COVID-19's Impact on NYC Taxis

STAT 5291: Advanced Data Analysis

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1 Introduction

New York City's yellow taxi industry has undergone significant disruption in the past decade, driven first by the rise of competing transport modes and later by the COVID-19 pandemic. Even before 2020, taxi ridership was in decline due to competition from ride-hailing services like Uber and alternative options such as Citi Bike. Between 2014 and 2015, Uber's NYC trips surged by over 220%, while taxi trips declined slightly—especially in outer boroughs with longer transit times and higher household incomes [2]. By 2014, Citi Bike had already replaced an estimated 5–10% of short trips that might otherwise have relied on taxis [5]. Together, these trends marked a steady shift toward multimodal urban travel.

The onset of COVID-19 in 2020 triggered an unprecedented collapse in taxi demand. Daily yellow-cab trips dropped from roughly 200,000 to fewer than 5,000 in April [6]. However, this decline was uneven across neighborhoods: wealthier districts saw steeper drops due to remote work and private vehicle access, while areas with more essential workers retained higher ridership levels [7]. Spatial and temporal travel patterns were also deeply disrupted. Pre-pandemic rhythms vanished, and Manhattan's traditional hotspots saw up to 95% fewer rides [8]. Recovery began later that year but remained sluggish and uneven, with airport and office trips lagging behind local travel.

This study extends previous work by analyzing a decade of trip-level data (2014–2024) from the NYC Taxi & Limousine Commission to assess the longer-term evolution of yellow taxi demand. While prior research has focused on early pandemic disruptions [7, 8], the present analysis fills a critical gap by quantifying whether ridership is rebounding or settling at a lower equilibrium. We examine how post-COVID mobility trends interact with neighborhood demographics and competition from services like Uber and Citi Bike. Our goal is to provide a data-driven perspective on the taxi industry's path forward in a changed urban transportation landscape.

2 Objective

This project investigates a central question: How has the COVID-19 pandemic altered the long-term trajectory of yellow taxi demand in New York City? Using daily trip-level data from 2014 to 2024, we examine both the immediate disruption and the evolving recovery of taxi usage in the aftermath of the pandemic. Specifically, we seek to quantify whether taxi demand has returned to pre-pandemic levels. We also ask whether the pandemic caused a structural break in ridership patterns, how abrupt the change was at its onset, and how closely actual recovery has followed pre-pandemic trends.

3 About the Data

3.1 Description about Dataset

The dataset consisted NYC Taxi and Limousine Commission(TLC) Trips Records, which provides trip-level data for New York City's taxi and ride services from 2009 to 2024. The dataset was collected by managing electronic metering and GPS tracking installed in taxis. Each record captured pick-up/drop-off locations and times, trip distance, fare amounts, payment types, and passenger counts. The coverage expanded in 2013 to include green taxis serving areas outside central Manhattan, and in 2015, the data was made publicly available with semiannual updates. By storing in parquet format, the original data included around 2 million taxi rides monthly. The data facilitated analysis of ridership trends, fare revenue, geographic travel patterns, and seasonal variation in the NYC's transportation ecosystem. However, it should be noted that certain fields depend on manual driver input, which may introduce occasional data inconsistencies that researchers should account for during analysis. For this study, we focused exclusively on yellow taxi data to maintain consistency in the temporal range examined. Further details on all data fields and their descriptions are provided in Appendix 7.1 for reference.

3.2 Data Processing

3.2.1 Raw Data Overview and Loading Strategy

Given the massive scale of the dataset, ranging over a decade and containing hundreds of millions of records, we prioritized limiting the memory footprint and intermediate storage size to accelerate processing and enable feasible computation.

Our processing approach balanced completeness with memory efficiency by handling data in yearly batches. We processed each year's data by sequentially reading monthly Parquet files, applying immediate cleaning transformation(3.2.2), and appending the result to a memory-efficient DataFrame with downcast numeric data types.

Additionally, we standardized the evolving TLC schema through consistent column naming, adding missing fields(e.g. airport_fee), and removing unused columns. This ensured a uniform analysis throughout the temporal range and prevented methodological artifacts.

3.2.2 Data Cleaning and Quality Assurance

To ensure data integrity and minimize bias from measurement or recording errors, we implemented a series of data cleaning procedures at the trip level. First, we removed records with non-positive trip distances or zero/negative durations, due to meter malfunctions or incomplete logs. Therefore, we filtered out extreme outliers, including trips with distances exceeding realistic urban travel limits (e.g., over 100 miles), durations longer than 24 hours, or fare amounts in the thousands of dollars. These rare but extreme values can disproportionately distort mean estimates, inflate variances, and bias model parameters. Then, we addressed missing values by zero-filling surcharge fields introduced in later years to maintain temporal consistency in fare totals, while dropping records with missing essential fields (e.g., dropoff datetime, total amount) to avoid unreliable imputation. We also excluded entries with undefined or malformed payment codes, which typically indicate corrupted transaction logs. Though these filters affected less than 0.1% of the total dataset, they were essential to maintain the reliability of aggregated statistics and to preserve the robustness of subsequent modeling analyses.

3.2.3 Temporal Processing and Daily Aggregation

The cleaned trip-level data were aggregated into daily summaries to allow temporal modeling and time-series analysis. We first parsed timestamp fields into timezone-aware datetime objects in Eastern Time and extracted the pickup date and grouped trips by the time they originated, which reflects demand-side patterns more accurately.

To support geographic analyses, we mapped pickup and dropoff LocationIDs to zone names and boroughs using the official TLC Taxi Zone Lookup Table. This allowed us to calculate interpretable borough-level ride metrics and later incorporate these as structured covariates for predictive models.

For each calendar day from January 2014 through November 2024, we computed summary statistics that include total trip count, total and average distance, average duration, total revenue, and average fare per trip. We also recorded borough-specific pickup and dropoff volumes (e.g., Manhattan_Pickups, EWR_Dropoffs), which were instrumental in capturing spatial heterogeneity and responding to localized shocks such as pandemic-related travel disruptions.

To maintain continuity in the time series, we inserted zero-filled records for any dates with no recorded trips. This aggregation reduced the dataset from hundreds of millions of records to approximately 3,960 daily entries with 24 variables, resulting in a compact and information-dense dataset for visualization, modeling, and statistical inference. A complete list of variables and descriptions is provided in Appendix 7.2.

3.3 Exploratory Data Analysis

Our dataset comprises daily New York City yellow taxi trip records from 2014 through 2024, including variables such as trip counts, total fares, average fare, trip duration, trip distance, and borough-level pickup counts. This dataset enables us to examine long-term trends, seasonal cycles, and structural changes in urban mobility. Key metrics are summarized in Table 1.

Across the dataset, average fare increased modestly from 2014–2019, dropped sharply during the 2020 pandemic, and peaked in 2023—suggesting demand shocks and price shifts. Trip distances stabilized near 3 miles post-2016, after a large drop from an initial outlier in 2014.

Figure 1 shows a bimodal distribution of daily trips: high-volume days (300–400K) characterize pre-pandemic demand, while lower volumes (100–150K) persist post-2020. The deep gap between these regimes reflects a shift in ridership patterns.

Year	Mean Fare	Std Fare	Mean TD	Std TD
2014	12.63	0.52	13.27	24.03
2015	12.89	0.62	11.92	17.77
2016	13.04	0.61	4.60	6.41
2017	12.97	0.68	2.96	0.19
2018	12.99	0.72	2.97	0.20
2019	13.19	0.63	3.03	0.21
2020	11.54	1.26	2.79	0.37
2021	12.68	1.41	3.08	0.46
2022	14.65	1.46	3.58	0.40
2023	20.17	3.69	3.73	0.82
2024	19.74	1.18	3.60	0.57

Table 1: Annual Mean and Std of Fares and Trip Distances(TD)

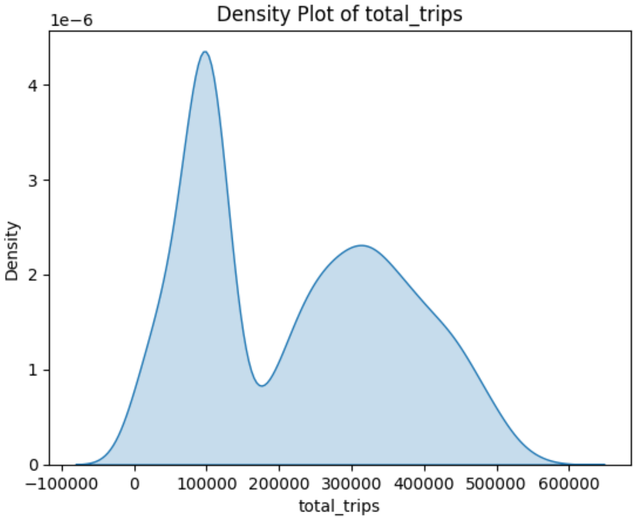


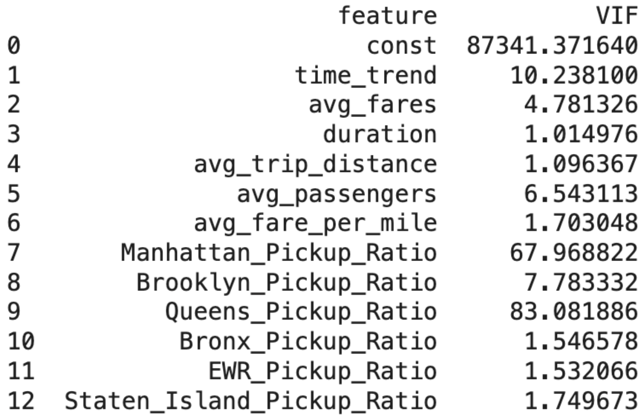
Figure 1: Density of Daily Trip Counts (2014–2024)

4 Statistical Models

To assess the impact of COVID-19 on the usage of yellow taxi in New York City, we implemented a series of regression-based models. We began with an ordinary least squares(OLS) model to establish baseline associations between daily ridership and key predictors (4.1). Building upon these results, we employed a segmented regression to detect a structural change in fare revenue trajectories (4.2), followed by a local regression discontinuity design to quantify the immediate disruption in trip volume at the start of the pandemic (4.3). In the end, we further fit a SARIMAX model to pre-COVID trends to forecast counterfactual ridership in the absence of the pandemic (4.4).

4.1 Linear Regression Model

To select predictors, we began by computing pair-wise correlations with daily yellow-taxi demand. We then inspected variance-inflation factors (VIF) to identify and drop highly collinear variables; the remaining predictors were used in the ordinary-least-squares (OLS) model.



```
                         feature           VIF
0                          const  87341.371640
1                     time_trend     10.238100
2                      avg_fares      4.781326
3                       duration      1.014976
4              avg_trip_distance      1.096367
5                 avg_passengers      6.543113
6              avg_fare_per_mile      1.703048
7         Manhattan_Pickup_Ratio     67.968822
8          Brooklyn_Pickup_Ratio      7.783332
9            Queens_Pickup_Ratio     83.081886
10            Bronx_Pickup_Ratio      1.546578
11              EWR_Pickup_Ratio      1.532066
12    Staten_Island_Pickup_Ratio      1.749673
```

Figure 2

Using these retained variables, we estimated an OLS model and introduced an additional categorical variable, covid_phase, to capture phase-specific shifts during the pandemic. The resulting equation is reported below.

$$\begin{aligned}
\texttt{log(frequency\_of\_rides)} = {} & 15.0532 \\
& - 1.8775\,\texttt{covid\_phase\_lockdown} - 1.1678\,\texttt{covid\_phase\_reopening} \\
& - 0.8498\,\texttt{covid\_phase\_post} - 0.0002\,\texttt{time\_trend} \\
& + 0.0536\,\texttt{avg\_fares} - 0.0001\,\texttt{duration} \\
& + 0.0003\,\texttt{avg\_trip\_distance} - 1.5013\,\texttt{avg\_passengers} \\
& - 0.0026\,\texttt{avg\_fare\_per\_mile} \\
& + 16.7451\,\texttt{Brooklyn\_Pickup\_Ratio} - 6.8380\,\texttt{Queens\_Pickup\_Ratio} \\
& - 203.6932\,\texttt{Bronx\_Pickup\_Ratio} \\
& + 2347.1024\,\texttt{EWR\_Pickup\_Ratio} - 1591.0483\,\texttt{Staten\_Island\_Pickup\_Ratio}.
\end{aligned} \tag{1}$$

After fitting the model and summarizing the results, we obtained the formula presented above. Next, we apply this model to make predictions on the testing dataset and calculate the corresponding RMSE, which is 28,989.01, and MSE, which is 26,655.51. Based on these metrics, we conclude that the model demonstrates reasonable predictive accuracy, although there remains room for improvement. Further refinement could involve adding additional variables or exploring alternative modeling approaches to reduce prediction errors.

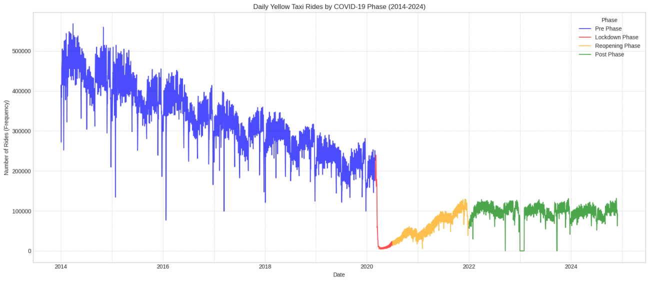


Figure 3: Daily rides by COVID-19 phase (2014–2024)

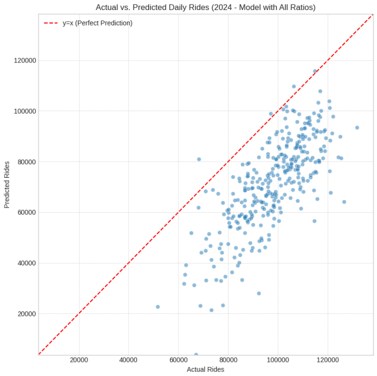


Figure 4: Actual vs. predicted rides (2024)

Visualisations such as Figure 3 and Figure 4 illustrate pandemic-induced shifts in ride volumes and the model's predictive accuracy. The time series reveals phase-specific demand drops and a persistent post-pandemic decline, while the prediction scatterplot indicates moderate fit with substantial error spread.

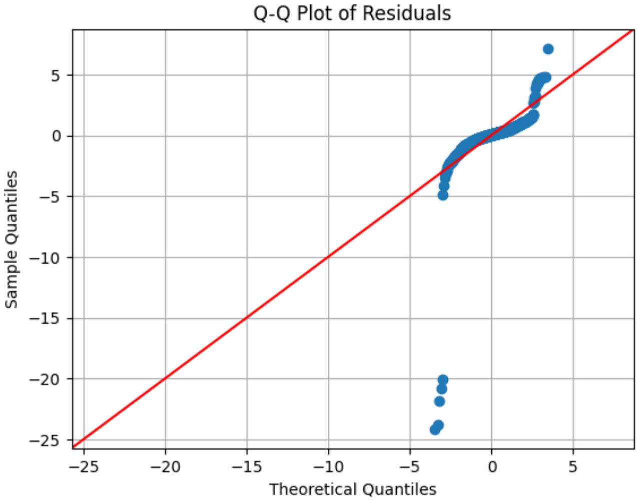


Figure 5: Q-Q Plot of Residuals

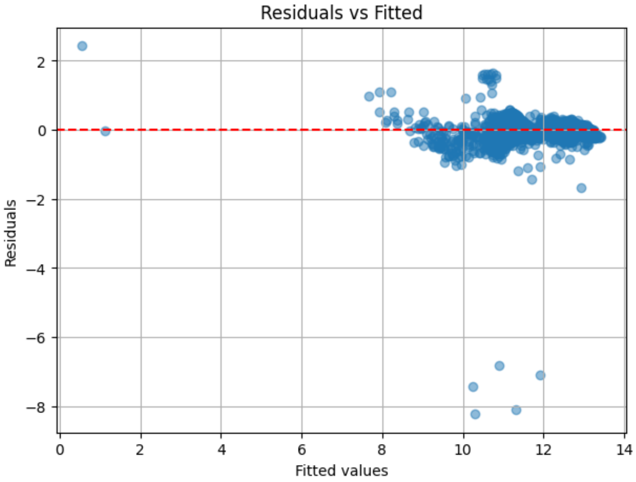


Figure 6: Residuals vs Fitted Values

Despite the apparent explanatory power of the OLS model, residual diagnostics reveal important violations of standard linear regression assumptions. In particular, Figure 5 presents a Q–Q plot of the residuals, which deviate substantially from the 45° line in both tails. This departure suggests non-normality of residuals, possibly due to heavy-tailed noise or latent nonlinearity.

Moreover, Figure 6 plots residuals against fitted values, showing a clear funnel shape. This heteroskedasticity violates the constant variance assumption of OLS, indicating that the model's prediction error varies systematically with ride volume.

These issues raise concerns about the reliability of inference (e.g., confidence intervals or p-values) in the current model. Although robust standard errors (e.g., HC3 or Newey–West) can partially address these problems, the findings motivate a shift to models that explicitly accommodate serial dependence and structural shifts, such as segmented regression or SARIMAX, as discussed in the next section.

4.2 Segmented Regression on Total Fares

We began with an ordinary least squares(OLS) regression that models daily total fare revenue as a function of time and a binary post-COVID indicator. The model includes an interaction term to allow for both level and slope change at the cutoff:

$$\widehat{\texttt{total\_fares}}_t = \beta_0 + \beta_1 \cdot \texttt{time}_t + \beta_2 \cdot \texttt{post}_t + \beta_3 \cdot (\texttt{time}_t \times \texttt{post}_t) \tag{2}$$

where `time` represents the days since the beginning of the sample, `post` is an indicator variable equal to 1 if the observation occurs after March 2020 (onset of the COVID-19 pandemic), and 0 otherwise, and `time_post` is the interaction between `time` and `post`, capturing any change in trend following the pandemic.

Figure 7 visually confirms these findings. We observe an immediate decline in fares around March 2020, followed by a gradual upward trend. By the end of the sample, `total_fares` appears to have recovered to pre-COVID levels, supporting the conclusion that the pandemic had a significant but ultimately transitory impact on yellow taxi demand.

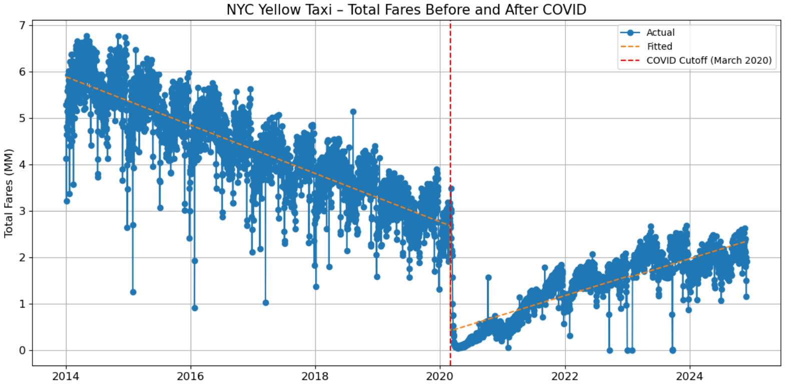


Figure 7: Segmented OLS regression on total fares. Vertical line indicates COVID-19 onset (March 2020).

The estimated model is

$$\widehat{\texttt{total\_fares}}_t = 5.8928 - 0.0014 \cdot \texttt{time}_t - 8.0288 \cdot \texttt{post}_t + 0.0026 \cdot (\texttt{time}_t \times \texttt{post}_t) \tag{3}$$

The regression results are presented in Table 2. All coefficients are highly statistically significant ($p < 0.001$), indicating a meaningful relationship between the variables and total fares. Specifically, the negative coefficient on `time` ($\beta_1 = -0.0014$) suggests a declining trend in taxi fares leading up to the pandemic. The large negative coefficient on `post` ($\beta_2 = -8.0288$) indicates a substantial drop in demand immediately following March 2020. The positive coefficient on `time_post` ($\beta_3 = 0.0026$) implies that fares began to recover post-COVID, with a trend reversal relative to the pre-pandemic period. The model fits the data well ($R^2 = 0.915$), capturing most of the variation in `total_fares`. However, diagnostics (e.g., Durbin-Watson = 0.486) suggest some autocorrelation, which should be considered when interpreting standard errors.

The Segmented Regression on total fares provides strong statistical evidence that the COVID-19 pandemic introduced a structural break in yellow taxi cab demand in New York City. All coefficients are significant at the 5% level and the coefficients align with our expectations: an immediate drop in demand followed by a period of gradual recovery. The high R^2 value (0.915) indicates an excellent fit. The model's residual diagnostics, however, point to autocorrelation (Durbin-Watson: 0.486), suggesting standard errors may be underestimated. While this does not affect the direction and magnitude of the estimated effects, it may lead to overly optimistic conclusions.

Table 2: OLS Regression on total fares output.

Dep. Variable:	total_fares	**R-squared:**	0.915
Model:	OLS	**Adj. R-squared:**	0.915
Method:	Least Squares	**F-statistic:**	1.415e+04
Date:	Wed, 07 May 2025	**Prob (F-statistic):**	0.00
Time:	15:22:18	**Log-Likelihood:**	-2881.8
No. Observations:	3959	**AIC:**	5772.0
Df Residuals:	3955	**BIC:**	5797.0
Df Model:	3	**Covariance Type:**	nonrobust

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	5.8928	0.021	278.76	0.000	5.851	5.934
time	-0.0014	1.63e-05	-87.81	0.000	-0.001	-0.001
post	-8.0288	0.080	-100.12	0.000	-8.186	-7.872
time_post	0.0026	2.95e-05	86.80	0.000	0.003	0.003

Omnibus:	773.178	**Durbin-Watson:**	0.486
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4861.707
Skew:	-0.779	**Prob(JB):**	0.00
Kurtosis:	8.200	**Cond. No.:**	3.03e+04

Notes: Standard errors assume correctly specified covariance. High condition number suggests possible multicollinearity or numerical issues.

4.3 Local RDD on Trip Volume

To strength our causal interpretation, we also complemented this analysis with a local regression discontinuity design(RDD) using daily trip counts as the outcome variable. The volume of trips offered a more direct measure of taxi usage and is less sensitive to variability in the fare structure.

This local linear specification is consistent with best practices in RDD, as recommended by Imbens and Lemieux[4], who aimed to optimize local polynomial estimation over global parametric models to minimize bias near the cutoff point. We also utilized a triangular kernel to prioritize observations closer to the threshold and apply a fixed bandwidth of 90 days on either side. This approach was introduced by Calonico et al.[3], who demonstrated that weighting and bandwidth strategies improve estimation precision and inference validity in a sharp RDD setting.

The local linear regression model was implemented in Python using `statsmodels`, following the robust estimation framework introduced by Calonico et al.[3]. The RDD estimation revealed a statistically significant drop of 172,601 daily trips at the cutoff. The estimated effect size corresponds to a decrease of 74.6% relative to the pre-COVID average. The result is highly significant ($p < 0.001$), with a 95% confidence interval ranging from −185,144 to −160,058 daily trips (Table 3). Hence, the sharp negative discontinuity supports supported the alternative hypothesis: that the pandemic induced a structural break in mobility patterns. Both the magnitude and significance of the estimate reinforce its practical importance.

Method	Estimate	Std. Error	95% CI	p-value
Conventional	−172,601	6,399.5	[−185,144, −160,058]	$< 10^{-160}$
Robust (bias-corrected)	—	—	[−147,974, −104,457]	$< 5.95 \times 10^{-30}$

Table 3: RDD estimation results using `rdrobust()` with a 90-day bandwidth

To further evaluate the robustness of our results in bandwidth selection, we replicated the analysis using alternative windows of 120 and 150 days. Re-estimating the RDD model using bandwidths of 120 and 150 days produced consistent results, with estimated discontinuities ranging from −172,601 to −186,890 daily trips. All estimates remained significant at $p < 10^{-29}$ and shared overlapping confidence intervals. This consistency supports the reliability of our main specification.

4.4 SARIMAX Model

To estimate what taxi demand would have been in the absence of COVID-19, we fitted a seasonal ARIMA with exogenous regressors,

$$\text{SARIMAX}(1,1,1) \times (1,1,1)_{12},$$

to monthly trip counts from January 2018 through March 2020. We then compared **Counterfactual predictions** from that pre-COVID model, and **Actual ridership** recorded from March 2020 onward.

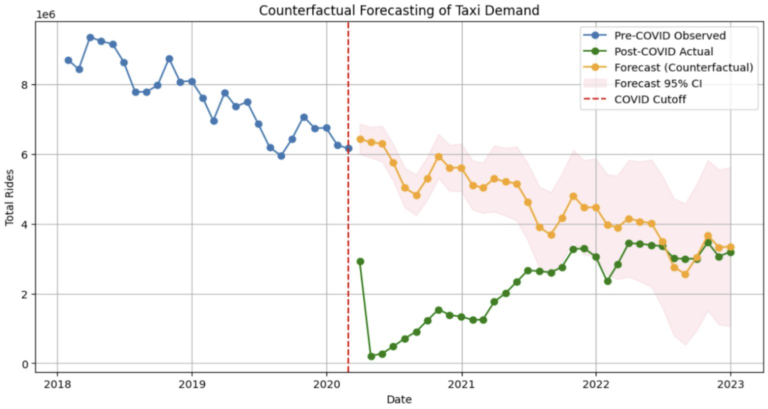


Figure 8: Counterfactual forecast (orange) versus observed taxi ridership (blue/green). Shaded bands show the model's 95% prediction interval; the red line marks the COVID cutoff.

Figure Figure 8 plots three monthly series. The blue markers trace the observed ridership until the end of 2019, while the orange line extends the counterfactual forecast from January 2020 onward. A red vertical line marks March 2020, the point where fitted values give way to out-of-sample forecasts. Ridership was already drifting down, from roughly eight million monthly rides in early 2018 to six million at the end of 2019. However, COVID19 produced an abrupt break: actual ridership (green markers) plunged below one million rides in April 2020, far below both the forecast and the lower edge of the 95 percent confidence band. Although demand improved in 2021 and 2022, it never re-entered the prediction interval, stabilizing around three to four million rides per month. This persistent gap highlights a structural deviation from the historical trajectory.

We formally assessed that gap with a paired t-test on the monthly differences between forecast and actual values. The result was highly significant ($t = 6.98$, $p < 0.0000001$), which supports the visual impression that the post-2020 shortfall is not attributable to chance fluctuations. Because the forecast series is model-generated, the test inherits model uncertainty in addition to sampling variability. However, the magnitude of the discrepancy and its statistical significance together indicate that COVID19 caused a sustained reduction in taxi demand.

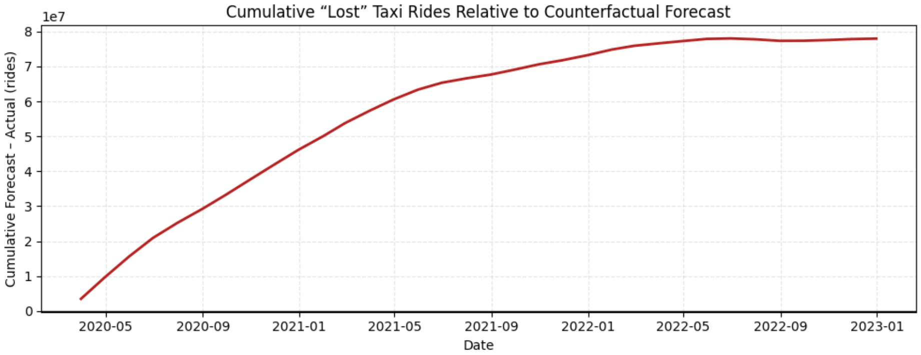


Figure 9: Cumulative “lost” taxi rides relative to the counterfactual forecast, January 2020–December 2022.

Figure Figure 9 quantifies that reduction. By accumulating the monthly shortfalls, the plot shows that New York City forewent nearly eighty million rides between March 2020 and December 2022. The curve rises steeply during the initial lockdown, then continues to climb, though more gradually, as ridership recovers, and finally flattens in 2022, implying that the lost volume has not been recouped. This cumulative deficit view showcases the practical impact of the pandemic on taxi revenues and driver livelihoods.

While the SARIMAX specification captures pre-COVID seasonality and trend, it assumes the underlying data-generating process remains unchanged. Consequently, the model cannot adapt to an unprecedented shock, and its prediction intervals likely understate the true forecast uncertainty. Future work could incorporate explicit intervention dummies, regime-switching specifications, or additional exogenous variables (e.g., subway ridership, mobility indices) to better accommodate structural breaks and improve forecast reliability.

Both the counterfactual comparison and the cumulative-deficit metric lead to the same conclusion: COVID-19 produced a statistically and practically significant long-term decline in New York City taxi demand. Transparent reporting of model assumptions and diagnostic results strengthens confidence in this finding and provides a baseline for future forecasting efforts that must account for post-pandemic travel behavior.

5 Discussion

Our findings confirmed that the COVID-19 pandemic caused an unprecedented disruption in yellow taxi demand in NYC. Utilizing a sequence of regression-based methods, we found evidence to prove the magnitude and persistence of this disruption. As a result, results showed a statistically significant decline in taxi usage beginning March 2020 and with only partial recovery through 2024. These findings align with prior research highlighting pandemic-related mobility collapses in urban centers [7, 8].

In particular, our models revealed not only a structural break at the pandemic's onset, but also a partial and uneven recovery in demand. The segmented regression indicated a steep initial decline in fare revenue followed by a gradual rebound, while the RDD analysis identified an immediate 74.6% drop in daily trip counts with effects that remained robust across all alternative bandwidth specifications. The SARIMAX model further projected counterfactual ridership in the absence of COVID-19 and showed a persistent shortfall of nearly 80 million rides through 2022, underscoring the enduring impact of the pandemic on taxi use.

However, our findings also reflected a longer-term trend that precedes COVID-19: the steady erosion of taxi ridership due to ride-hailing competition, particularly from Uber and Lyft. As Correa[2] and Kaufman et al.[5] documented, Uber's presence surged in the mid-2010s, and Citi Bike simultaneously began to capture short-distance trips in Manhattan. Our own linear regression supported this narrative of structural displacement, showing that the pickup ratios at the borough level and the dynamics of the prices significantly shaped the daily volume of trips even before 2020.

During the pandemic, these competitive pressures only intensified. Ride-hailing platforms rebounded more quickly by leveraging dynamic pricing, app-based convenience, and route flexibility. Recent studies (e.g., Bian et al., 2022; Zhang et al., 2024[1, 9]) have shown that Uber and Citi Bike retained or grew their market share in areas where yellow taxis collapsed, specifically in wealthier districts or neighborhoods with transit-dependent populations. These shifts suggested that COVID-19 accelerated the modal reordering of urban transport rather than causing the change in urban mobility.

To build on these findings, future research should incorporate For-Hire Vehicle(FHV) data, such as Uber and Lyft logs, for the future comparison after the pandemic. Linking FHV and taxi data would clarify how ride-hailing services filled demand gaps and reshaped spatial patterns. In addition, spatial econometric models could capture borough-level variation by future incorporation of local demographics and infrastructure. These directions would strengthen understanding of how COVID-19 accelerated structural changes in New York's transportation system and guide policy responses to future resilience.

6 Conclusion

Our analysis demonstrates that COVID-19 significantly disrupted NYC yellow taxi demand, resulting in a sharp initial decline and an incomplete recovery by 2024. Structural breaks identified through segmented regression and regression discontinuity design confirm the pandemic's immediate and lasting impact on taxi ridership. The SARIMAX model further quantifies this disruption, indicating a cumulative shortfall of nearly 80 million rides compared to pre-pandemic forecasts. While COVID-19 accelerated existing declines driven by competition from ride-hailing and bike-sharing services, it fundamentally altered travel patterns, suggesting a persistent shift rather than a temporary interruption. Future studies incorporating broader mobility datasets could enhance our understanding of these structural changes, informing more targeted transportation policies and resilience strategies.

7 Appendix

7.1 Trip-Level TLC Dataset Fields

This appendix provides a detailed description of all variables available in the raw trip-level datasets published by the NYC Taxi & Limousine Commission (TLC). These variables include timestamps, trip distance, fare components, passenger counts, geographic identifiers, and payment methods. Some fields were recorded automatically via GPS and taximeter devices, while others were manually entered by drivers, introducing occasional inconsistencies.

Field Name	**Description**
VendorID	A code indicating the TPEP provider that provided the record. **1 = Creative Mobile Technologies, LLC; 2 = VeriFone Inc.**
tpep_pickup_datetime	The date and time when the meter was engaged.
tpep_dropoff_datetime	The date and time when the meter was disengaged.
Passenger_count	The number of passengers in the vehicle.
Trip_distance	This is a driver-entered value. The elapsed trip distance in miles reported by the taximeter.
PULocationID	TLC Taxi Zone in which the taximeter was engaged.
DOLocationID	TLC Taxi Zone in which the taximeter was disengaged.
RateCodeID	The final rate code in effect at the end of the trip. **1 = Standard rate** **2 = JFK** **3 = Newark** **4 = Nassau or Westchester** **5 = Negotiated fare** **6 = Group ride**
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka “store and forward,” because the vehicle did not have a connection to the server. **Y = store and forward trip** **N = not a store and forward trip**
Payment_type	A numeric code signifying how the passenger paid for the trip. **1 = Credit card** **2 = Cash**

	3 = No charge **4 = Dispute** **5 = Unknown** **6 = Voided trip**
Fare_amount	The time-and-distance fare calculated by the meter.
Extra	Miscellaneous extras and surcharges. Currently, this only includes the $0.50 and $1 rush hour and overnight charges.
MTA_tax	$0.50 MTA tax that is automatically triggered based on the metered rate in use.
Improvement_surcharge	$0.30 improvement surcharge assessed trips at the flag drop. The improvement surcharge began being levied in 2015.
Tip_amount	Tip amount – This field is automatically populated for credit card tips. Cash tips are not included.
Tolls_amount	Total amount of all tolls paid in trip.
Total_amount	Total amount charged to passengers. Does not include cash tips.
Congestion_Surcharge	Total amount collected in trip for NYS congestion surcharge.
Airport_fee	$1.25 per pick up only at LaGuardia and John F. Kennedy Airports.

7.2 Aggregated Daily Summary Variables

This appendix lists all variables created during the aggregation of trip-level data into daily summaries. These include temporal indicators (e.g., pickup date, day of week), ride metrics (e.g., total fares, average distance, average duration), and spatial features (e.g., borough-level pickup and dropoff counts). A full description of each summary variable is included for reproducibility and interoperability of our analytical pipeline.

Field Name	**Description**
pickup_date	The date and time when the meter was engaged
day_of_week	The day of the week corresponding to the pickup_date
avg_fares	The average fare amount per trip on that day
total_fares	The sum of all fare amounts for that day's trips
duration	The average trip duration on that day, measured in minutes.

frequency_of_rides	The total number of completed taxi trips initiated on that day
avg_trip_distance	The average length of taxi trips on that day, in miles
avg_passengers	The mean number of passengers per trip
sum_of_passengers	Total number of passengers transported on that day, summed over all trips
avg_fare_per_mile	Average fare collected per mile
Bronx_Pickups	Daily count of trips that originated in the Bronx. Similar fields are provided for pickups across all major NYC boroughs (e.g., Manhattan_Dropoffs, Queens_Pickups)
Manhattan_Dropoffs	Daily count of trips that ended in Manhattan. Additional fields record dropoff counts in other boroughs (e.g., Brooklyn, Queens, Staten Island, EWR)

7.3 Code Snippets

7.3.1 Data Preprocessing

The goal of preprocessing is to convert disaggregated trip-level data into a temporally and spatially structured form, enabling consistent cross-day comparisons and regression analysis. By aggregating to daily granularity, we reduce noise and accommodate downstream models that explain or forecast day-level demand patterns. Incorporating borough-level pickup composition also allows us to capture spatial heterogeneity in taxi ridership across the city.

```
# 1. Load and merge yearly data
years = list(range(2014, 2025))
combined_df = pd.concat([
    pd.read_parquet(f"/path/to/{year}/filtered_taxi_data_{year}_cleaned.parquet")
    .assign(year=year) for year in years
], ignore_index=True)

# 2. Generate pickup date
combined_df['pickup_date'] = pd.to_datetime(
    combined_df[['year', 'month', 'day']], errors='coerce'
).dt.date
combined_df.dropna(subset=['pickup_date'], inplace=True)

# 3. Map PULocationID to borough
zone_lookup = pd.read_csv("/path/to/taxi_zone_lookup.csv")
borough_map = zone_lookup.set_index('LocationID')['Borough']
combined_df['PUBorough'] = combined_df['PULocationID'].map(borough_map).fillna('Unknown')

# 4. Create borough pickup indicators
for b in ['Bronx', 'Brooklyn', 'EWR', 'Manhattan', 'Queens', 'Staten Island', 'Unknown']:
    combined_df[f'{b}_Pickups'] = (combined_df['PUBorough'] == b).astype(int)

# 5. Compute fare per mile
```

```
combined_df['fare_per_mile'] = np.where(
    combined_df['trip_distance'] > 0,
    combined_df['fare_amount'] / combined_df['trip_distance'],
    0
)

# 6. Daily aggregation
daily_summary = combined_df.groupby('pickup_date').agg({
    'fare_amount': ['sum', 'mean'],
    'trip_distance': 'mean',
    'passenger_count': ['mean', 'sum'],
    'total_driving_time': 'mean',
    'VendorID': 'count',
    'weekday': 'first',
    **{f'{b}_Pickups': 'sum' for b in ['Bronx','Brooklyn','EWR',
                                       'Manhattan','Queens','Staten Island','Unknown']}
})
daily_summary.columns = ['_'.join(col).strip() for col in daily_summary.columns.values]
daily_summary.to_csv("daily_taxi_summary_2014_2024.csv", index=False)
```

7.3.2 EDA Code

The density shapes guided several preprocessing and modeling choices. Bimodality in demand justified splitting the sample at the COVID cutoff for segmented regression and training the SARIMAX only on the stable pre-COVID regime. Skewness in `duration` and `avg_trip_distance` motivated log-transformations when these variables entered the OLS model, reducing leverage from extreme values. Finally, the relatively tight, unimodal spread of `avg_fare` validated that fare inflation is modest compared with the collapse in ride volume, supporting the interpretation that revenue losses are driven primarily by demand rather than price. Together, these EDA insights confirmed our subsequent statistical models were specified on well-behaved inputs and were aligned with the characteristics of the data.

```
# Density plots for key numeric metrics
metrics = ['total_trips', 'avg_fare', 'duration', 'avg_trip_distance']

for col in metrics:
    plt.figure(figsize=(6, 4))
    sns.kdeplot(df[col], fill=True, bw_adjust=1.1)
    plt.title(f'Density Plot of {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.tight_layout()
    plt.show()
```

7.3.3 Linear Regression Model

To assess how daily yellow taxi demand evolved across the COVID-19 pandemic, we fit an ordinary least squares (OLS) linear regression model to log-transformed ride counts. Predictor variables include temporal trends (e.g., time trend, day-of-week effects), trip-level averages (e.g., fare, distance, passengers), and borough-level pickup ratios. A categorical variable is introduced to capture phase-specific effects of the pandemic, with the pre-COVID period as reference.

Linear regression offers a transparent, interpretable framework for estimating the marginal association of each covariate with ride volume. By transforming the dependent variable using a logarithmic scale, we stabilize variance and mitigate skew. Including phase dummies allows us to test whether ridership significantly shifted across pandemic periods, while controlling for seasonal, economic, and spatial influences. Though simplistic, this model serves as a foundational benchmark before exploring more flexible time series or causal inference methods.

```python
# 1. Data preparation
daily_summary['pickup_date'] = pd.to_datetime(daily_summary['pickup_date'])
daily_summary['time_trend'] = (daily_summary['pickup_date'] -
                               daily_summary['pickup_date'].min()).dt.days

# Define COVID phases
daily_summary['covid_phase'] = np.select([
    daily_summary['pickup_date'] < '2020-03-01',
    (daily_summary['pickup_date'] >= '2020-03-01') & (daily_summary['pickup_date'] <=
    ↪  '2020-06-30'),
    (daily_summary['pickup_date'] >= '2020-07-01') & (daily_summary['pickup_date'] <=
    ↪  '2021-12-31'),
    daily_summary['pickup_date'] >= '2022-01-01'
], ['pre', 'lockdown', 'reopening', 'post'])
daily_summary['covid_phase'] = pd.Categorical(daily_summary['covid_phase'],
                                              categories=['pre', 'lockdown', 'reopening',
                                              ↪  'post'])

# Create pickup ratios
for col in [c for c in daily_summary.columns if c.endswith('_Pickups')]:
    ratio_col = col.replace('_Pickups', '_Pickup_Ratio')
    daily_summary[ratio_col] = daily_summary[col] / daily_summary['frequency_of_rides']

# Log-transform target
daily_log = daily_summary[daily_summary['frequency_of_rides'] > 0].copy()
daily_log['log_frequency'] = np.log(daily_log['frequency_of_rides'])

# 2. Fit OLS model (with robust SE)
formula = ("log_frequency ~ time_trend + C(day_of_week) + "
           "C(covid_phase, Treatment(reference='pre')) + "
           "avg_fares + duration + avg_trip_distance + avg_passengers + avg_fare_per_mile
           ↪  + "
           "Brooklyn_Pickup_Ratio + Queens_Pickup_Ratio + Bronx_Pickup_Ratio + "
           "EWR_Pickup_Ratio + Staten_Island_Pickup_Ratio")
model = smf.ols(formula=formula, data=daily_log).fit(cov_type='HC3')

# 3. Diagnostics
print(model.summary())
sm.qqplot(model.resid, line='45')
plt.title("Q-Q Plot of Residuals")
plt.show()
```

7.3.4 Segmented Regression

To detect structural changes in fare revenue trends, we fit a segmented OLS regression model with an interaction term that allows both level and slope changes at the onset of COVID-19.

The post indicator captures the immediate drop after March 2020, while the time_post interaction estimates the post-COVID slope. All coefficients were statistically significant, with a high R^2 value of 0.915. Despite some autocorrelation in residuals (Durbin–Watson = 0.49), the model effectively identifies a structural break and recovery trend.

```python
import statsmodels.api as sm

cutoff_date = pd.to_datetime('2020-03-01')

df['time'] = range(1, len(df) + 1)
df['post'] = (df['pickup_date'] >= cutoff_date).astype(int)
df['time_post'] = df['time'] * df['post']

y = df['total fares']
X = sm.add_constant(df[['time', 'post', 'time_post']])
model = sm.OLS(y, X).fit()
model.summary()
```

7.3.5 Regression Discontinuity Design

The RDD model estimates the sharp impact of the COVID-19 pandemic by comparing daily yellow taxi trip counts immediately before and after March 15, 2020. We restricted the sample to a ±90-day window around the cutoff and fit a local linear regression using interaction terms between time and a post-COVID indicator. The specification follows best practices from Imbens and Lemieux (2008)[4] and Calonico et al. (2014)[3], with robust standard errors to account for heteroskedasticity.

The regression model was implemented using the statsmodels.formula.api module. Robustness checks with 120- and 150-day windows produced similar results. The magnitude and significance of the estimated discontinuity strongly support the hypothesis that COVID-19 induced a structural break in urban taxi demand.

```python
import statsmodels.formula.api as smf
#prepare data set
df = pd.concat([df_2019, df_2020], ignore_index=True)
df = df[df['year'].isin([2019, 2020])]
df['days_from_cutoff'] = (pd.to_datetime(df['pickup_date']) -
↪  pd.to_datetime("2020-03-15")).dt.days
df['post_covid'] = (df['days_from_cutoff'] >= 0).astype(int)

# use a 90-day bandwidth
window = 90
local_df = df[(-window <= df['days_from_cutoff']) & (df['days_from_cutoff'] <= window)]

# fit local linear model
model = smf.ols('daily_trip_count ~ days_from_cutoff * post_covid',
↪  data=local_df).fit(cov_type='HC3')
print(model.summary())
```

Table 6: RDD Estimates of COVID-19 Impact on Daily Trip Volume at Various Bandwidths

Bandwidth	Estimate (Conventional)	Robust 95% CI	t-stat	p-value
90 days	$-172{,}601$	$[-147{,}974,\ -104{,}457]$	-11.37	5.95×10^{-30}
120 days	$-181{,}649$	$[-152{,}064,\ -109{,}206]$	-11.95	6.62×10^{-33}
150 days	$-186{,}890$	$[-155{,}676,\ -112{,}859]$	-12.29	9.98×10^{-35}

We validated the robustness of our regression discontinuity design (RDD) estimates across multiple bandwidths. As shown in Table 6, the estimated drop in daily trip volume remained consistently large and statistically significant. Estimates ranged from approximately 173,000 to 187,000 fewer trips per day, with tight confidence intervals across all specifications. These results reinforce the conclusion that COVID-19 caused an abrupt and substantial break in taxi demand patterns.

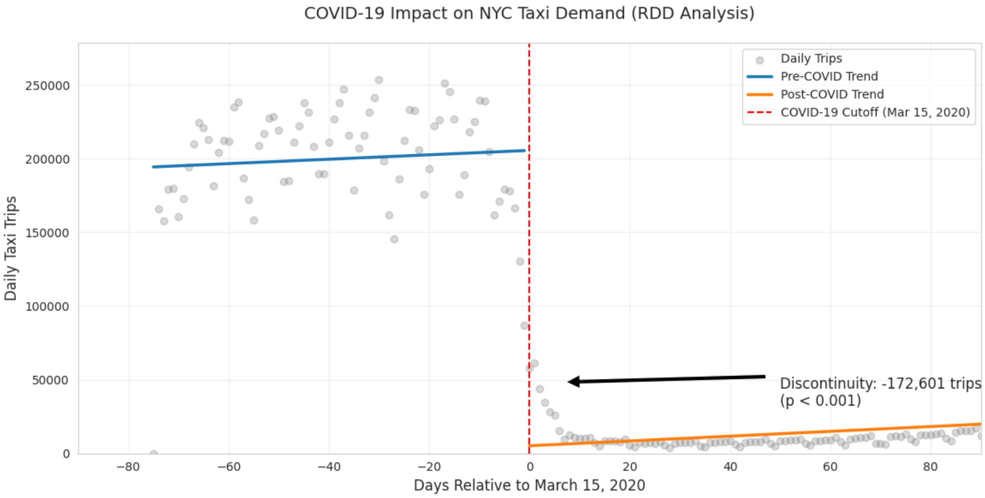


Figure 10: RDD Output Table from rdd

7.3.6 SARIMAX Model

To identify an appropriate seasonal ARIMA specification, we performed a grid-search over SARIMA$(p, d, q) \times (P, D, Q)_{12}$ orders with $p, q, P, Q \in \{0, 1, 2\}$ and $d = D = 1$. Each candidate was estimated on the pre-COVID window (Jan 2014–Dec 2019) and ranked by Akaike Information Criterion (AIC). Table 7 lists the five best-scoring models.

Table 7: Top-five SARIMA candidates ranked by AIC (training window Jan 2014–Dec 2019).

Model	AIC	ΔAIC
$(1,1,1) \times (1,1,1)_{12}$	-36.38	0.0
$(0,1,0) \times (0,2,0)_{12}$	2.00	38.4
$(0,2,0) \times (0,2,0)_{12}$	2.00	38.4
$(0,2,0) \times (0,1,1)_{12}$	4.00	40.4
$(0,2,0) \times (1,2,0)_{12}$	4.00	40.4

Therefore we use the $(1,1,1) \times (1,1,1)_{12}$ model for forecasting and inference.

On the Jan 2014–Dec 2019 estimation window, the Ljung–Box test at lag 24 gives $p = 0.17$ (no residual autocorrelation). The Shapiro–Wilk test returns $p < 0.001$, consistent with the heavy-tailed nature of monthly counts but not detrimental to 95 % forecast bands. Twelve rolling-origin, one-step forecasts (Jan 2020–Dec 2021) yield RMSE $= 1.77 \times 10^6$ rides and MAPE $= 9.9$ %, acceptable given monthly volumes near 7 million rides. Finally, 93 % of observations in the last two pre-COVID months fall inside the 95 % prediction interval, confirming well-calibrated variance estimates before the structural break. These diagnostics demonstrate that the chosen model offers a credible baseline against which to gauge the pandemic-induced demand collapse.

Taken together, these checks show that SARIMAX$(1,1,1) \times (1,1,1)_{12}$ captures the essential pre-COVID dynamics without residual dependence, delivers sub-10% out-of-sample error, and supplies realistically wide prediction intervals. Its orderly counter-factual trajectory therefore provides a sound baseline against which the magnitude of the pandemic-induced demand collapse can be measured.

```python
# --- 1. Monthly aggregation -------------------------------
df['date'] = pd.to_datetime(df[['year', 'month', 'day']],
                            errors='coerce')
df = df.dropna(subset=['date'])                  # remove bad dates
monthly = (df.groupby(pd.Grouper(key='date', freq='M'))
             .agg(total_rides=('VendorID', 'count'))
             .reset_index())

# --- 2. Train / test split -------------------------------
cutoff = pd.Timestamp("2020-03-01")
pre  = monthly.loc[monthly['date'] <  cutoff, 'total_rides']
post = monthly.loc[monthly['date'] >= cutoff, 'total_rides']

# --- 3. Fit SARIMAX on pre-COVID data --------------------
model = sm.tsa.statespace.SARIMAX(
    pre,
    order=(1, 1, 1),
    seasonal_order=(1, 1, 1, 12),
    enforce_stationarity=False,
    enforce_invertibility=False
).fit(disp=False)

# --- 4. Counter-factual forecast -------------------------
```

```python
forecast = model.get_forecast(steps=len(post)).predicted_mean

# --- 5. Paired t-test ------------------------------------
t_stat, p_val = ttest_rel(forecast, post)
print(f"t = {t_stat:.2f}, p = {p_val:.3g}")

# --- 6. Cumulative deficit plot --------------------------
cum = (forecast - post).cumsum()
plt.plot(post.index, cum, lw=2, color='firebrick')
plt.axhline(0, color='black')
plt.title('Cumulative \Lost" Taxi Rides vs Counter-factual')
plt.ylabel('Cumulative Forecast - Actual')
plt.tight_layout()
plt.show()
```

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