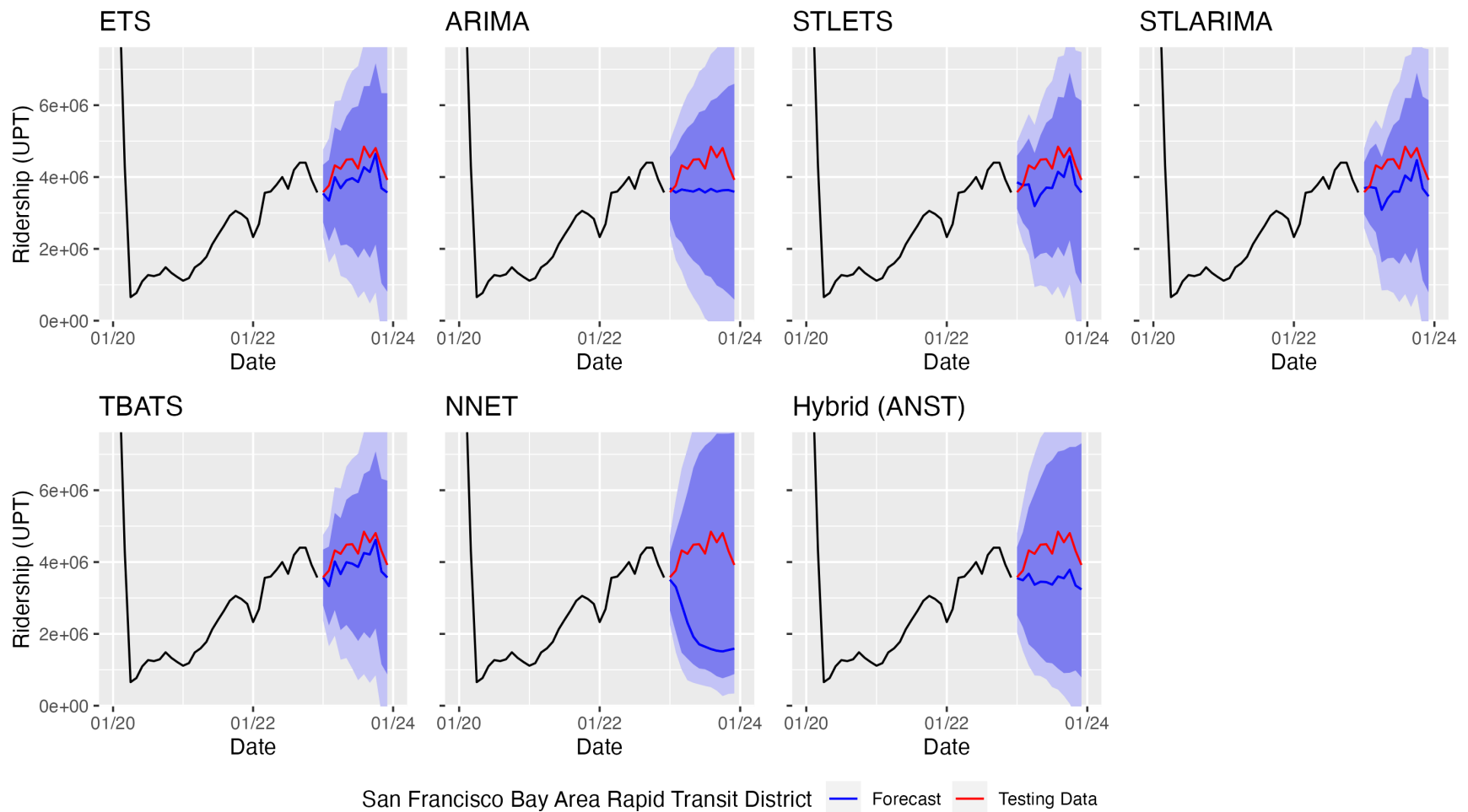


Figure E-10 Full Series Forecasts of Ridership at the San Francisco Bay Area Rapid Transit District for 2023

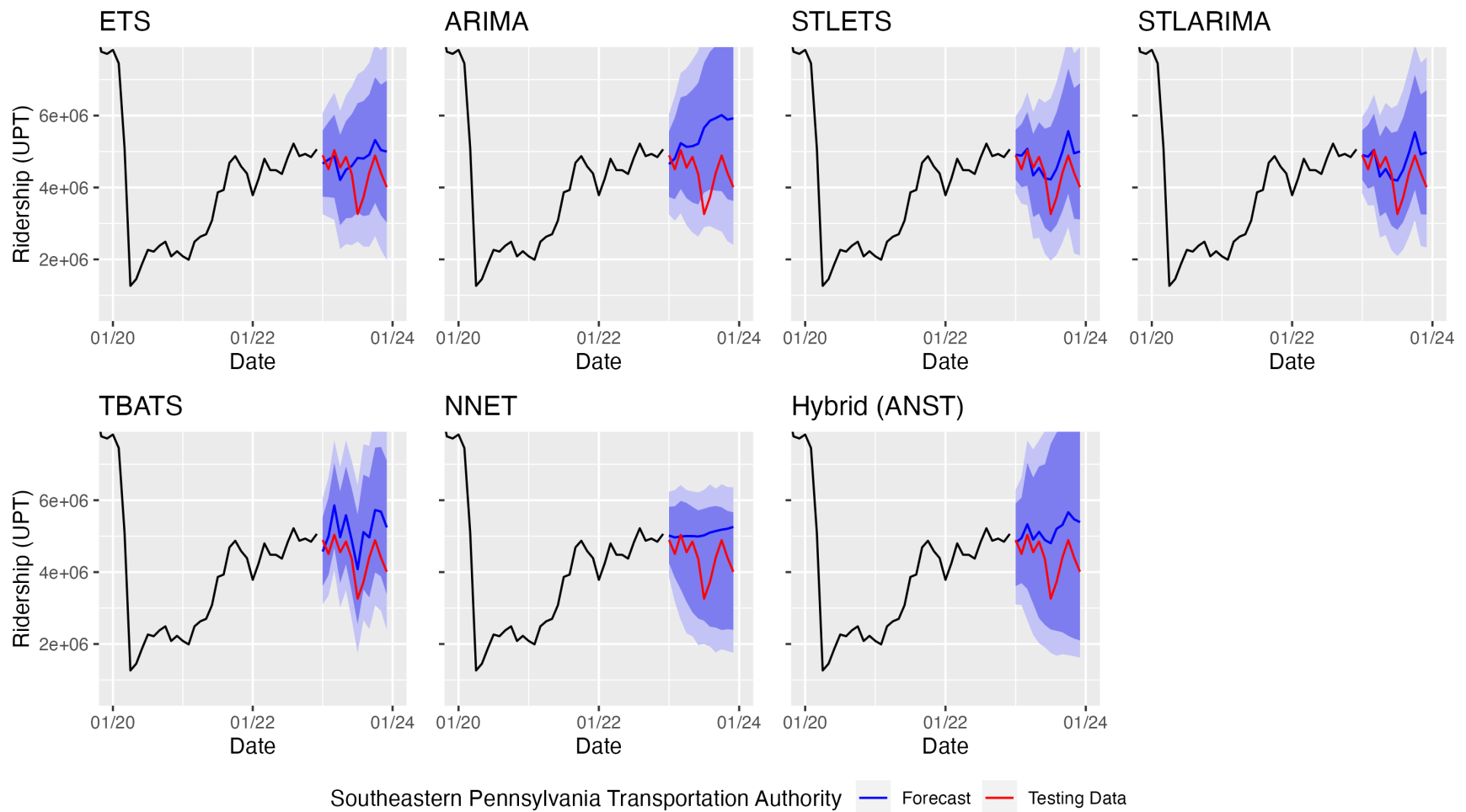


Figure E-11 Full Series Forecasts of Ridership at the Southeastern Pennsylvania Transportation Authority for 2023

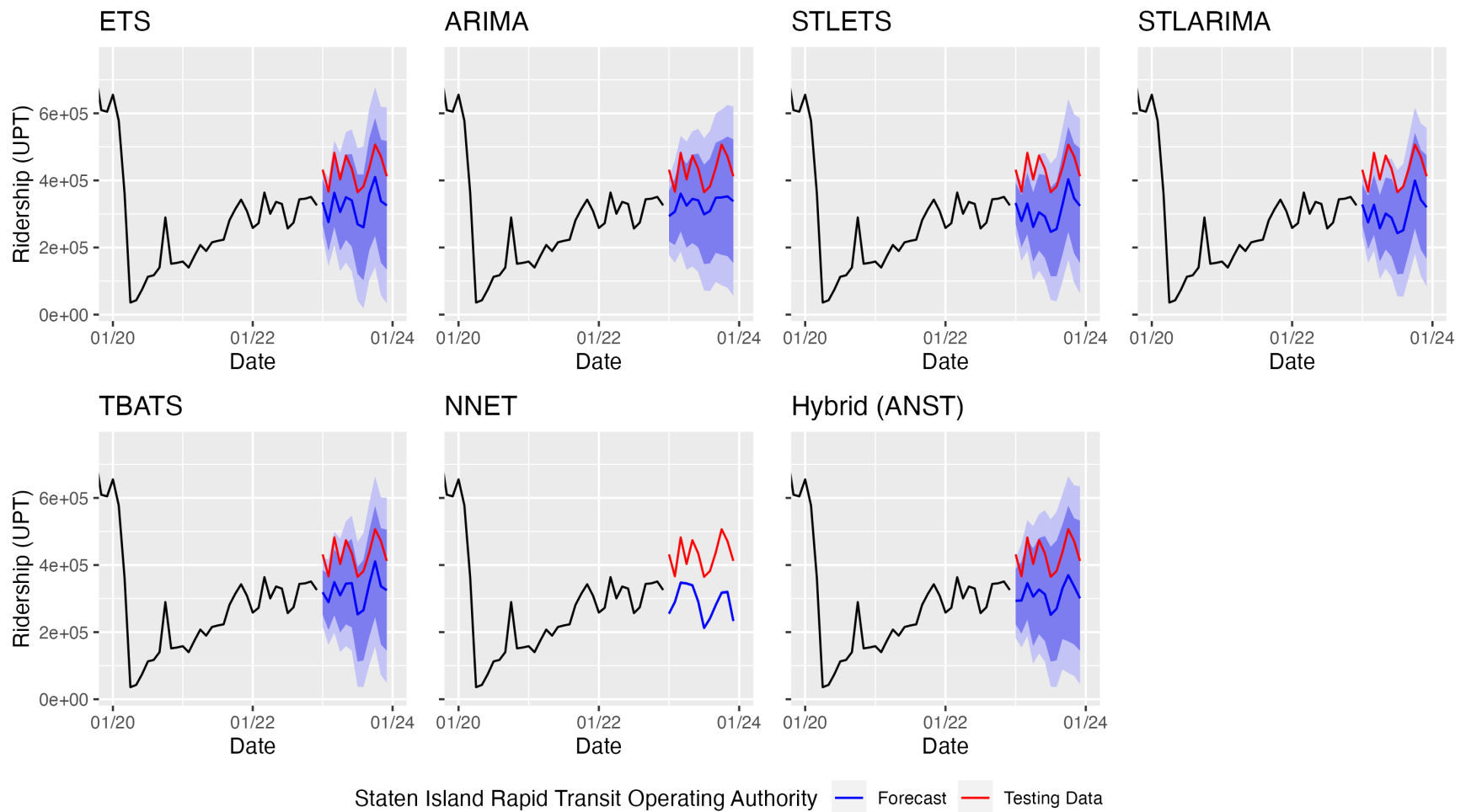


Figure E-12 Full Series Forecasts of Ridership at the Staten Island Rapid Transit Operating Authority for 2023

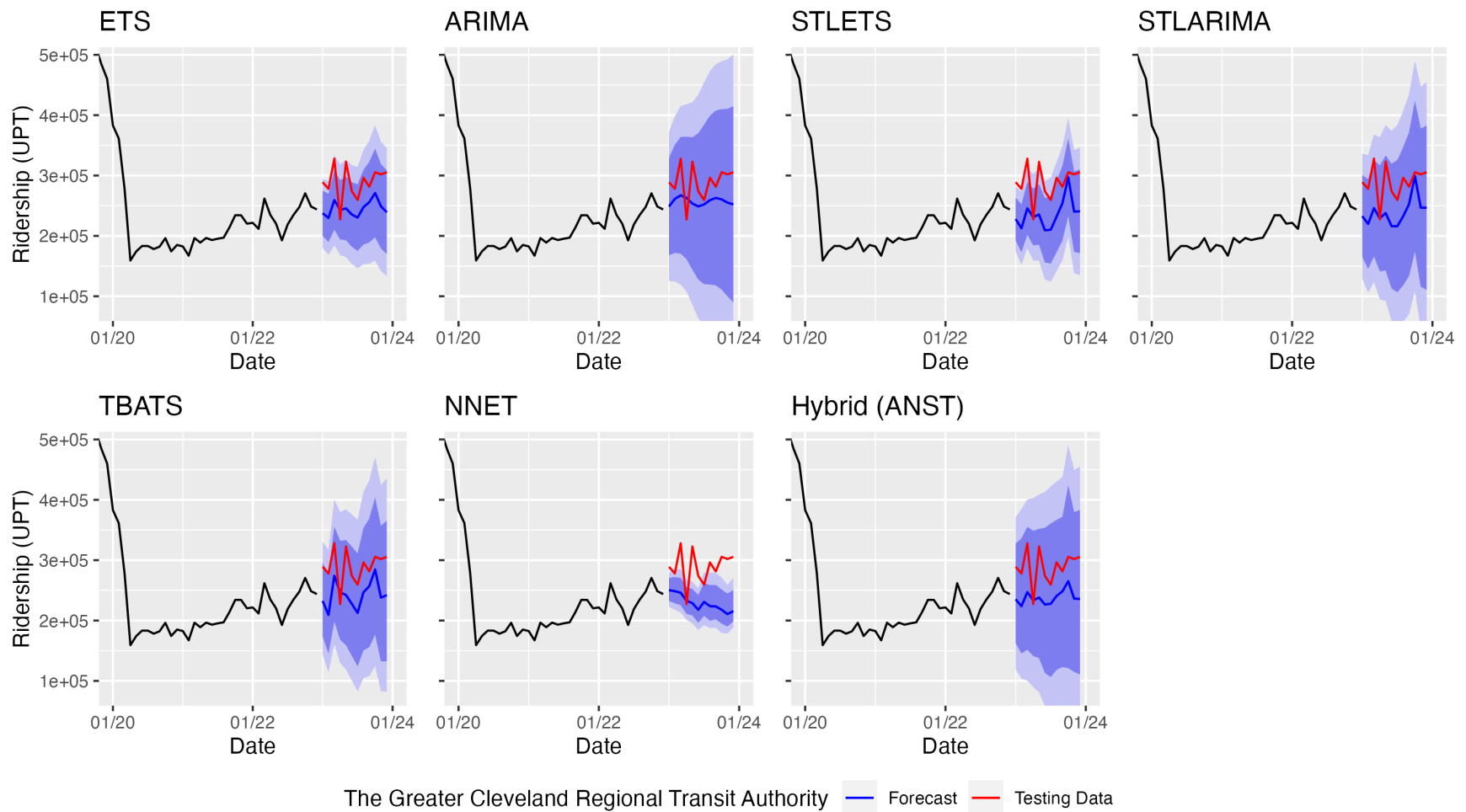


Figure E-13 Full Series Forecasts of Ridership at the Greater Cleveland Regional Transit Authority for 2023

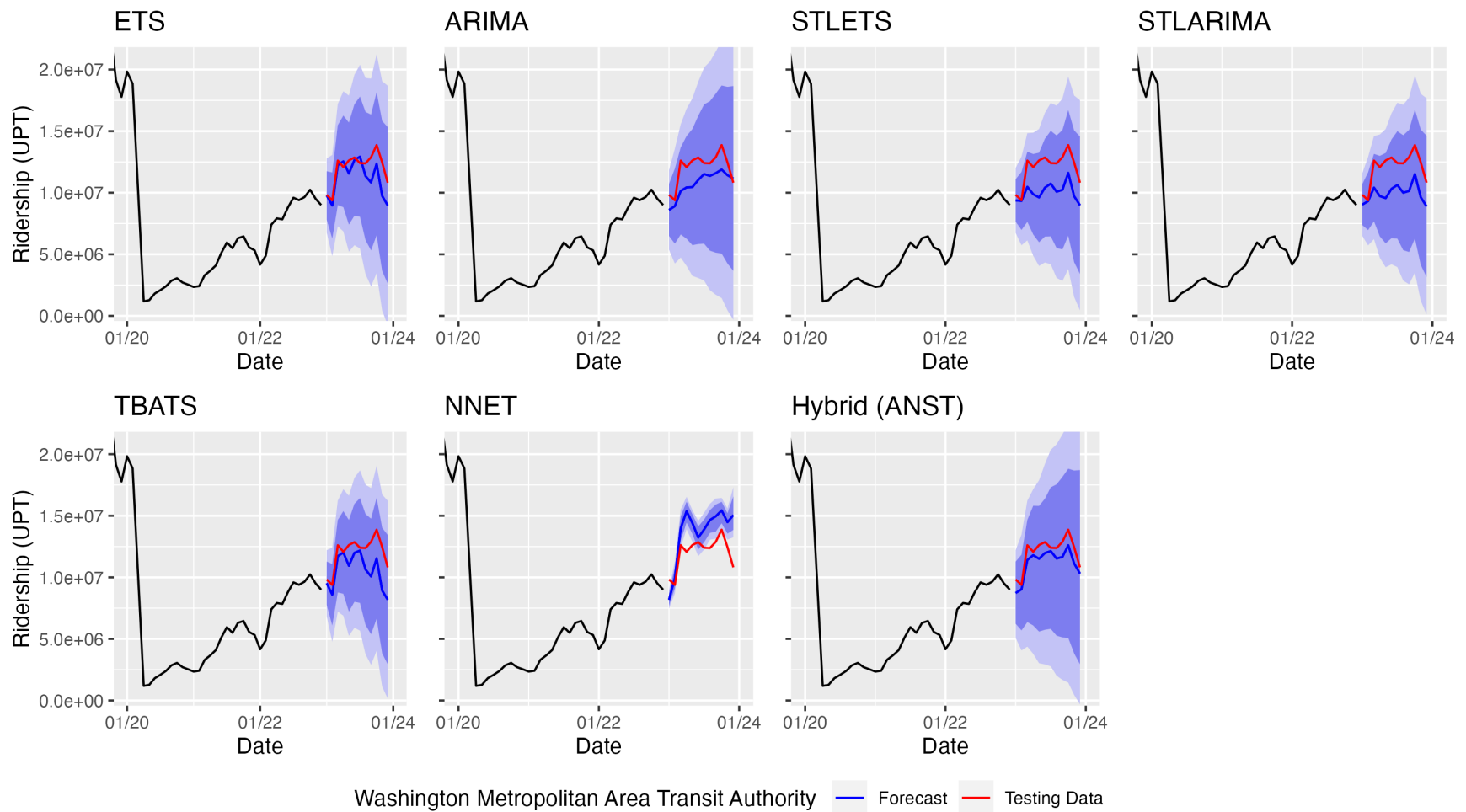


Figure E-14 Full Series Forecasts of Ridership at the Washington Metropolitan Area Transit Authority for 2023

Part F: Post-COVID Forecasts for 2023

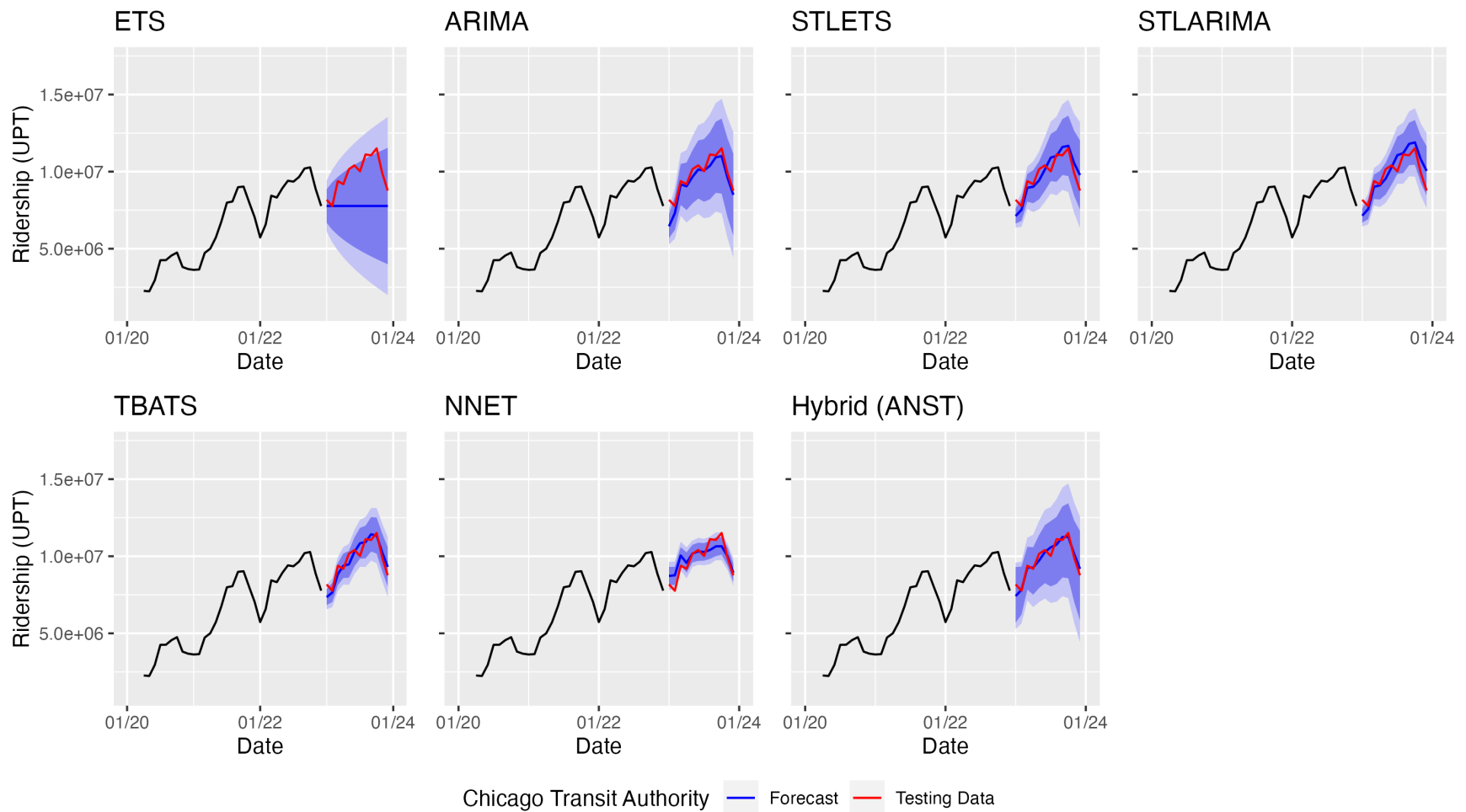


Figure F-1 Post-COVID Forecasts of Ridership at the Chicago Transit Authority for 2023

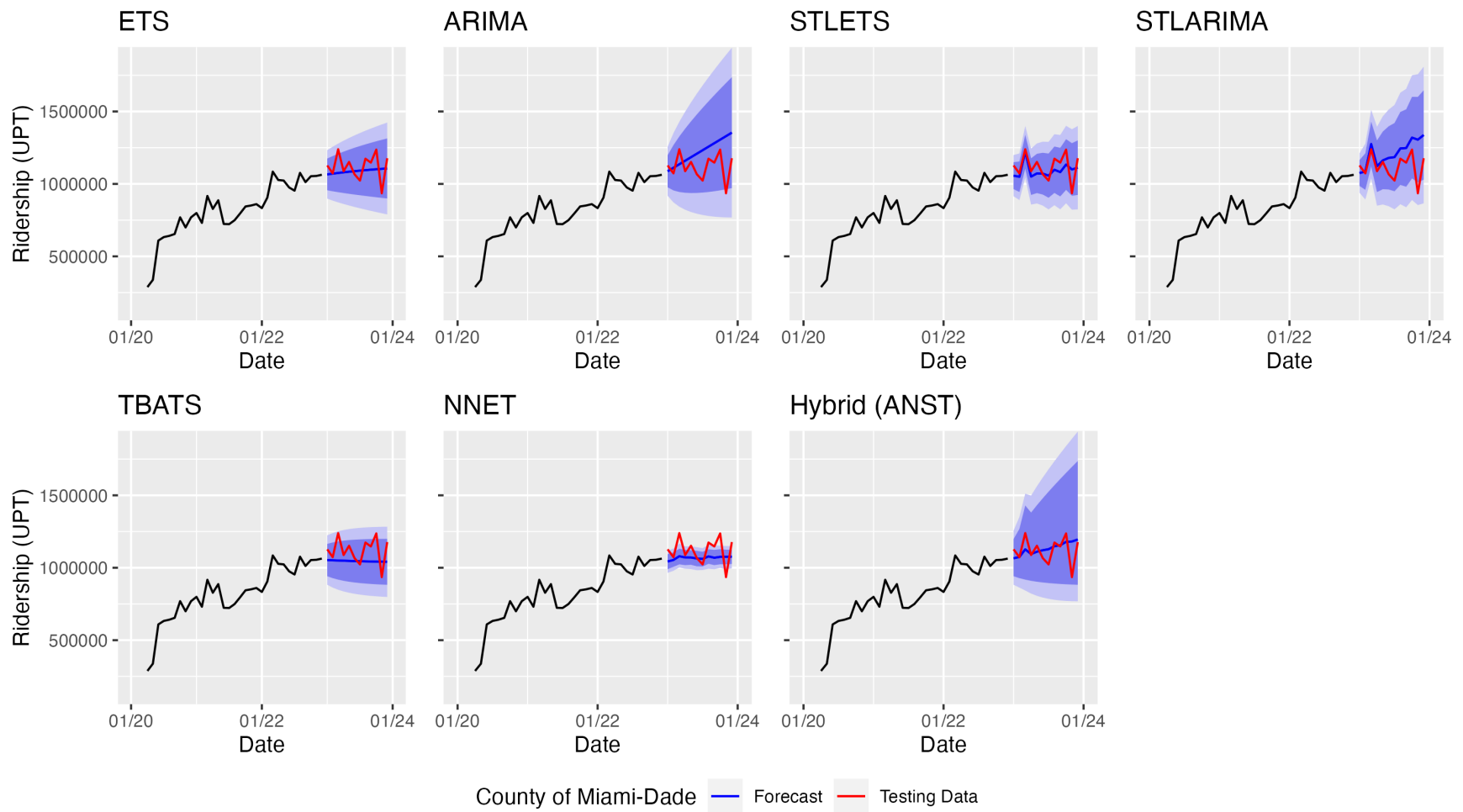


Figure F-2 Post-COVID Forecasts of Ridership at the County of Miami-Dade for 2023

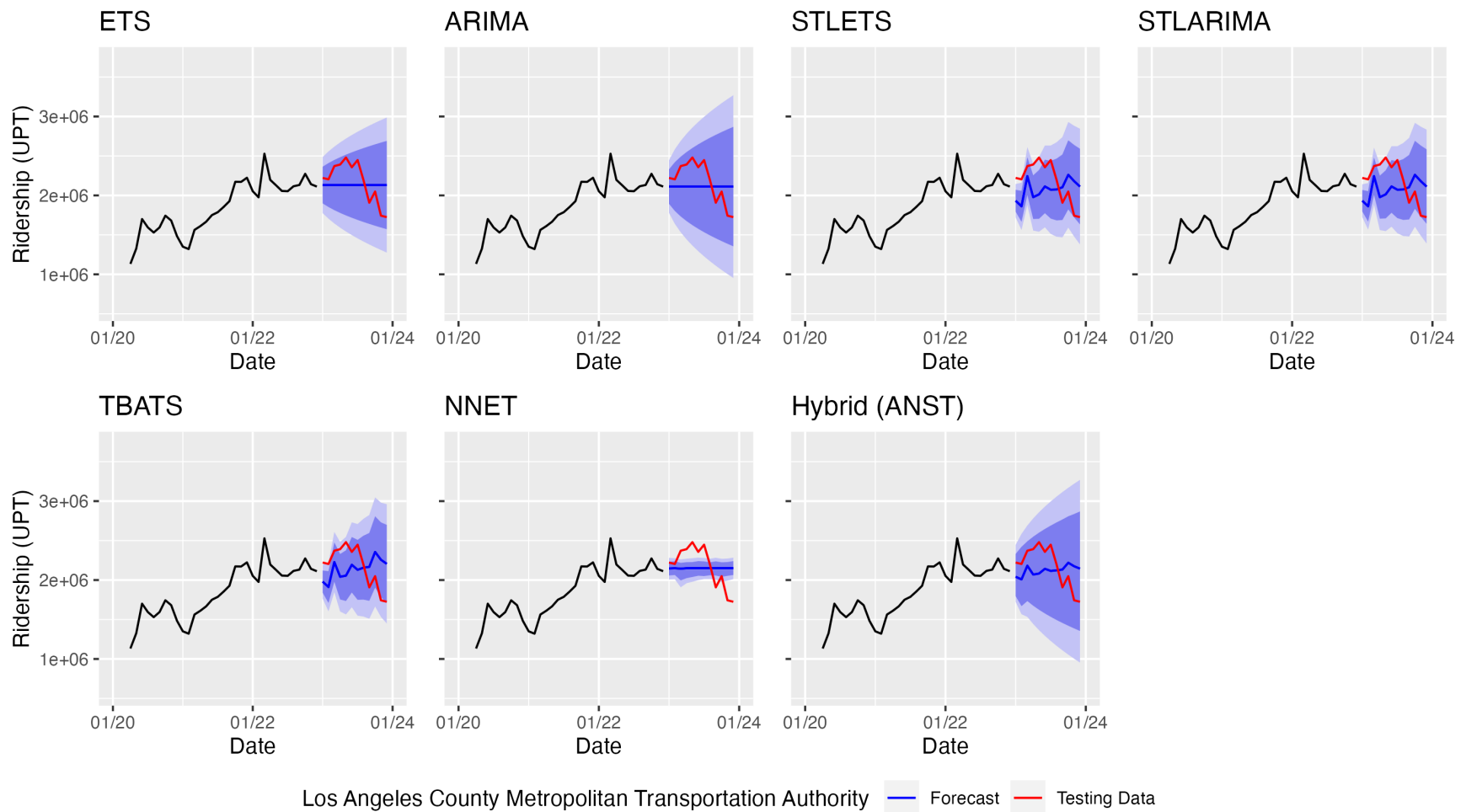


Figure F-3 Post-COVID Forecasts of Ridership at the Los Angeles County Metropolitan Transportation Authority for 2023

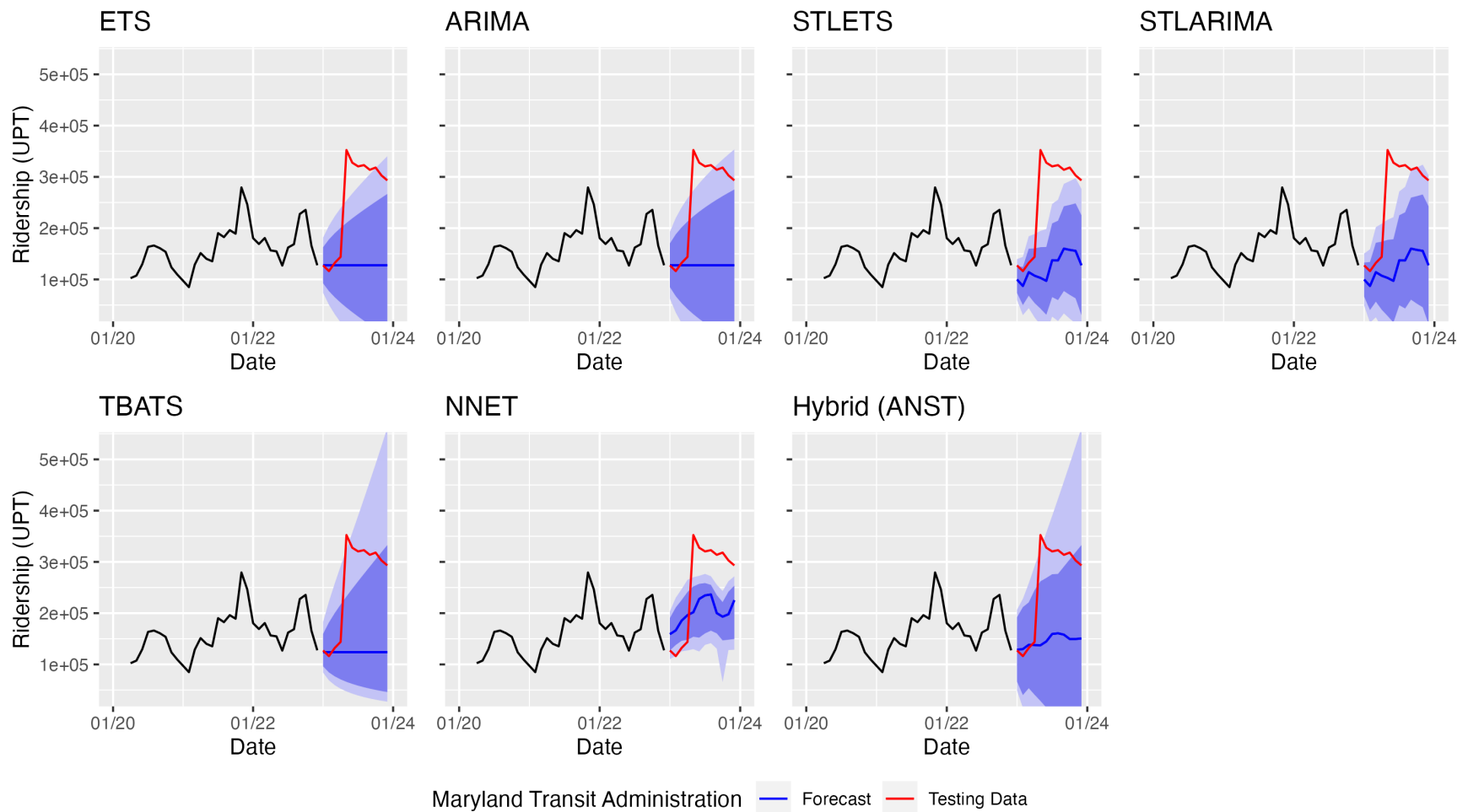


Figure F-4 Post-COVID Forecasts of Ridership at the Maryland Transit Administration for 2023

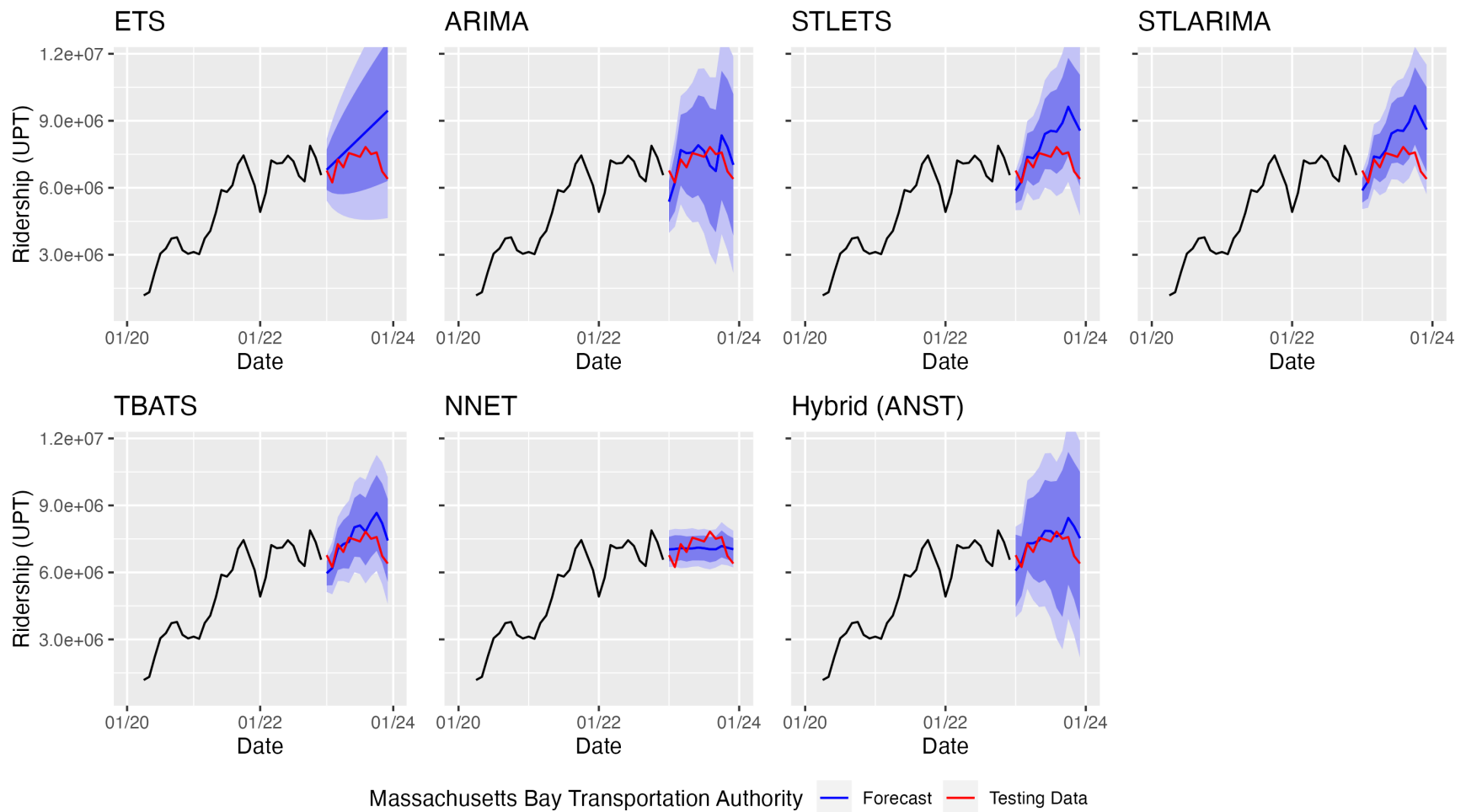


Figure F-5 Post-COVID Forecasts of Ridership at the Massachusetts Bay Transportation Authority for 2023

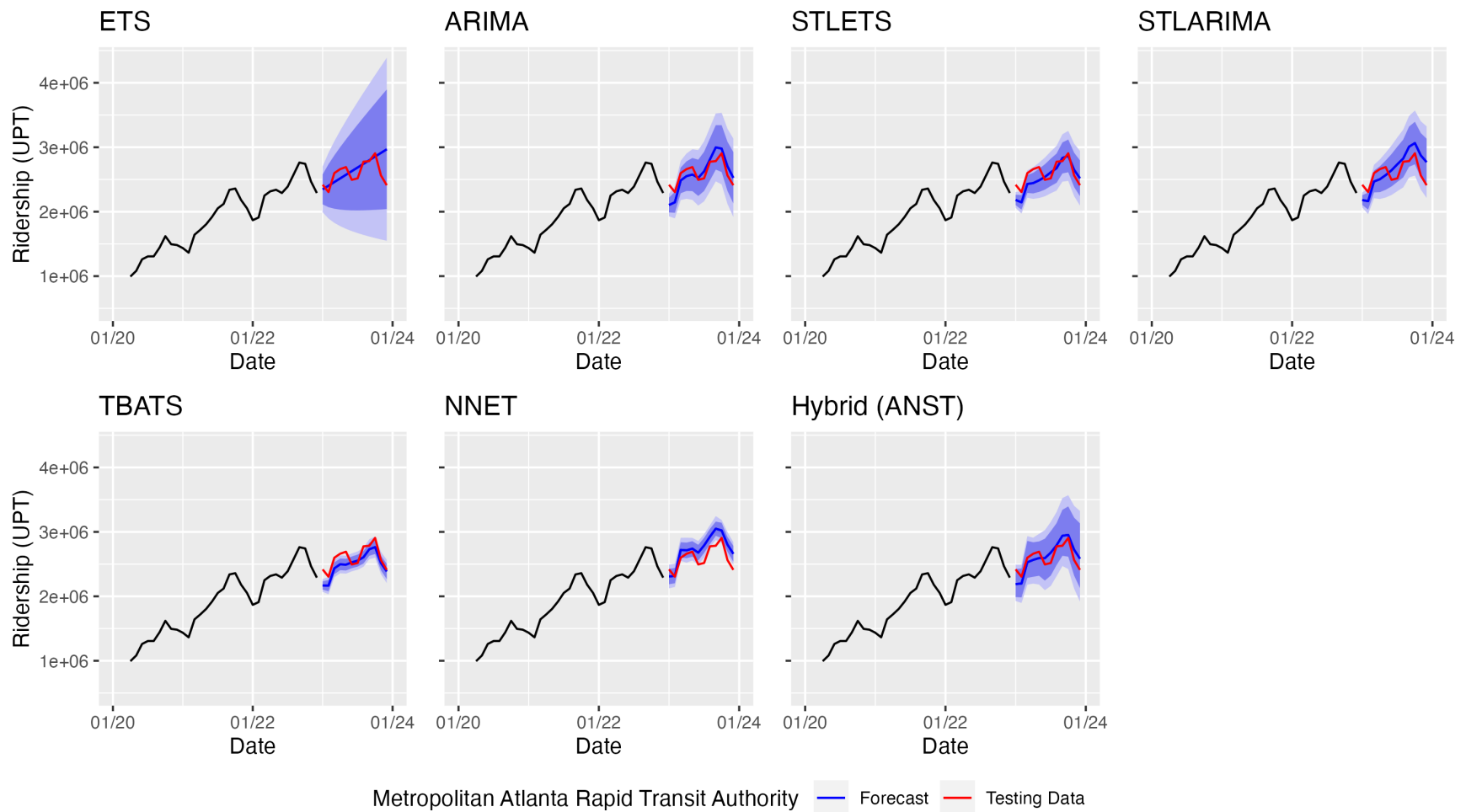


Figure F-6 Post-COVID Forecasts of Ridership at the Metropolitan Atlanta Rapid Transit Authority for 2023

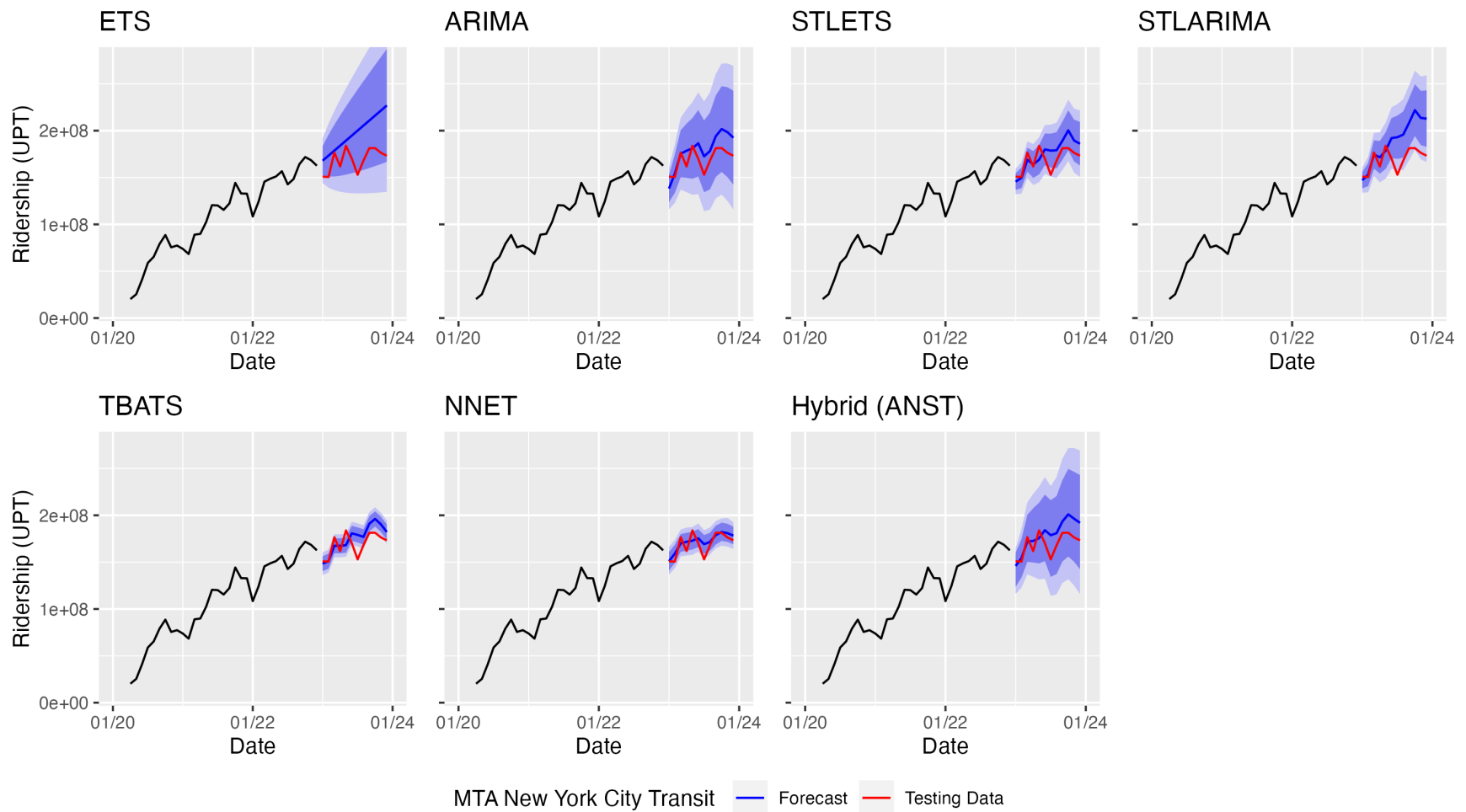


Figure F-7 Post-COVID Forecasts of Ridership at MTA New York City Transit for 2023

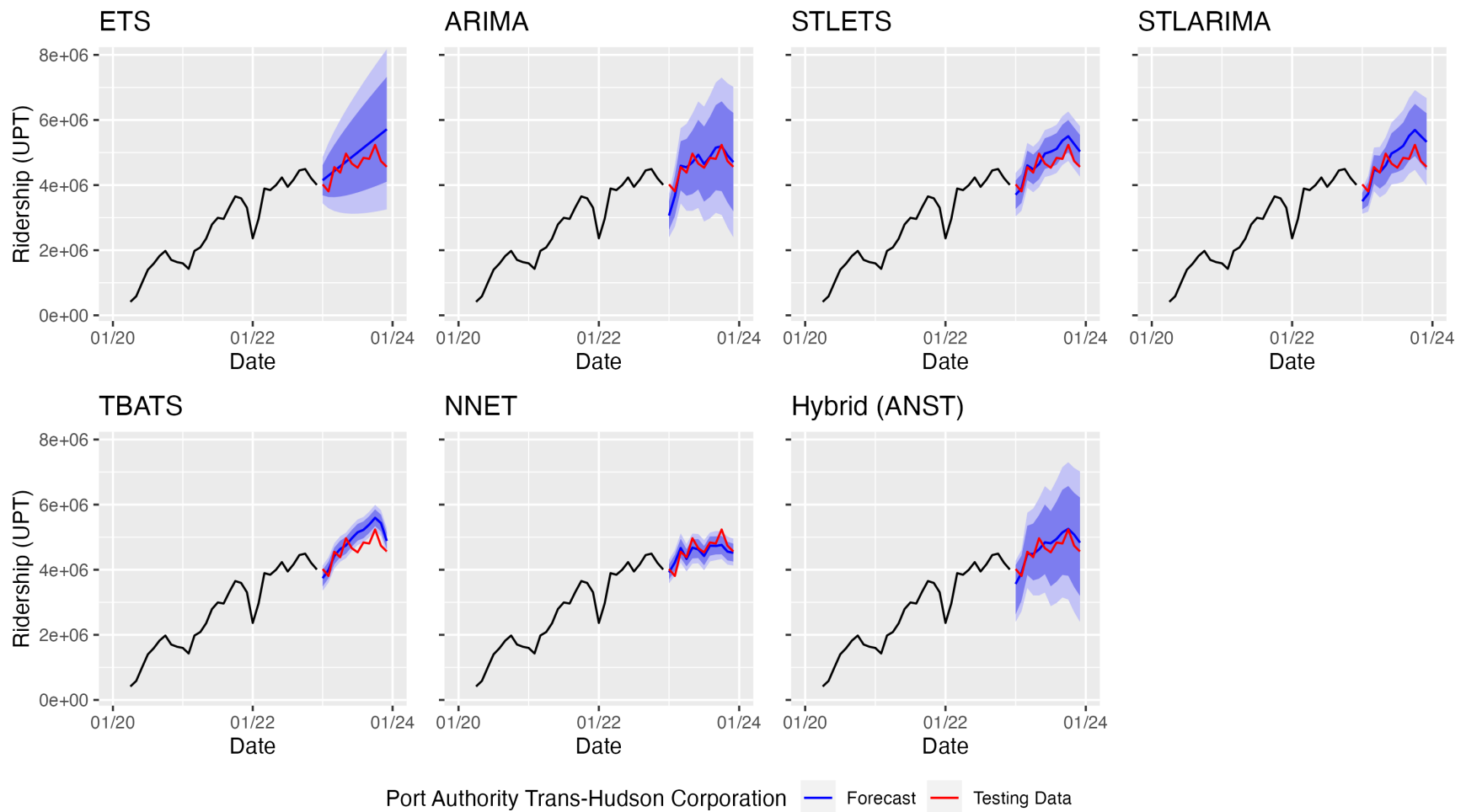


Figure F-8 Post-COVID Forecasts of Ridership at the Port Authority Trans-Hudson Corporation for 2023

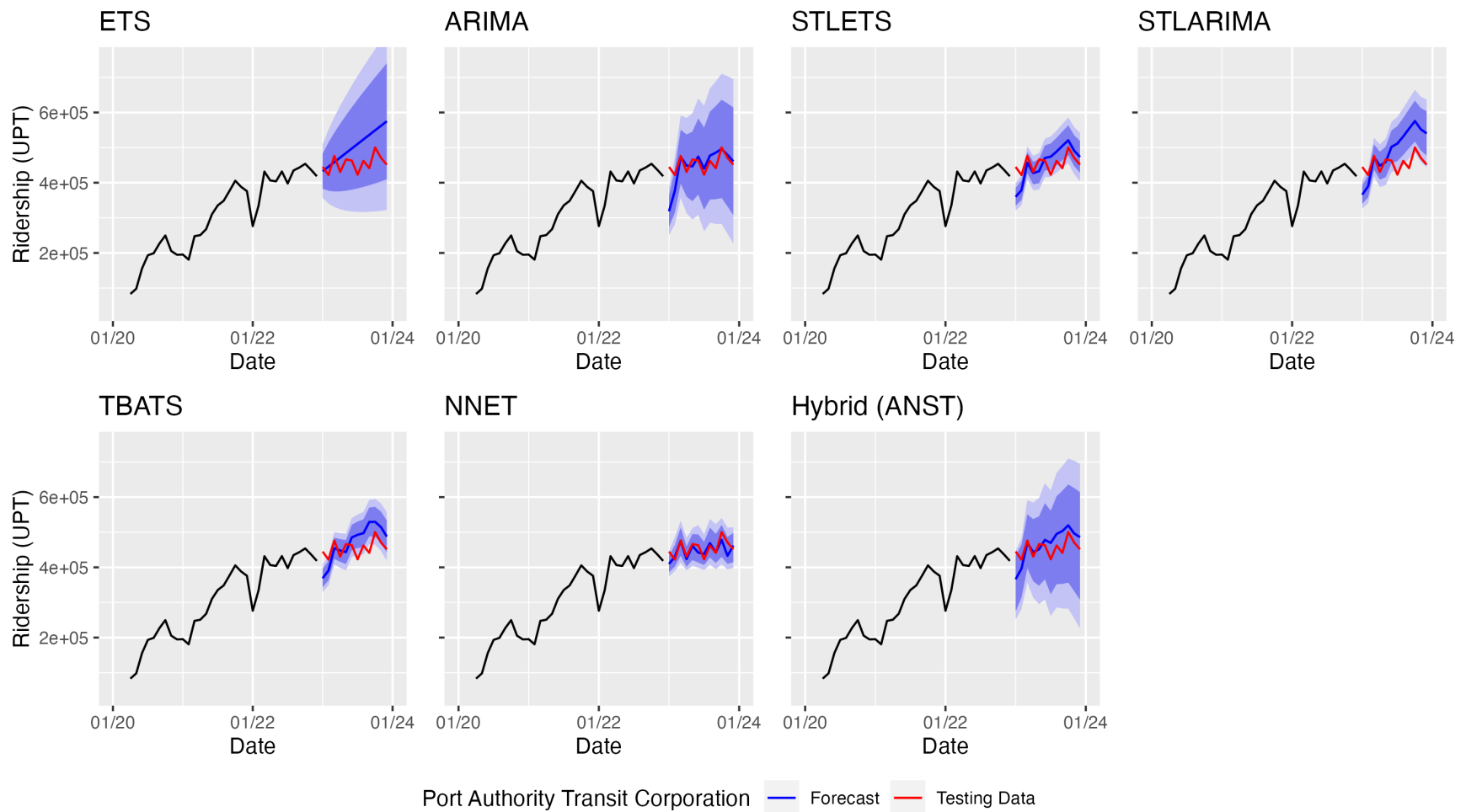


Figure F-9 Post-COVID Forecasts of Ridership at the Port Authority Transit Corporation for 2023

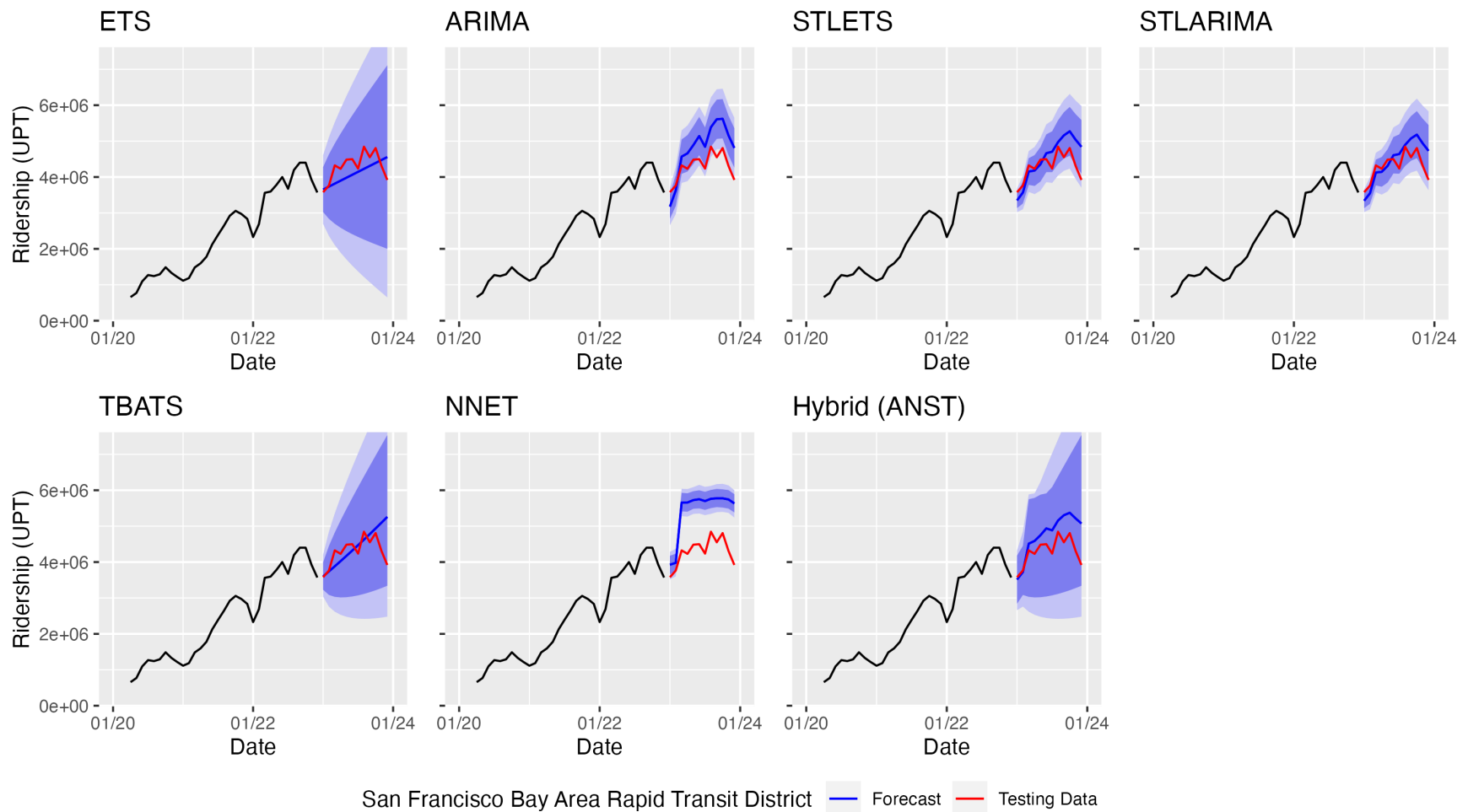


Figure F-10 Post-COVID Forecasts of Ridership at the San Francisco Bay Area Rapid Transit District for 2023

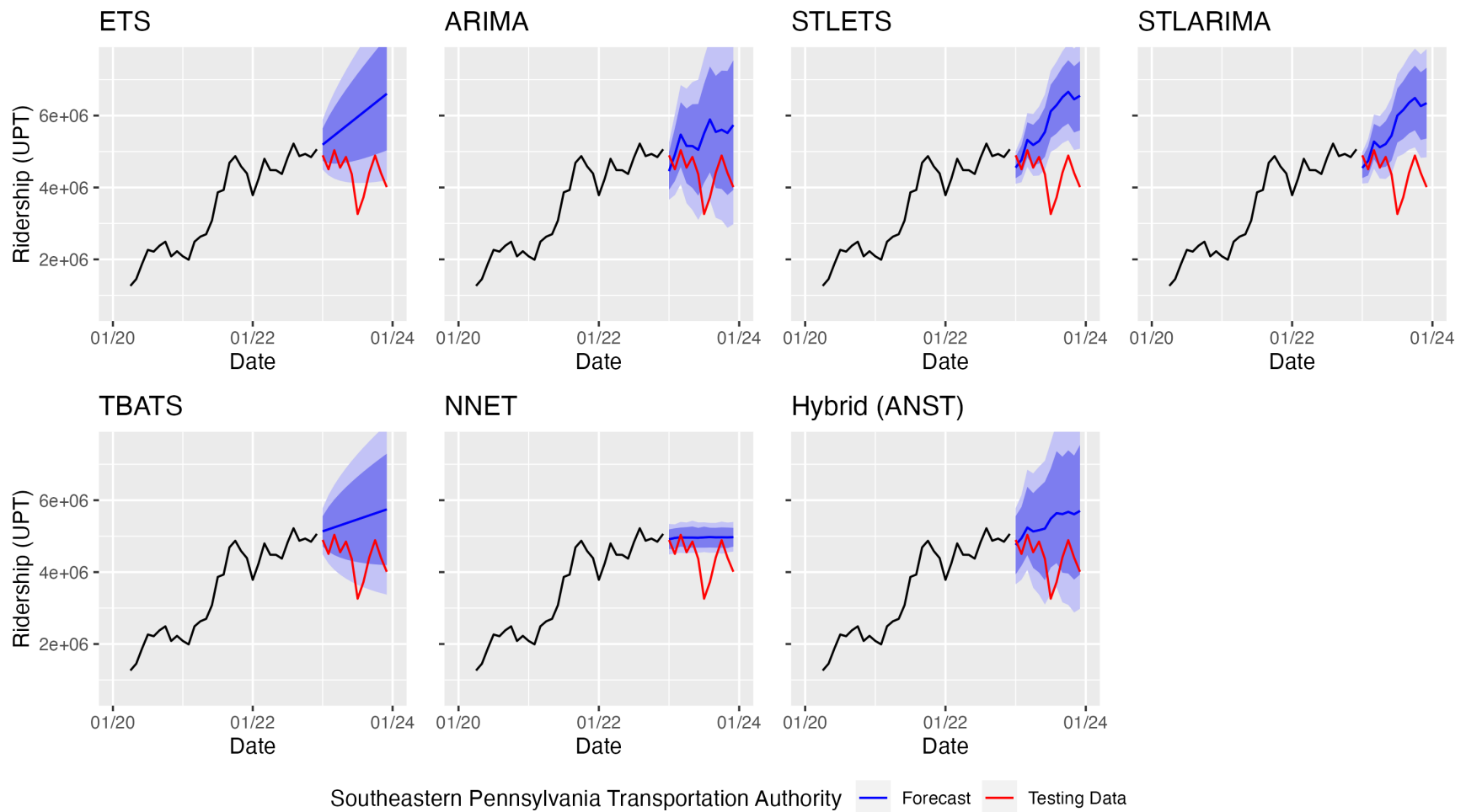


Figure F-11 Post-COVID Forecasts of Ridership at the Southeastern Pennsylvania Transportation Authority for 2023

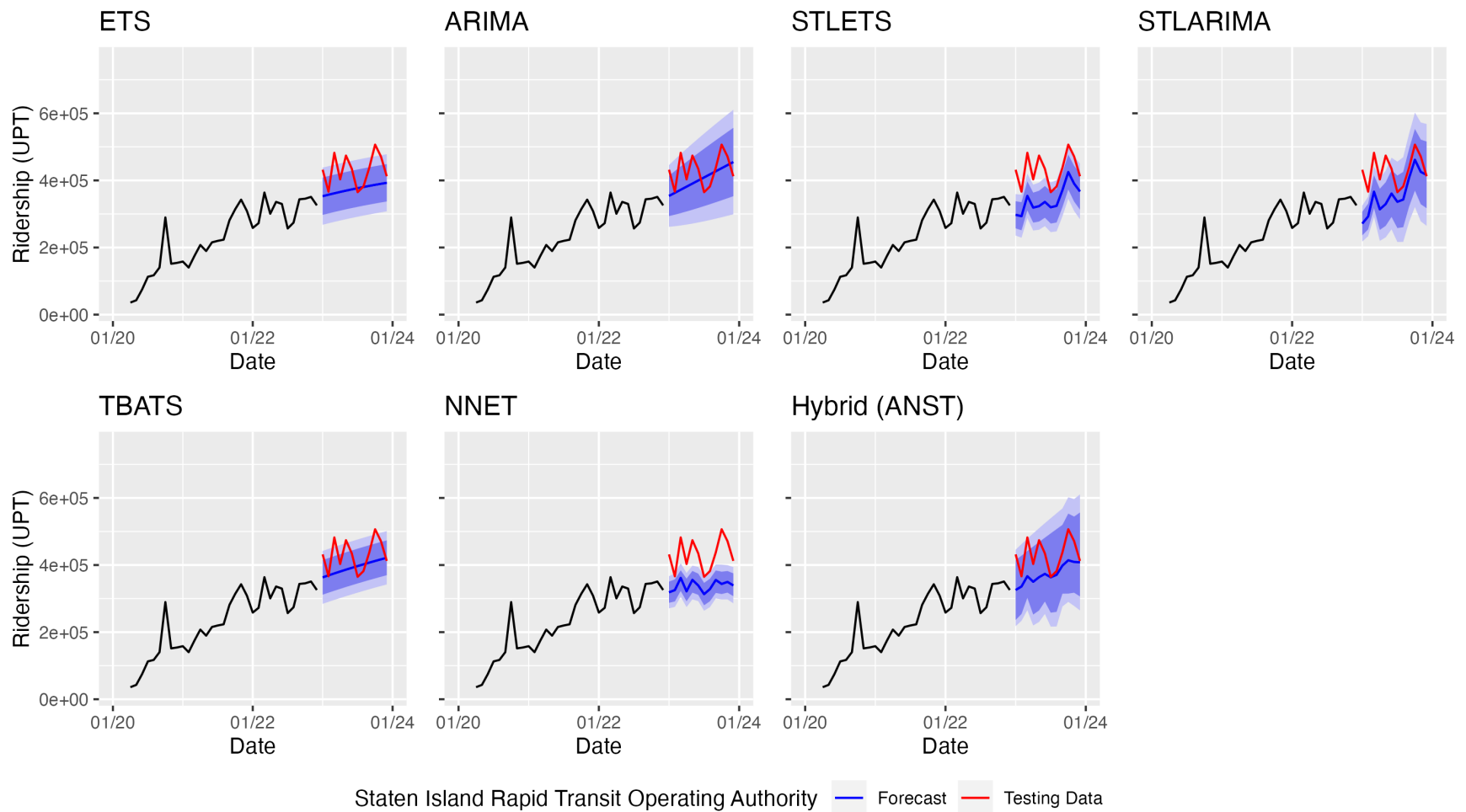


Figure F-12 Post-COVID Forecasts of Ridership at the Staten Island Rapid Transit Operating Authority for 2023

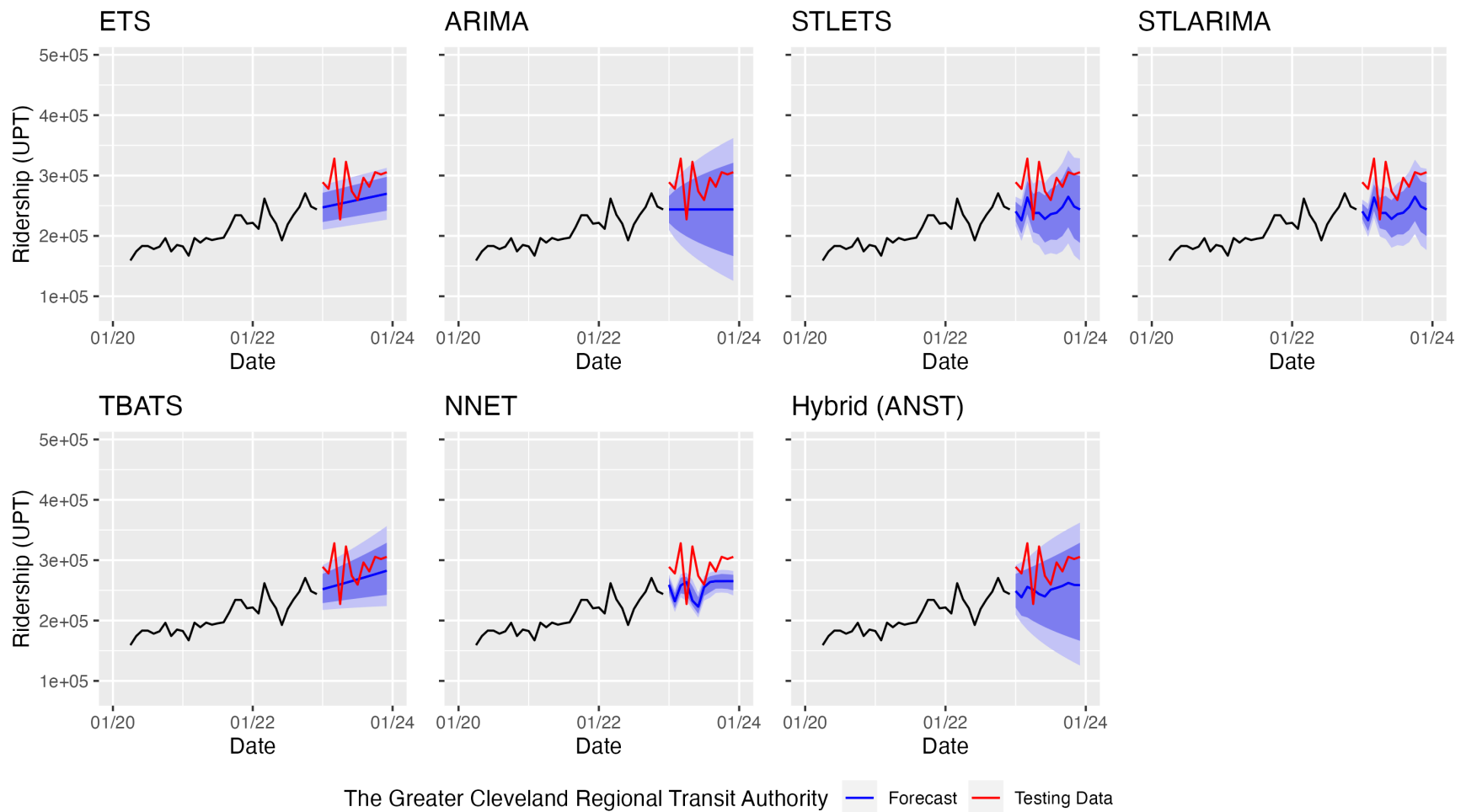


Figure F-13 Post-COVID Forecasts of Ridership at the Greater Cleveland Regional Transit Authority for 2023

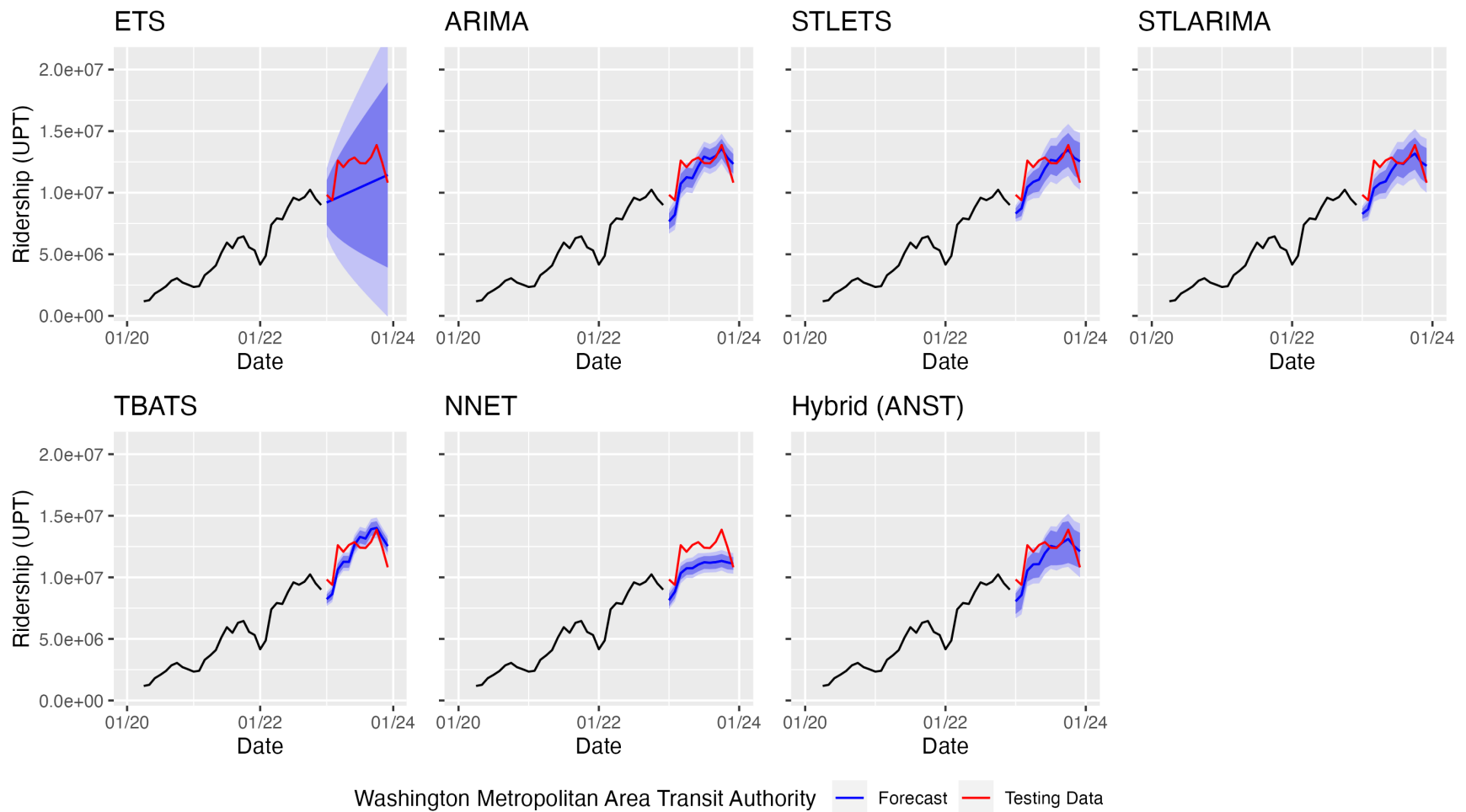


Figure F-14 Post-COVID Forecasts of Ridership at the Washington Metropolitan Area Transit Authority for 2023

VITA

Ashley Hightower was born and raised in the suburbs of Memphis, TN. She got her first degree, a Bachelor of Art in Foreign Languages, from the University of Memphis in 2016. During her first degree, she was able to study abroad, where she developed an interest in public transit. Upon graduation, Ashley worked for several years in management while saving up tuition for a second bachelor's in transportation engineering. Ashley received her Bachelor of Science in Civil Engineering from the University of Tennessee Knoxville in 2023. Immediately after graduating with her second bachelor's, Ashley began her Master of Science in Civil Engineering at the University of Tennessee Knoxville. During the course of her master's, Ashley received a full fellowship from the Dwight David Eisenhower Transportation Fellowship Program for the 2023-2024 academic year.