Did the COVID-19 vaccine rollout impact transportation demand? A case study in New York City

Justin Drummond [a], Md Sami Hasnine [b],*

[a] *Department of Civil and Environmental Engineering, Howard University, 2300 Sixth Street, NW, Washington, DC, 20059, USA*
[b] *Department of Civil and Environmental Engineering, Howard University, 2300 Sixth Street, NW #1026, Washington, DC, 20059, USA*

A B S T R A C T

Introduction: This study investigates the influence of vaccination along with other pandemic-related factors on driving, transit, and walking in New York City (NYC). The results of this study help inform policymakers of the weight of their decisions in a pandemic setting as well as factors to consider when modeling transportation during a pandemic.
Methods: In this study, ARIMAX time series analysis was performed on driving, transit, and walking data from Apple Mobility Trends Reports. The data was segmented into two categories "pre-vaccine" and "post-vaccine" for both Manhattan and Brooklyn. The independent variables were primarily COVID-19 statistics (vaccination, case counts, deaths, etc.) along with additional predictors aggregated from Google Community Mobility Reports, Google Trends, Citi Bike, National Oceanic and Atmospheric Administration (NOAA), and the Oxford Covid-19 Government Response Tracker (OxCGRT).
Results: Vaccination led to increases in driving, transit, and walking in Brooklyn but was not as statistically significant in Manhattan (the only effect being on walking trips). Despite this, vaccination was not the strongest influencer on transportation. The COVID-19 policy score variable had the highest standardized β in nearly every model, indicating that stricter lockdown policies were the main factor discouraging travel. Furthermore, the lifting of these policies contributed to increases in travel numbers more than vaccination.
Conclusions: In the event of future pandemics or health crises, NYC policymakers should be aware that they play a significant role in mitigating infectious diseases. The public is seemingly more responsive to policy than anything else. Similar studies should be conducted in other cities as the public response may vary based on other factors.

1. Introduction

Individuals traveling via modes such as transit significantly contributed to the initial outbreak of the COVID-19 virus and the resurges after (Harris, 2020; Zhao et al., 2020). An accurate forecast of travel demand early in the pandemic would have helped decision-makers implement the correct policies to reduce the number of individuals traveling thus, mitigating the rapid spread of the virus. Aggregate trip generation models and disaggregate mode choice models are very popular tools for travel demand forecasting. Unfortunately, decision-makers were not equipped with accurate trip generation and mode choice information because the models

were unable to accurately forecast travel demand during the pandemic (Abdullah et al., 2021). Trip generation models generally use aggregate socio-demographic data such as income, employment status, vehicle ownership, and household size, within a region. Mode choice models also typically, depend on disaggregate socio-demographic data, with the addition of variables related to perceptions such as travel time, cost, distance, comfort, and safety (Vredin Johansson et al., 2005). These existing travel models failed to account for pandemic-related factors such as vaccination status, COVID-19 policies, perceptions of social distancing, mask usage, and cleanliness (Abdullah et al., 2020; Chen et al., 2022; Liu et al., 2020; Wang and Noland, 2021).

Transportation demand during the pandemic has also been affected by COVID-19 statistics such as cases, hospitalizations, and deaths (Barbieri et al., 2021; Chen et al., 2022; Teixeira and Lopes, 2020; Tokey, 2021). The findings were that higher COVID-19 statistics led to reduced transportation numbers across all modes. However, the influence of COVID-19 vaccination on travel has scarcely been investigated in transportation-based studies thus far. Zhong et al. (2021) observed that transit ridership increased by 0.439% for every percent increase in first-dose vaccination rates and 0.676% for every percent increase in complete vaccination rates, in the United States. There were a few limitations to this study with regards to transportation planning: 1) modes such as driving, and walking were excluded which are crucial for urban planning 2) the study was across the United States which does not accurately reflect transit demand in specific locations and does not allow for comparison of vaccination impacts by location. 3) there is no comparison between the effects of COVID-19 statistics and vaccination. In our study, these limitations are addressed by:

1) investigating the influence of first dose and complete set (2+ dose) vaccination on increases in the number of driving, walking trips (in addition to transit) during the pandemic
2) comparing this influence in two different boroughs in NYC: Manhattan, and Brooklyn
3) comparing the influence of COVID-19 cases, deaths, hospitalizations, and policy against the influence of vaccination on transportation

2. Literature review

There is a scarcity of literature on the impact of vaccination on transportation. As mentioned before, Zhong et al. (2021) observed that transit ridership increased by 0.439% for every percent increase in first-dose vaccination rates and 0.676% for every percent increase in complete vaccination rates, in the United States, but it was also stated that "the role of vaccination in public transportation has been minimally discussed." Zhong et al. (2021) was cited by two other papers, which we reviewed to see if there was any further insight into the impact of vaccination on transportation. The first paper used regression models in a secondary analysis finding that expenditure related to transportation increased by 0.0093 units for every percent increase in vaccination rates and the transportation variable was significant at $\alpha = 0.01$ (Aslim et al., 2022). Being a secondary analysis, there were few details about the transportation spending data, therefore conclusions concerning the effect of vaccination on transportation cannot be drawn. It is unclear what was included in transportation expenditure and what the units were. Furthermore, increases in transportation spending do not necessarily equate proportionally to increases in the number of trips. The second paper is a literature review paper that suggested that vaccination would reduce the public risk perception of COVID-19 leading to increases in public transit ridership (Albalate et al., 2022).

However, most studies primarily focus on how vaccination led to reductions in infection, hospitalization, and death rates (Chen et al., 2022; Eyre et al., 2022; Wang et al., 2022). The study from Wang et al. (2022) used an interesting approach, rather than looking at vaccination numbers, vaccination-related policies were the focus of the study. It was found that vaccination policies did mitigate the spread of the virus which in turn led to increases in mobility. This begs the question of whether vaccination numbers or policy was influencing transportation demand. While our study does take into consideration the impact of COVID-19 restriction policies it does not include vaccination policies.

3. Methods

3.1. Modeling approach

In this study autoregressive integrated moving average (ARIMA) models with additional regressors, also known as ARIMAX models were estimated:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{i=1}^{q} \Theta_i \varepsilon_{t-i} + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_t$$

φ_i is the coefficient for the autoregressive term and p is the number of times that the autoregressive term is lagged. Rather than using just the previous value (y_{t-1}) or one lag, like in a basic time series model, y_{t-i} is used, allowing for any number of lags. Θ_i is the coefficient for the moving average term and q is the number of times the moving average term is lagged. The moving average term uses previous errors as predictors for y_t. This assumes that previous variance from unexplained factors is affecting the current value. The term β_i refers to the coefficient for the regressor or predictor variables, X_i and n depend on the number of regressors. β_i and X_i constitute a typical regression model. Adding regressors to the ARIMA model can improve its accuracy by reducing the unexplained variance found in the error term (Kongcharoen and Kruangpradit, 2013; Rizalde et al., 2021). ε_t is the remaining error or variance that was not capture by the model.

3.2. Data aggregation

The predictor variables in Fig. 1 were aggregated from the New York State Health Department, Google Community Mobility Reports, Google Trends, Citi Bike, NOAA and the OxCGRT/New York Times News. The dependent variables were from Apple Mobility Trends Report. The variables used in this study were selected based on the following criterion: 1) the data sources are open access, 2) the data relates to transportation demand based on previous research, 3) the data is available at the city-wide level 4) the data is collected and changing at a daily level or weekly level (which can be manipulated to the daily level) and 5) the dataset is available from February 15th, 2020, to January 27th, 2022. As a result of our criteria, socio-economic data did not fit well in the model specification. These kinds of variables, which do not change frequently, would not provide meaningful results for our time series analysis.

3.3. Data Description and Processing

Google Community Mobility Reports reported the daily percent deviations of the activities (found in the orange box in Fig. 1) from their baseline values (Google, 2022). The baseline was equated to 0% and was determined using the median value of each activity from January 3rd to February 6th, 2020.

Apple Mobility Trends Reports granted access to daily percent deviations in the number of navigation requests for car trips, transit rides, and walking (Apple, 2022). The baselines were the car, transit, and walking requests made on January 13, 2020. Apple mobility Reports data used 100% as the baseline.

The New York State Health Department website provided access to daily COVID-19 Vaccination numbers as well as the number of COVID-19 tests, positive tests, hospitalizations, and deaths, at the county level (New York State Health Department, 2022). For clarification, the number of tests refers to the total number of COVID-19 tests performed irrespective of the result (positive, negative, or inconclusive) while, the number of positive tests strictly refers to the number of tests that's results were positive. The first dose variable refers to the number of individuals with one dose of an mRNA vaccine while series complete refers to the number fully vaccinated either by one dose of the J&J vaccine or two doses of the mRNA vaccine. The first dose and series-complete variables were cumulative and converted to daily totals by subtracting the following day's cumulative number from the current day's cumulative number.

Google Trends provided access to searches made on Google's search engine (Google, 2022). It did not give the total number of searches, rather a relative ranking from 0 to 100 based on the popularity of a word or topic over a period. This data was on a weekly level, so the same weekly value was applied for each day in a week (to get data at the daily level).

Citi Bike is a bike-sharing platform located in the NYC area and provided open access to all bike-sharing trips since 2014 (Citi Bike, 2022). The coordinates of each trip were reverse geo-coded in order to determine if they were in Manhattan or Brooklyn, then aggregated at the daily level.

NOAA provided weather data including wind, precipitation, snowfall, and temperature (NOAA, 2022).

The policy score variable was calculated based on the OxCGRT (Hale et al., 2021). The OxCGRT has a list of categories for COVID-19 related policies (indicators) and maximum scores assigned to each policy (index composition and values). The New York Times released a timeline of when various COVID-19 policies were put in place and lifted, from March 2020 to March 2022 (New York Times, 2022). Using the OxCGRT, scores were assigned to each policy from the New York Times. The policy score variable is a daily sum of all policies currently implemented on each given day. The score started at 0 when there were no COVID-19 policies effective. Each time a policy was implemented the corresponding OxCGRT score was added to the daily Policy Score value (likewise, if a policy was removed, the corresponding score was removed).

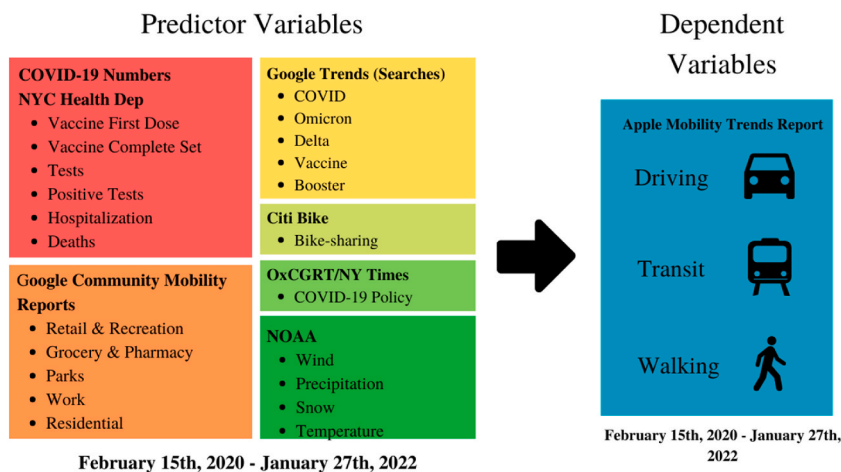Min-max normalization was used to scale the data between 0 and 1 using the following equation:

Fig. 1. List of predictor variables and their data sources for the time series analysis (left). Dependent variables from Apple Mobility Trends Reports (right).

$$y_{norm} = \frac{y - y_{min}}{y_{max} - y_{min}}$$

Where y_{norm} is the normalized value for the predictor variable used in the model, y is the set of values for the predictors, y_{min} and y_{max} are the minimum and maximum values if the set of values in for the given predictor variable.

The covariance matrix and Variance Inflation Factor (VIF) of the variables used in each of the modeling scenarios can be found in Appendix A (Fig. 3, Fig. 4, Fig. 5, and Fig. 6). Variables with a correlation of 0.7 were considered unacceptable due to a high risk of multicollinearity and were removed (Kumari, 2012; Salih, 2019). Therefore, all the variables shown in Fig. 1 were not included in every model. Only the combination of variables that did not threaten multicollinearity were included. There were four modeling scenarios because models were run for Brooklyn and Manhattan and in both cities, there were pre-vaccine (2/15/20-12/13/2020) and post-vaccine (12/2020-1/27/2022) models. The 4 modeling scenarios are shown in Fig. 2: 1. Manhattan Pre-Vaccine 2. Manhattan Post-Vaccine, 3. Brooklyn Pre-Vaccine, 4. Brooklyn Post-Vaccine. For each modeling scenario, there were three modes of transportation: driving, walking and transit, rendering a total of 12 models (4 modeling scenarios * 3 transportation modes = 12 models).

4. Results

Tables 1–4 display the model results for each mode of transportation, pre-and post-vaccine in both Manhattan and Brooklyn. The superscript numbers [1-12] correspond to the "Model # 1–12" in Fig. 2. Insignificant variables were removed from the model denoted by the "-" symbol. The significant level in this study was 0.05 with a sample size of n = 303 (degrees of freedom = 302) for the pre-vaccine models and n = 410 (degrees of freedom = 409) for the post-vaccine models. Therefore, the critical values were 1.967 and 1.966, respectively. Coefficients (β) were standardized, allowing for comparison of the predictor variables. Autoregressive terms are denoted by "AR" and moving average terms are denoted by "MA" in the tables.

4.1. Manhattan pre- and post-vaccine

In Manhattan, before the vaccine out roll (Table 1), increases in the number of COVID-19 Positive Tests/cases (β = −0.241, T = −2.253) negatively influenced driving demand. For transit and walking, the number of COVID-19 Positive Tests were not statistically significant, but the number of COVID-19 Tests were (β = −0.237, T = −3.432 and β = −0.322, T = −3.137, respectively). The COVID-19 Tests variable refers to the number of tests taken regardless of the result (positive, or negative) while the COVID-19 Positive Tests variable only refers to the number of confirmed positive cases. This could indicate that fears from the increasing numbers of individuals taking COVID-19 tests were strong enough to dissuade the public from using transit or from walking. On the other hand, the choice to drive was only influenced when the test was confirmed to be positive. This could suggest an increased risk perception of COVID-19 for modes like transit and walking regardless of the number of confirmed cases. This would align with previous research suggesting that there was a lower risk perception of COVID-19 for drivers than individuals using modes where they could potentially be exposed to other infected individuals (Beck and Hensher, 2021; Khaddar and Fatmi, 2021; Paydar and Kamani Fard, 2021). Increases in searches for COVID-19 on google led to decreases in driving, transit, and walking trips. Finally, the strongest predictor (highest standardized β) for all three modes was the policy score: Driving (β = −0.694, T = −14.852), Transit (β = −0.631, T = 12.094), Walking (β = −0.400, T = −4.656). This indicates that stricter COVID-19 related policies were the primary influencer of decreases in travel in Manhattan before the vaccine out roll.

After the vaccine rollout (Table 2) first dose and complete set of vaccinations had almost no impact on driving, transit, or walking. The only statistically significant effect was first-dose vaccination on walking which was negative (β = −0.140, T = −2.575). This

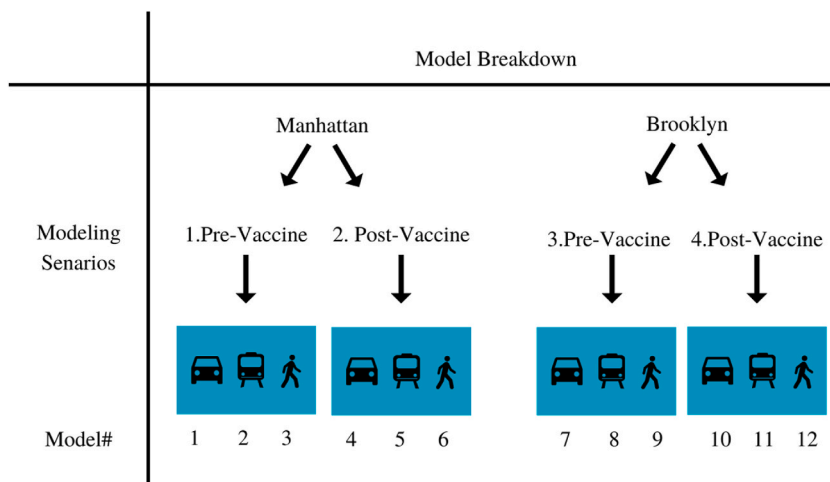**Fig. 2.** Breakdown of the modeling scenarios for Manhattan and Brooklyn.

Table 1
Pre-vaccine model results in Manhattan.

	Driving Pre-Vaccine - ARIMA (3,0,0)[a]		Transit Pre-Vaccine - ARIMA (3,0,2)[b]		Walking Pre-Vaccine - ARIMA (3,0,1)[c]	
	Coefficient (β)	T-statistic	Coefficient (β)	T-statistic	Coefficient (β)	T-statistic
AR1	0.768	13.526	−0.067	−0.138	1.694	28.096
AR2	−0.339	−6.025	0.487	4.927	−1.025	−10.545
AR3	–	–	−0.132	−0.528	0.324	5.534
MA1	–	–	0.898	1.803	−0.912	−25.464
MA2	–	–	−0.062	−0.13	–	–
Intercept	−64.998	−5.156	−33.233	−3.847	−70.973	−4.469
COVID-19 Tests	0.026	0.342	**−0.237***	−3.432	**−0.322***	−3.137
COVID-19 Positive Tests	**−0.241***	−2.253	−0.063	−0.689	−0.192	−1.389
COVID-19 Deaths	0.121	0.836	−0.001	−0.01	0.049	0.316
Search: COVID-19	**−0.380***	−8.89	**−0.354***	−8.675	**−0.289***	−3.98
Bike Trips	**0.178***	7.398	**0.111***	6.548	**0.176***	7.637
Temperature	–	–	**−0.099***	−3.217	–	–
Policy Score	**−0.694***	−14.852	**−0.631***	−12.094	**−0.400***	−4.656

*Significant predictors at the 95% confidence level.
[a] Sigma squared = 61.73, AIC = 2120.58, BIC = 1933.07.
[b] Sigma squared = 27.6, AIC = 1881.08, BIC = 2157.71.
[c] Sigma squared = 71.91, AIC = 2169.7, BIC = 2214.27.

Table 2
Post-vaccine model results in Manhattan.

	Driving Post-Vaccine - ARIMA (3,0,0)[a]		Transit Post-Vaccine - ARIMA (3,0,2)[b]		Walking Post-Vaccine - ARIMA (3,0,1)[c]	
	Coefficient (β)	T-statistic	Coefficient β	T-statistic	Coefficient (β)	T-statistic
AR1	0.953	12.924	0.676	13.855	0.363	0.531
AR2	−0.547	−10.455	−1.246	−26.73	–	–
AR3	–	–	0.718	15.146	–	–
AR4	–	–	−0.748	−14.064	–	–
MA1	−0.318	−3.798	0.166	2.457	0.386	0.566
MA2	–	–	1.25	26.756	−0.017	−0.033
MA3	–	–	0.102	1.517	−0.129	−0.678
MA4	–	–	0.589	12.346	−0.001	−0.01
Intercept	144.715	4.141	162.962	4.429	199.647	2.528
COVID-19 Vaccine First-dose	−0.011	−0.301	0.016	0.588	**−0.140***	−2.575
COVID-19 Vaccine Complete-set	0.001	0.016	−0.04	−1.224	0.009	0.156
COVID-19 Tests	**−0.080***	−2.17	**−0.065***	−2.371	−0.02	−0.491
COVID-19 Positive Tests	0.153	0.809	**0.467***	2.773	0.047	0.146
COVID-19 Deaths	−0.151	−0.894	**−0.296***	−1.884	−0.056	−0.198
Search: COVID-19	**−0.205***	−3.795	**−0.288***	−5.496	−0.14	−1.699
Search: Delta	**0.194***	7.872	**0.136***	5.121	**0.187***	4.222
Search: Booster	**0.230***	5.742	–	–	**0.249***	2.951
Grocery & Pharmacy (%)	**0.329***	13.028	**0.247***	11.335	–	–
Working (%)	–	–	**−0.076***	−2.056	**0.142***	5.343
Precipitation	–	–	–	–	**−0.079***	−4.475
Snow	–	–	**0.028***	2.758	–	–
Policy Score	**−0.245***	−5.352	**−0.511***	−12.997	**−0.412***	−5.195

*Significant predictors at the 95% confidence level.
[a] Sigma squared = 150.6, AIC = 3236.03, BIC = 3111.33.
[b] Sigma squared = 88.38, AIC = 3026.99, BIC = 3111.33.
[c] Sigma squared = 391, AIC = 3629.98, BIC = 3702.27.

means increases in the number of individuals with first-dose vaccination led to decreases in walking. This may seem counter-intuitive, but it is justifiable. As individuals were stuck at home during the pandemic, they began developing a "fatigue" (Ding and Zhang, 2021). Many resorted to walking to exercise and as a replacement for typical leisurely travel, which was canceled due to the restrictions (Hunter et al., 2021). As the pandemic progressed lockdown restrictions and the overall fear of COVID-19 began diminishing causing individuals to shift back towards more "normal" behavior (Jia et al., 2022). Therefore, it would make sense that people were less engaged in walking for exercise and leisurely travel, after vaccination. Grocery and pharmacy shopping was a significant influencer for both driving (β = 0.329, T = 13.028) and transit (β = 0.247, T = 11.335). Increases in searches for the delta variant on google led to increases in all three modes driving (β = 0.194, T = 7.872), transit (β = 0.136, T = 5.121), walking (β = 0.187, T = 4.222). This is likely because in the latter half of the post-vaccine period delta cases were decreasing significantly. After seeing the decline in delta-related cases after searching, individuals likely started gaining confidence to travel again. Searches for the booster shots led to increases in driving (β = 0.230, T = 5.742) and walking (β = 0.249, T = 2.951). It is likely that as individuals were seeing increases in the number of

Table 3
Pre-vaccine model results in Brooklyn.

	Driving Pre-Vaccine - ARIMA (5,1,2)[a]		Transit Pre-Vaccine - ARIMA (2,1,3)[b]		Walking Pre-Vaccine - ARIMA (0,0,1)[c]	
	Coefficient (β)	T-statistic	Coefficient β	T-statistic	Coefficient (β)	T-statistic
AR1	0.238	1.794	−0.436	−24.472	0.104	1.665
AR2	−0.743	−11.275	−0.977	−56.462	−0.81	−17.301
AR3	−0.203	−2.346	–	–	−0.248	−3.425
AR4	−0.346	−6.625	–	–	−0.375	−8.606
AR5	−0.433	−5.315	–	–	−0.613	−11.162
MA1	−0.71	−4.673	0.206	3.271	−0.721	−9.405
MA2	0.516	4.916	0.918	15.281	0.784	13.228
MA3	–	–	−0.42	−5.276	−0.215	−3.307
MA4	–	–	0.041	0.62	–	–
MA5	–	–	−0.329	−6.344	–	–
Intercept	–	–	–	–	–	–
[a] COVID-19 Positive Tests	–	–	–	–	−0.220*	−3.638
[b] COVID-19 Hospitalizations	−1.282	−1.659	0.081	0.18	–	–
[c] COVID-19 Deaths	1.223	1.588	−0.101	−0.227	–	–
Search: COVID-19	−0.285*	−3.986	−0.516*	−7.702	−0.270*	−4.556
Search: Delta	–	–	–	–	–	–
Search: Booster	–	–	–	–	–	–
Search: Vaccine	–	–	–	–	–	–
Grocery & Pharmacy (%)	**0.155***	5.278	**0.076***	4.654	**0.153***	7.978
Parks (%)	**0.080***	2.852	**0.126***	7.965	**0.298***	17.028
Wind	–	–	–	–	–	–
Precipitation	–	–	–	–	–	–
Temperature	–	–	−0.068*	−2.128	–	–
Policy Score	**−0.230***	−3.101	**−0.208***	−2.767	**−0.213***	−4.027

*Significant predictors at the 95% confidence level.

[a), b), c)] The COVID-19 Positive Tests variable is only included in the walking model because the Hospitalization and Death variables were not statistically significant. When Deaths and Hospitalizations were removed, Positive Tests no longer posed a threat to multicollinear which is why it was only included in the walking model.

[a] Sigma squared = 80.41, AIC = 1847.58, BIC = 1901.56.

[b] Sigma squared = 24.84, AIC = 1847.58, BIC = 1901.56.

[c] Sigma squared = 42.58, AIC = 2012.42, BIC = 1901.56.

people receiving boosters, they felt more comfortable traveling (Jia et al., 2022). COVID-19 related searches still had a negative impact on driving (β = −0.205, T = −3.795) and transit (β = −0.288, T = −5.496) indicating there was still an overall fear of the pandemic, despite vaccination. Overall, policy was the strongest influencer for transit (β = −0.245, T = −5.352) and walking (β = −0.511, T = −12.997) and the second strongest influencer for driving (β = −0.412, T = −5.195) behind grocery shopping. Just like pre-vaccine, stricter COVID-19 related policies were the primary influencer for decreases in all modes of travel.

4.2. Brooklyn pre- and post-vaccine

In Brooklyn, before the vaccination (Table 3), COVID-19 cases, deaths, and hospitalizations had almost no influence on travel. Only walking was negatively affected by positive case counts (β = −0.220, T = −3.638). Similar to Manhattan, increases in searches for COVID-19 on google and stronger COVID-19 policies led to decreases in travel for all three modes. One notable difference is that searches for COVID-19 were stronger influencers than policies in Brooklyn, whereas, in Manhattan, policies were the strongest influencer. Grocery/pharmaceutical shopping and travel to parks were also positive influencers for all three modes.

Post-vaccine (Table 4) first-dose vaccination was a significant influencer, leading to increases in car and transit trips (β = 0.133, T = 4.019, β = 0.121, T = 3.654). Complete vaccination was a significant influencer leading to increases in the number of walking trips (β = 0.123, T = 3.265). Similar to Manhattan (after vaccination), COVID-19 searches on google, and policies led to decreases in travel for all three modes. After vaccination, COVID-19 policies were stronger influencers than COVID-19 searches in Brooklyn. Grocery/pharmaceutical shopping and travel to parks were also influencers for all three modes just like in the pre-pandemic setting.

5. Discussion

5.1. Was vaccination the main contributor to increases in transportation?

The results of this study suggest that vaccination did not have as strong of an effect on transportation as expected. Vaccination did not statistically contribute to an increase in any mode of transportation in Manhattan. In Brooklyn, only first-dose vaccination led to increases in car and transit trips and only complete vaccination led to increases in walking. Rather, the policy variable was the strongest predictor (highest standardized β) for nearly every mode both pre-and post-vaccine. This indicates that stronger COVID-19 policies led to a greater reduction in travel and thus, the lifting of these policies also contributed to increases in travel. This seems to

Table 4
Post-vaccine model results in Brooklyn.

	Driving Post-Vaccine - ARIMA (0,0,1)[a]		Transit Post-Vaccine - ARIMA (2,1,3)[b]		Walking Post-Vaccine - ARIMA (0,0,1)[c]	
	Coefficient (β)	T-statistic	Coefficient (β)	T-statistic	Coefficient (β)	T-statistic
AR1	–	–	0.448	21.936	–	–
AR2	–	–	0.94	34.185	–	–
MA1	0.395	8.747	0.236	5.423	0.429	9.612
MA2	–	–	0.42	8.094	–	–
MA3	–	–	0.76	19.388	–	–
Intercept	57.584	3.317	–	–	46.409	1.903
COVID-19 Vaccine First-dose	**0.133***	4.019	**0.121***	3.654	–	–
[d] COVID-19 Vaccine Complete-Set	–	–	–	–	**0.123***	3.265
COVID-19 Positive Tests	0.14	1.951	0.14	1.59	**0.206***	2.69
COVID-19 Hospitalizations	0.053	0.179	−0.068	−0.334	−0.039	−0.141
COVID-19 Deaths	0.086	0.292	−0.073	−0.37	−0.143	−0.513
Search: COVID-19	**−0.282***	−3.755	**−0.213**	−3.613	**−0.226***	−3.122
Search: Delta	**0.148***	4.139	–	–	**−0.098***	2.372
Search: Vaccine	–	–	–	–	–	–
Grocery & Pharmacy (%)	**0.254***	9.429	**0.080***	3.997	**0.130***	4.832
Working (%)	**0.113***	4.105	**0.162***	7.869	**0.202***	7.58
Wind	–	–	–	–	–	–
Precipitation	–	–	**−0.057***	−3.523	**−0.087***	−3.639
Snow	–	–	–	–	–	–
Temperature	–	–	–	–	**0.196***	3.312
Policy Score	**−0.376***	−6.362	**−0.217***	−2.333	**−0.294***	−4.502

*Significant predictors at the 95% confidence level.
[a] Sigma squared = 188.4, AIC = 3142.6, BIC = 3372.61.
[b] Sigma squared = 304.9, AIC = 3142.6, BIC = 3205.43.
[c] Sigma squared = 304.9, AIC = 3524.71.7, BIC = 3579.87.
[d] The COVID-19 Vaccine Complete set variable was removed from the set of post-vaccine variables in Brooklyn due to high correlation with First-dose vaccination numbers. It is included in the table because it was modeled separately and was statistically significant (for walking only).

agree with a regression study conducted on attitudes in Japan which also standardized its parameters, stating that "policymaking capacity is most influential in inducing changes in behaviors" (Ding and Zhang, 2021). The finding was that attitudes towards the policy variable had the strongest influence on risk perception of the virus (β = −0.517). Another study conducted in New York and Seattle using Break Point (BP) Detection Regression found significant changes in road traffic, public transportation, and biking after the implementation and removal of COVID-19 policies (Bian et al., 2021). The second strongest influencing variable all around in this study was the Search: COVID-19 variable. This means an increasing number of searches involving COVID-19 led to reductions in travel for all modes. This also agrees with existing literature suggesting that individuals' behaviors were strongly influenced by information from governmental authorities and the spreading of news concerning COVID-19-related events (Chang and Meyerhoefer, 2021; Ding and Zhang, 2021). It appears that social awareness of the virus and policy influence travel decisions more than the actual COVID-19 case counts, hospitalization deaths, and vaccination numbers. As previously mentioned, Zhong et al. (2021), found that transit ridership increased by 0.439% for every percent increase in first-dose vaccination and 0.676% for every percent increase in complete vaccination rates in the United States. These findings suggest two things, 1) that vaccination did increase travel (at least for transit), and 2) complete vaccination was a stronger influence on travel than first dose vaccination. Our study did not find a positive influence of first dose vaccination on transit in Manhattan or Brooklyn but did confirm a positive influence of complete vaccination on transit in Brooklyn. This difference likely occurred because the study from Zhong et al. (2021) was reflective of net changes across the country. While our study specifically looked at two sub-sections of NYC. This suggests that the net influence of vaccination on transportation is not reflective of smaller-scale impacts in specific regions, states, and cities. The influence of vaccination on transportation should be studied at in each city.

5.2. Comparison and contrast of results in Manhattan and Brooklyn

Transportation in Manhattan appeared to be more influenced by COVID-19 count variables (tests, positive tests, hospitalizations, or deaths) than transportation in Brooklyn. All six models for Manhattan (all modes pre- and post-vaccine) showed a statistically significant response to COVID-19 count variables whereas only two of the six models (walking pre- and post-vaccine) showed a response for Brooklyn. This could confirm the idea conveyed in previous literature that the effects of the pandemic were perceived as less dangerous in more suburban environments like Brooklyn than in urban environments like Manhattan (Chauhan et al., 2021). Though Brooklyn has a larger population Manhattan has nearly twice the population density (United States Census Bureau, 2021). Being surrounded by a larger density of individuals likely heightened perceptions of the virus (Paydar and Kamani Fard, 2021). On the other hand, vaccination affected all three of the post-vaccine models in Brooklyn but only one of the post-vaccine models in Manhattan (walking model). This seems to indicate was Brooklyn was less responsive to COVID-19 counts but more responsive to vaccination. Due to the risk of multicollinearity, most of the Google Community Trends Report variables were not able to be used, so it was difficult to

compare differences in trip purpose between the two boroughs (Manhattan and Brooklyn). The only similarity observed was that grocery/pharmaceutical shopping was an influencer for nearly every mode of transportation both pre-and post-vaccine in both boroughs, which makes sense because travel for groceries/pharmaceuticals is essential.

5.3. Interpretation of the "COVID-19 tests" variable

An increase in COVID-19 tests may be an indicator of heightened fears of COVID-19 due to potential exposure. The problem is that the impact of this variable on transportation is also dependent upon the result of that test. For instance, if a large number of individuals are being tested and the results are generally negative, then those individuals would be more likely to travel because there would be no risk of them transmitting the virus. On the other hand, if a large number of individuals are tested and the results are generally positive then those individuals would be less likely to travel. Therefore, in future work, it may be worthy of using another variable such as the "% Positive of COVID-19 tests". This variable would be equal to the number of COVID-19 Positive Tests divided by the total number of COVID-19 tests helping to clarify the results of the variable "COVID-19 tests". This variable was not included in our study because it threatened high multicollinearity (refer to Section 3.3 Data Description and Processing).

6. Conclusion

The objective of this study was to investigate the influence of the COVID-19 vaccine on transportation in NYC. An ARIMAX time series analysis was performed on driving, transit, and walking data from Apple Mobility Trends Reports. The predictor variables were aggregated from Apple Mobility Reports, the New York State Health Department (Vaccination and COVID-19 numbers), Google Community Mobility, Google Trends, Citi Bike, NOAA and OxCGRT. The result of the time series analysis showed that vaccination led to increases in driving, transit, and walking, but was not the main influencer of travel demand. The COVID-19 policy variable was the strongest influencer of any other variable used in the study. The presence of more COVID-19 lockdown policies led to decreases in demand for all modes of transportation and thus the lifting of the policies led to increases. The second strongest influencer was the number of COVID-19 related searches on google. These findings suggest that the NYC public is more responsive to policy and social awareness of the virus than actual COVID-19 case counts, hospitalizations, deaths, and vaccination rates. Therefore, in the event of another public health crisis, NYC policymakers should be aware the implementation and lifting of health policies will likely influence the public's decision more than statistics and their safety/risk perception of the health crisis. This study is only reflective of the influence of vaccination on transportation in NYC, thus the results may vary in different locations.

There are several limitations in this study: 1) Driving, transit, and walking data from Apple Mobility Reports came from the number of navigation requests made on Apple Maps (Hu et al., 2021; Zhang et al., 2022). Apple phone users make up only about 47% of the U.S. population and of that group, only about 50% request navigation for travel. Therefore, the travel demand data may not accurately represent the NYC population. 2) Driving and transit are general categories, which do not allow for a distinguishment between ride-hailing, car-sharing, or private car, and train or bus. Using a more robust data set is recommended for future work to better understand how vaccination and policy affected more specific modes. 3) The policy score variable does not distinguish which specific policies had the strongest influence on travel. Future work could divide the policy information into separate policy categories, to identify which policies were the most effective in discouraging travel 4) Google trends did not provide data at the county (borough) level unlike COVID-19 so data from all of NYC was used which may not have been representative of searches specific to Manhattan and Brooklyn.

Author statement

Justin Drummond: Conceptualization, Data curation, Visualization, Writing-Original draft, Writing-Reviewing, and Editing. **Md Sami Hasnine:** Conceptualization, Methodology, Writing-Reviewing, and Editing. All authors reviewed the results and approved the final version of the manuscript.

Data availability

Data will be made available on request.

Appendix A. Correlation Matrix

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)
a)	1.0											
b)	0.1	1.0										
c)	-0.4	0.66	1.0									
d)	-0.5	0.5	0.5	1.0								
e)	-0.4	-0.4	-0.3	0.3	1.0							
f)	-0.3	0.0	0.1	0.5	0.3	1.0						
g)	0.4	0.5	0.0	0.3	-0.1	0.0	1.0					
h)	0.4	-0.6	-0.6	-0.6	0.1	-0.1	-0.2	1.0				
i)	-0.1	0.2	0.2	0.2	0.0	0.0	0.1	-0.4	1.0			
j)	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.3	0.2	1.0		
k)	0.1	-0.5	-0.3	-0.4	-0.1	-0.1	-0.4	0.6	-0.3	0.0	1.0	
l)	0.1	0.2	0.3	-0.1	-0.6	-0.3	-0.1	0.0	-0.1	0.0	0.4	1.0

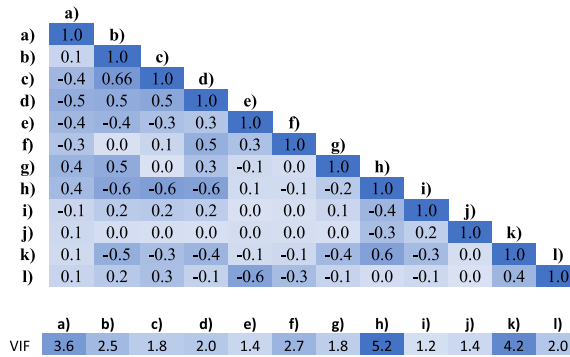|	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)
VIF	3.6	2.5	1.8	2.0	1.4	2.7	1.8	5.2	1.2	1.4	4.2	2.0

Fig. 3. Covariance matrix (upper) and VIF (lower) for variables used in Manhattan model Pre-Vaccine Models. a) COVID-19 Tests, b) COVID-19 Positive Tests, c) COVID-19 Deaths, d) Search: COVID-19, e) Search: Delta, f) Search: Booster, g) Search: Vaccine, h) Bike Trips, i) Wind, j) Precipitation, k) Temperature, l) Policy Score
Note: All the variables shown in the above figure were not included in every model. Only the combinations of variables that did not threaten multicollinearity were included.

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)	m)	n)
a)	1.0													
b)	0.68	1.0												
c)	0.1	-0.1	1.0											
d)	-0.1	-0.2	0.66	1.0										
e)	0.3	0.1	0.4	0.4	1.0									
f)	0.4	0.1	0.4	0.6	0.6	1.0								
g)	-0.3	-0.3	-0.3	-0.2	-0.4	-0.3	1.0							
h)	-0.3	-0.4	0.6	0.6	-0.1	0.0	-0.1	1.0						
i)	-0.2	-0.1	0.1	-0.1	-0.6	-0.6	0.2	0.4	1.0					
j)	-0.2	-0.2	-0.3	-0.1	-0.2	-0.3	0.0	0.2	0.4	1.0				
k)	0.1	0.0	0.1	0.0	0.3	0.1	-0.2	0.0	-0.3	-0.1	1.0			
l)	0.0	0.0	-0.1	0.0	0.0	0.0	0.1	0.0	-0.3	-0.1	0.1	1.0		
m)	-0.1	0.0	0.0	0.1	0.1	0.1	-0.1	0.0	-0.3	-0.1	0.2	0.2	1.0	
n)	0.4	0.2	-0.1	0.0	0.6	0.6	-0.3	-0.6	-0.69	-0.3	0.2	0.0	0.2	1.0

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)	m)	n)
VIF	3.1	2.8	3.5	2.4	2.1	1.8	1.2	2.6	5.1	1.9	1.1	1.3	1.1	3.4

Fig. 4. Covariance matrix (upper) and VIF (lower) for variables used in Manhattan model Post-Vaccine Models a) COVID-19 Vaccine First-dose, b) COVID-19 Vaccine Complete-set, c) COVID-19 Tests, d) COVID-19 Positive Tests, e) COVID-19 Deaths, f) Search: COVID-19, g) Search: Delta, h) Search: Booster, i) Grocery & Pharmacy (%), j) Working (%), k) Wind, l) Precipitation, m) Snow, n) Policy Score
Note: All the variables shown in the above figure were not included in every model. Only the combinations of variables that did not threaten multicollinearity were included.
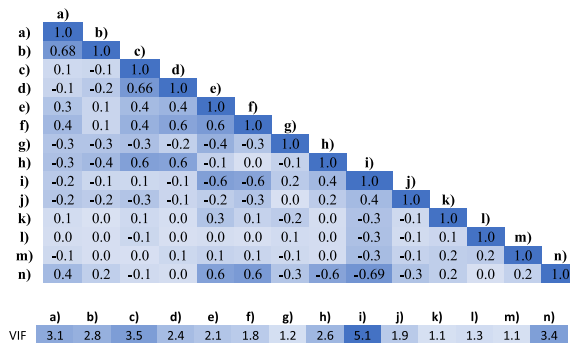
	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)
a)	1.0											
b)	0.68	1.0										
c)	0.6	0.6	1.0									
d)	-0.3	-0.3	0.3	1.0								
e)	0.67	0.4	0.3	-0.1	1.0							
f)	0.0	0.0	0.5	0.3	0.0	1.0						
g)	-0.3	-0.4	0.0	0.6	0.1	0.2	1.0					
h)	-0.6	-0.5	-0.4	0.1	-0.3	-0.1	0.4	1.0				
i)	0.2	0.3	0.2	0.0	0.1	0.0	-0.2	-0.4	1.0			
j)	0.1	0.0	0.0	0.0	0.0	0.0	-0.3	-0.3	0.2	1.0		
k)	-0.5	-0.4	-0.4	-0.1	-0.4	-0.1	0.1	0.7	-0.3	0.0	1.0	
l)	0.0	0.2	-0.1	-0.6	-0.1	-0.3	-0.5	0.1	-0.1	0.0	0.4	1.0

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)
VIF	1.6	1.7	1.4	1.5	1.4	1.4	1.6	3.2	1.2	1.4	3.7	1.6

Fig. 5. Covariance matrix (upper) and VIF (lower) for variables used in Brooklyn model Pre-Vaccine Models a) COVID-19 Hospitalizations, b) COVID-19 Deaths, c) Search: COVID-19, d) Search: Delta, e) Search: Booster f) Search: Vaccine, g) Grocery & Pharmacy (%), h) Parks (%), i) Wind, j) Precipitation, k) Temperature, l) Policy Score
Note: All the variables shown in the above figure were not included in every model. Only the combinations of variables that did not threaten multicollinearity were included.
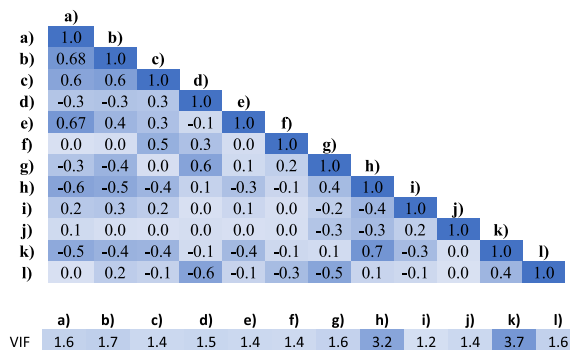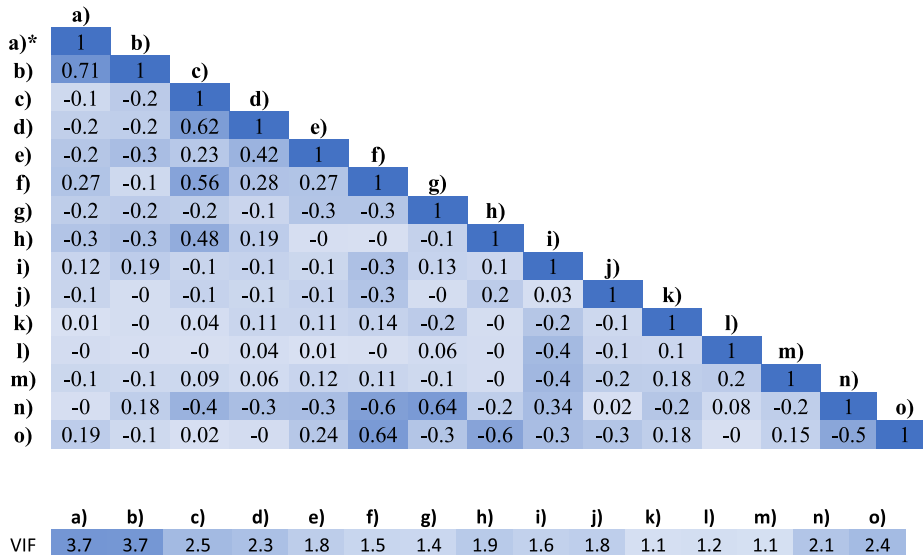
	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)	m)	n)	o)
a)*	1														
b)	0.71	1													
c)	-0.1	-0.2	1												
d)	-0.2	-0.2	0.62	1											
e)	-0.2	-0.3	0.23	0.42	1										
f)	0.27	-0.1	0.56	0.28	0.27	1									
g)	-0.2	-0.2	-0.2	-0.1	-0.3	-0.3	1								
h)	-0.3	-0.3	0.48	0.19	-0	-0	-0.1	1							
i)	0.12	0.19	-0.1	-0.1	-0.1	-0.3	0.13	0.1	1						
j)	-0.1	-0	-0.1	-0.1	-0.1	-0.3	-0	0.2	0.03	1					
k)	0.01	-0	0.04	0.11	0.11	0.14	-0.2	-0	-0.2	-0.1	1				
l)	-0	-0	-0	0.04	0.01	-0	0.06	-0	-0.4	-0.1	0.1	1			
m)	-0.1	-0.1	0.09	0.06	0.12	0.11	-0.1	-0	-0.4	-0.2	0.18	0.2	1		
n)	-0	0.18	-0.4	-0.3	-0.3	-0.6	0.64	-0.2	0.34	0.02	-0.2	0.08	-0.2	1	
o)	0.19	-0.1	0.02	-0	0.24	0.64	-0.3	-0.6	-0.3	-0.3	0.18	-0	0.15	-0.5	1

	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)	k)	l)	m)	n)	o)
VIF	3.7	3.7	2.5	2.3	1.8	1.5	1.4	1.9	1.6	1.8	1.1	1.2	1.1	2.1	2.4

Fig. 6. Covariance matrix (upper) and VIF (lower) for used in Brooklyn model Post-Vaccine Models a) COVID-19 Vaccine First-dose, b) COVID-19 Vaccine Complete-set, c) COVID-19 Positive Tests, d) COVID-19 Hospitalizations, e) COVID-19 Deaths, f) Search: COVID-19, g) Search: Delta, h) Search: Vaccine, i) Grocery & Pharmacy (%), j) Working (%), k) Wind, l) Precipitation, m) Snow, n) Temperature, o) Policy Score. *The correlation between a) and b) exceeded the threshold of 0.70. When modeled one of the two variables was removed to avoid the multicollinearity
Note: All the variables shown in the above figure were not included in every model. Only the combinations of variables that did not threaten multicollinearity were included.

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