Wheels on the Bus: Impact of Vaccine Rollouts on Demand for Public Transportation

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Problem definition: The COVID-19 pandemic led to a sharp decline in public transit ridership, resulting in budget deficits and service cuts that disproportionately affect vulnerable riders who lack alternative transportation options. Understanding the causal relationship between vaccination and demand for public transportation is important for planning demand recovery as vaccination efforts progress. This study examines this relationship, with particular emphasis on heterogeneous effects among vulnerable populations. ***Methodology/Results:*** Estimating the impact of vaccination is challenging due to a lack of fine-grained data and potential endogeneity issues. To overcome these hurdles, we exploit the distinctive features of the COVID-19 vaccination progress to identify an instrumental variable. By merging the U.S. COVID-19 vaccination data with county-level mobility data, we construct a sample that links vaccination rates to the demand for public transportation and follow the instrumental variable approach to estimate the impact. We show that increases in vaccination rates led to significant increases in demand for public transportation, as measured by mobility in public transit stations. Furthermore, we find a 40% greater impact of vaccination on public transit demand in counties with a larger uninsured population, and a 70% greater impact in counties with a higher percentage of residents without a college degree. ***Managerial implications:*** Our results demonstrate the significant impact of vaccination on public transit demand, particularly in socioeconomically disadvantaged communities. Our findings also suggest vaccination alone is not enough to revive demand. As public health authorities roll out vaccines, there is an immediate need for public transit agencies to proactively revitalize their infrastructure to meet the expected surge in demand from vaccinated populations. This strategic, anticipatory approach could accelerate an equitable recovery of public transportation systems.

Key words: COVID-19 vaccination, public transportation, social inequality, vaccine distribution

> At this time last year, tens of millions of Americans were riding subways, busses, trains and street cars for their daily commutes, quietly paying the required fare in both directions. But in the dumpster-fire year of 2020, in which COVID-19 upended how we live, that routine now seems inconceivable, at least until a vaccine is widely available.
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> *TIME* magazine, December 17, 2020 (Vesoulis 2020)

1. Introduction

Public transit ridership plummeted with the onset of the COVID-19 pandemic. By July 2020, average U.S. ridership was 73% below pre-pandemic levels; ridership remained at approximately the same low level until early 2021 (American Public Transportation Association 2023). The significant decline in transit ridership has "fueled extreme budget shortfalls, forcing transit agencies to cut routes and delay planned expansions" (Vesoulis 2020). These service cuts are consequential because they can trigger a vicious cycle—inadequate public transit service leads some riders to switch to private or shared vehicles, further depressing ridership and justifying even more limited service—and end up hurting socioeconomically disadvantaged groups, including low-income essential workers who depend on public transit and cannot afford to switch to other options (Glaeser et al. 2008).

Less than one year after the onset of the pandemic, multiple effective and safe vaccines had been successfully developed and approved for emergency use in the U.S. The unprecedented pace of vaccine development itself, however, cannot put an immediate end to the pandemic; the endgame of the pandemic is vaccination, a "mind-bogglingly complex" operation (Weise 2020). A unique feature of the U.S. COVID-19 vaccination is the parallel nature of various steps in rolling out vaccines—manufacturers ramp up their production capacity at the same time as they deliver vaccines to various states week after week (Dai and Song 2021). The overlapping processes of vaccine production, distribution, delivery, and administration provide a compelling window through which to study the impact of the vaccination progress.

The phenomenon of vaccine-fueled airline travel has attracted substantial media attention (see, e.g., McCartney 2021). By contrast, the impact of vaccination on public transportation has been minimally discussed.[1] The rollout of COVID-19 vaccines was envisioned as a stepping stone towards the recovery of the public transportation sector (Vesoulis 2020). However, the near-term impact of vaccination *progress* on the demand for public transportation is not immediately clear (Yen and Weber 2021). A critical question arises: How does the progress of COVID-19 vaccination influence the demand for public transportation? The answer to this question could guide public

[1] The Centers for Disease Control and Prevention (CDC) defines the scope of public transportation to include "a variety of transit options such as buses, light rail, and subways" (Centers for Disease Control and Prevention 2018). We focus our analysis on this scope.

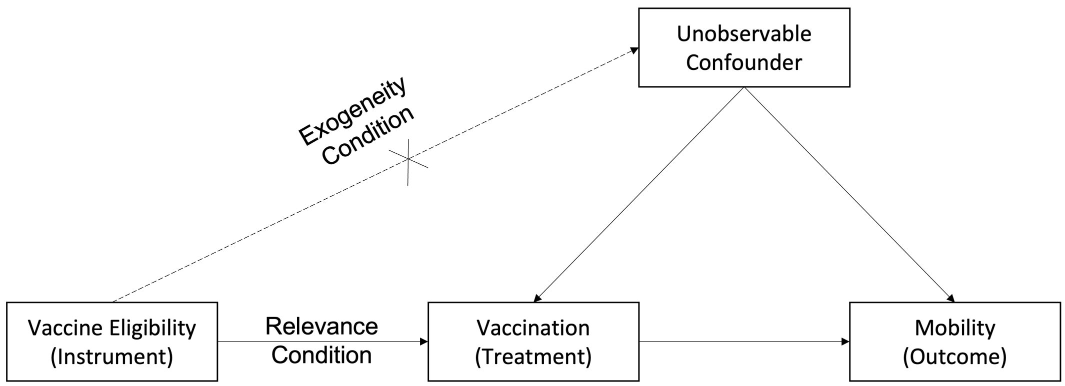

Figure 1 **Relationship between Vaccine Eligibility, Vaccination, and Mobility.**

transportation agencies in their recovery strategies, helping them preemptively ramp up services to match the vaccine-buoyed demand and break the vicious cycle of declining ridership (Vesoulis 2020).

Yet, estimating the causal effect of vaccination progress is a daunting task for two main reasons. One hurdle is the lack of fine-grained vaccination and related data (e.g., population mobility, travel, and public transportation)—systematic data-collection efforts were rare before the COVID-19 pandemic. Another hurdle is potential endogeneity concerns in estimating the effect of vaccination. For example, inclement weather conditions may reduce vaccination rates and public transportation demand. One familiar strategy to overcome endogeneity concerns entails using an instrumental variable (IV) approach. In an extensive literature review, Groenwold et al. (2010, p. 132) conclude that finding a valid IV for estimating the impact of influenza vaccination amounts to a "mission impossible."

Fortunately, the simultaneous production and distribution of the COVID-19 vaccine in the U.S. offer a compelling opportunity to overcome both hurdles. On the one hand, in contrast to the paucity of data reporting in previous epidemics (e.g., the 2009–2010 H1N1 pandemic), the allocation, distribution, and administration of COVID-19 vaccines have been closely tracked and reported daily. In addition, we compiled information from various sources to obtain data about population mobility across the U.S. On the other hand, although identifying a suitable IV for influenza or other vaccine rollouts is difficult, the process of rolling out COVID-19 vaccines provides a novel IV, namely, vaccine eligibility of different population groups: vaccine eligibility per se has little to do with population mobility. In the meantime, vaccine eligibility directly drives vaccine distribution, and its effect on population mobility is through vaccine distribution. Figure 1 illustrates the interplay between vaccine eligibility, vaccination, and mobility.

Using our IV approach, we estimate a one-percentage-point increase in the fully vaccinated population led to a 0.435-percentage-point increase in mobility in public transit centers. The result means that as more people are vaccinated, they are more likely to use public transportation. In addition, we examine the heterogeneous impacts of COVID-19 vaccination on the demand for public transportation, with a particular emphasis on vulnerable populations. Our analysis reveals that socioeconomic factors, such as education level and health insurance coverage, correlate with the impact of vaccination on mobility in public transit stations. We find the impact of vaccination on mobility is 70% larger in counties with higher percentages of individuals without a college degree and 40% larger in counties with higher percentages of uninsured individuals. These findings highlight the importance of considering the heterogeneous treatment effects in evaluating the impact of vaccination on mobility, particularly among vulnerable populations.

Informed by our findings, it is critical that public transportation agencies coordinate with public health authorities during a pandemic. As vaccines are distributed, the demand for public transportation is likely to increase. Therefore, transit agencies should proactively expand their services to meet this surge in demand. Our findings support investments aimed at restoring and revitalizing public transportation service offerings *in advance of* demand recovery, echoing the strategy adopted by Metra, a commuter rail system in the Chicago metropolitan area: "We want to be ahead of demand, because we don't want people who haven't ridden in a while to show up at the train and encounter a crowded situation" (Freishtat 2021). Such investments help prevent long-term losses of demand for public transportation and avoid a vicious cycle of deteriorating public transportation options that end up hurting the most vulnerable groups who have few outside options. Our findings provide an empirical foundation for revitalizing public transit in the wake of a pandemic, emphasizing the need for proactive measures in anticipation of vaccine-fueled demand recovery. In the aftermath of the COVID-19 crisis, this strategy promotes the resilience of public transportation systems and equips them to effectively address the needs of vulnerable populations.

2. Literature Review

Our paper contributes to five streams of literature related to vaccination, transportation and health, the COVID-19 pandemic, social inequality, and empirical healthcare operations.

First, the design, manufacturing, contracting, and distribution of vaccines, especially influenza vaccines, is a vibrant topic that has attracted much attention from the operations management community (see, e.g., Arifoğlu et al. 2012, Arifoğlu and Tang 2022, Bertsimas et al. 2022, Bravo et al. 2023, Chick et al. 2008, 2017, Craft et al. 2005, Cummings et al. 2021, Dai et al. 2016, Deo and Corbett 2009, Mak et al. 2022, Niewoehner and Staats 2022, Özaltın et al. 2011, Tebbens and Thompson 2009, Yamin and Gavious 2013). To our best knowledge, this literature is mostly theoretical, notwithstanding that several papers (e.g., Bertsimas et al. 2022, Bravo et al. 2023, Deo and Corbett 2009, Mak et al. 2022) use real-world vaccination data. Our paper contributes to this literature by empirically estimating the impact of vaccine rollouts on the demand for public services.

Second, our paper is related to the operations management and transportation economics literature on the interaction between transportation and health. Wang et al. (2022) estimate the effect of the airline transportation network on the sharing of kidneys for transplantation across geographical regions. Using an online survey of cancer patients, Etminani-Ghasrodashti et al. (2021) show the quality of transportation options affects patients' travel behavior and plays an important role in shaping their decisions to stop or continue treatments. A systematic literature review conducted by the Centers for Disease Control and Prevention (2018) identifies evidence that introducing or expanding public transportation services has significant public health benefits, including fewer traffic accidents, better air quality, and improved physical fitness. In contrast to these papers that focus on how transportation affects public health and access to healthcare, our paper is possibly the first to examine the impact of healthcare—in this case, COVID-19 vaccination—on transportation, which has important implications for public transit riders, especially socioeconomically disadvantaged groups whose mobility depends on public transportation (Glaeser et al. 2008).

Third, the COVID-19 pandemic has inspired a new stream of operations management literature on topics ranging from nonpharmaceutical interventions (e.g., Kaplan 2020, Wang 2022) to forecasting (e.g., Betcheva et al. 2021) to diagnostic testing (e.g., Dai and Singh 2022, Jain et al. 2023). A few recent papers, including those by Chen et al. (2020), Jain et al. (2020), Pekoz et al. (2020), Song et al. (2020a), Sun and Wang (2021), and Wang et al. (2021), examine the effect of the pandemic on healthcare delivery. Different from these papers, ours is among the very few papers (e.g., Bertsimas et al. 2022, Mak et al. 2022) that study COVID-19 vaccination.

Fourth, our study is related to the recent stream of operations management literature on social inequality. Ganju et al. (2020) study the role of clinical decision support systems (CDSS) in mitigating systematic bias among Black patients and find that the imposition of standardized protocols via CDSS in hospitals reduces amputation rate disparities between Black and White patients. Samorani et al. (2022) examine racial disparities in medical appointment scheduling and find that Black patients wait longer than non-Black patients in scheduling systems that maximize clinic performance. Cui et al. (2022) study the effect of the COVID-19 lockdown on female and male academic research productivity in the social sciences and find that the productivity of female academics falls significantly relative to that of male academics. Wang (2022) study the effect of stay-at-home orders on resident mobility and find that uninsured and less educated residents are less likely to comply with the orders because their jobs prevent them from working from home. Sun and Wang (2021) investigate whether the expansion of telehealth during the COVID-19 pandemic reduces rural-urban disparities in access to care and find that the expansion benefits urban populations more than their rural counterparts. Our study contributes to this stream of literature by highlighting the social inequality caused by the pandemic and how vaccination can help reduce inequality.

Finally, from a methodological perspective, our work is connected to a large body of empirical operations management literature that uses an IV approach to address problems arising from the healthcare industry; see KC (2018), KC et al. (2020), and Terwiesch et al. (2020) for comprehensive reviews of this literature. For example, in characterizing the unintended consequences of hospital capacity pooling, Song et al. (2020b) use measures of preadmission service utilization as IVs to infer the causal effect of assigning patients from a fully occupied inpatient service to a bed in a different service category. As another example, Kim et al. (2015) use an indicator of ICU busyness (i.e., whether ICU bed occupancy is above the 95th percentile) as an IV to estimate the effect of denied ICU admission on patient outcomes. Other applications of the IV approach to the healthcare operations literature include Bartel et al. (2020), Ibanez et al. (2018), Jin et al. (2023), KC and Terwiesch (2011), Lu et al. (2018), and Wang et al. (2023). Joining this literature, our paper identifies a novel IV to estimate the impact of the vaccination progress, achieving what was previously deemed a "mission impossible" (Groenwold et al. 2010, p.132), albeit for the case of influenza vaccination.

3. Background and Data

In this section, we first describe the related background information in Section 3.1. Next, in Section 3.2, we introduce the five main data sources used in the study and describe how we prepare and merge these datasets for our empirical estimation.

3.1. U.S. COVID-19 Vaccine Rollout

As of May 2021, three COVID-19 vaccines, manufactured by Pfizer/BioNTech, Moderna, and Johnson & Johnson, respectively, were distributed in the U.S. These three vaccines were authorized by the Food and Drug Administration (FDA) for emergency use for adults on December 11, 2020, December 18, 2020, and February 28, 2021, respectively. Of these three vaccines, the Pfizer/BioNTech and Moderna vaccines are based on messenger RNA (mRNA) technology and require two doses for a recipient to be considered fully vaccinated, whereas the Johnson & Johnson vaccine is based on the viral vector technology and requires a single dose. The recommended interval between two vaccine doses is three weeks for the Pfizer/BioNTech vaccine and four weeks for the Moderna vaccine. Due to its relatively late approval and limited production capacity, the Johnson & Johnson vaccine accounts for only a small proportion—3.43% as of September 30, 2022, according to the CDC[2]—of COVID-19 vaccines administered in the U.S. In April 2021, the U.S.

[2] https://covid.cdc.gov/covid-data-tracker/#vaccinations

government suspended the distribution of the Johnson & Johnson vaccine after the emergence of cases of blood clotting.

December 14, 2020, marked the first day of administering the Pfizer/BioNTech vaccine.[3] With the three-week lead time between the two doses, January 4, 2021, was the earliest date on which an individual could be fully vaccinated. The U.S. COVID-19 vaccine rollout was initially sluggish, with only 2 million doses administered by the end of 2020, significantly below the 20-million-dose target (Dai and Song 2021). To provide guidance for the planning and implementation of the COVID-19 vaccination program, the Advisory Committee on Immunization Practices (ACIP) has advised on the population groups and circumstances for vaccine use, prioritizing essential workers in healthcare and residents of long-term care facilities in the initial phase to focus on averting deaths. As the vaccine supply increased, more individuals became eligible for vaccine based on age, occupation, and underlying health conditions. However, because some states designed their own vaccination program, variations may exist in the eligibility rules outlined by the CDC (Raifman et al. 2020). The pace of vaccine rollout accelerated after January 2021 and peaked on April 12, 2021, with a seven-day average of 3.49 million doses administered per day.[4] As of June 30, 2021, the seven-day average number of daily doses remained around 0.58 million.

3.2. Data Description and Preparation

Our study builds on five data sources covering different aspects such as mobility, vaccine administration and eligibility, weather patterns, COVID-19 case counts, and county-specific characteristics. In the following section, we describe each data source in detail and explain our process for preparing the data for empirical analysis.

First, we obtained mobility data from Google's COVID-19 Community Mobility Reports.[5] The population-level aggregated and deidentified dataset tracks the change in mobility in different locations with respect to their pre-COVID baseline values. The mobility data are based on the location history collected by Google, and the computational algorithm considers factors such as *the number of visits* and *visit duration* in order to represent mobility in different places (Aktay et al. 2020). The pre-COVID baseline values are identified by calculating the median values on the corresponding day of the week from January 3, 2020, to February 6, 2020. The six location categories are transit stations, grocery and pharmacy stores, retail and recreation facilities, parks, workplaces, and residential areas. In this study, we focus on the transit station category, which includes public transportation hubs such as bus stops, subway stations, and train stations. Mobility

[3] https://nyti.ms/3uEiWYa

[4] https://n.pr/2Raxmkq

[5] https://www.google.com/covid19/mobility/index.html?hl=en

data were collected from February 15, 2020, and aggregated at both county and state levels in the U.S.

Second, we collected county-level COVID-19 vaccine distribution and administration data about the COVID-19 vaccination in the U.S. from the CDC.[6] The tracker was updated daily with new vaccination data before June 22, 2022, and updated weekly afterward. Related to the measurement of vaccination progress, the data contain many vaccination-related variables, such as the vaccine coverage of the first dose, the second dose, and the booster shot among various populations. They report the raw number as well as the population percentage in each county or state on each day.

Third, to gather information on vaccine eligibility, we leveraged the COVID-19 State Policy database (Raifman et al. 2020). This database contains information on the vaccine distribution plan for different sub-populations in each state. Based on the guidelines set by the CDC (Dooling et al. 2020), states determine their vaccine distribution schedule by considering various factors such as age, the number of underlying health conditions, and occupation. To determine the eligible population for each phase, we acquired population age and occupation-distribution data from the 2015-2019 American Community Survey (ACS) conducted by the U.S. Census Bureau (Census Bureau 2022a) and cross-referenced them with the workers' categorization from the CDC (Centers for Diseases Control and Prevention 2021)

Fourth, realizing both mobility and vaccination can be affected by weather, we obtained daily weather information (e.g., temperature and precipitation) at various weather observation stations across the U.S. from the National Centers for Environmental Information.[7] To obtain a county-wise measurement, we calculate the averages based on the information reported by weather observation stations within the county. In addition, we obtain the federal holiday schedule from 2020 to 2021 from the Office of Personnel Management because both people's movement and vaccination patterns might change during holidays.[8]

Finally, to perform additional analyses, we obtain COVID-19 cases data from the *New York Times* GitHub repository,[9] and county-characteristics data (e.g., the percentage of the population that is uninsured and the percentage of the population that holds a college degree) from the County Health Rankings and Roadmaps (CHR&R) program created by the Population Health Institute at the University of Wisconsin.[10]

[6] https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-County/8xkx-amqh

[7] https://www.ncdc.noaa.gov/cdo-web/datatools

[8] https://www.opm.gov/policy-data-oversight/pay-leave/federal-holidays

[9] https://github.com/nytimes/covid-19-data

[10] https://www.countyhealthrankings.org/explore-health-rankings/rankings-data-documentation

To ensure consistency across different types of data, we compiled the data at the county level. The data preparation and integration process entailed merging the mobility, vaccine administration, and weather data using the date and Federal Information Processing Standard (FIPS) code for each county as key identifiers. Subsequently, we linked the aggregated data with county-level vaccine eligibility information through the FIPS code and combined them with holiday information based on the date. The final consolidated dataset incorporated 47 states and the District of Columbia from December 15, 2020, to April 30, 2021. We excluded Alaska and Hawaii due to a lack of consistent mobility records throughout our analysis period, and we excluded Texas because the CDC reported incomplete vaccination records before October 22, 2021.[11]

4. Empirical Model

In this section, we first describe the variables of interest. We then discuss the empirical challenges of using an ordinary least squares (OLS) regression model to establish causality. Finally, we present our identification strategy by introducing an IV specific to COVID-19 vaccination progress.

4.1. Variable Description

To assess the impact of vaccine rollouts on mobility, we focus on the public transportation sector for three reasons: (1) It is one of the sectors most severely affected by the pandemic (Sylvers 2020); (2) its recovery serves as a reliable indicator of progress toward pre-pandemic normalcy, as anticipated from the mass-vaccination campaign (Vesoulis 2020); and (3) it plays a significant role in the daily lives of millions of Americans, particularly socioeconomically disadvantaged groups who predominantly rely on public transportation and possess limited alternatives (Glaeser et al. 2008). With this focus in mind, we represent the mobility of residents in county i on day t as $Mobility_{it}$. As outlined in Section 3.2, $Mobility_{it}$ corresponds to the percentage change in mobility compared to pre-COVID values.

In our main and supplemental analyses, we focus on mobility in transit stations, which include public transportation hubs such as bus stops, subway stations, and train stations. Google's COVID-19 Community Mobility Reports record mobility relative to baseline days, so our dependent variable is negative if mobility in a county on a given day is less than the baseline day, and positive otherwise. We use the original rather than the log-transformed mobility as the dependent variable because (1) the original mobility is normally distributed and (2) a log transformation of mobility relative to baseline days makes our results difficult to interpret. To ensure the integrity and comprehensiveness of our data, we focused on a subset of counties that satisfied specific inclusion criteria. Out of 3,142 counties in the U.S., we exclude 2,416 counties from our analysis due to incomplete records

[11] https://www.cdc.gov/coronavirus/2019-ncov/vaccines/reporting-vaccinations.html

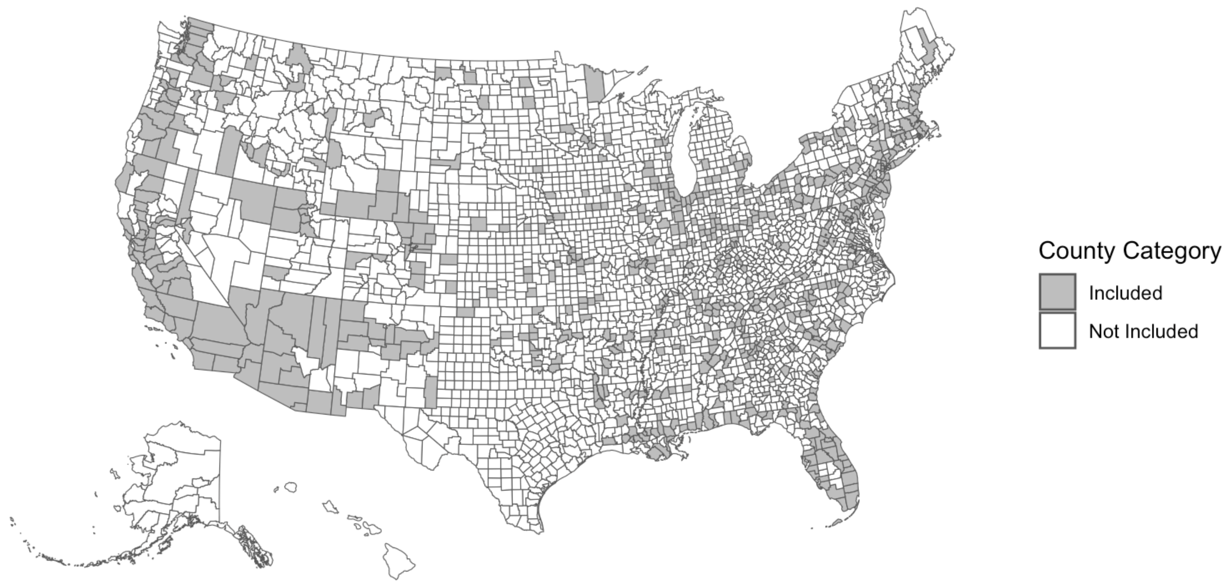

Figure 2 Counties Included in the Analysis

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of mobility at transit stations, as identified in the Google Community Mobility Report. Also, we refine our selection by excluding an additional 68 counties in Texas according to the CDC's reports on incomplete vaccination records in Texas before October 22, 2021.[12] By excluding counties with incomplete or unreliable data, we conduct our analyses with the remaining 658 counties. Note that although the 658 counties included in our analysis represent 21% of the total 3,142 U.S. counties, they account for approximately 65% of the total U.S. population. Because the counties we selected cover a substantial population, our findings are generalizable to a significant portion of the U.S. population.

Our main independent variable is the percentage of the population that is vaccinated. This variable can be measured in two ways: (1) the percentage of the population that is fully vaccinated in county i on the day before day t (denoted by $Vaccination_{it-1}$), and (2) the percentage of the population that receives at least the first dose of vaccine in county i on the day before day t (denoted by $FirstDoseVaccination_{it-1}$). In the main analysis, we use $Vaccination_{it-1}$ as an independent variable. As a robustness check, we use $FirstDoseVaccination_{it-1}$ as an alternative independent variable. Our main analysis uses a one-day time lag between vaccination and mobility to address a potential concern that increased mobility may result from people travelling for vaccination. To understand the effect of a time lag, we perform a robustness check in Section 5.3.8 to analyze the effect of vaccine rollouts on mobility with several lagged versions of the vaccination variable.

[12] https://www.cdc.gov/coronavirus/2019-ncov/vaccines/reporting-vaccinations.html

Weather can have a significant impact on both mobility and vaccination. Adverse weather conditions can negatively impact immunization on both the demand and supply sides by limiting the mobility of individuals. On the demand side, citizens may be reluctant to get vaccinated due to the inconvenience of commuting during inclement weather. On the supply side, vaccination centers may face shutdowns or partial operations due to adverse weather conditions (see, e.g., Petrie 2021). To control for the effect of weather, we include the maximum temperature (denoted by $MaxTemperature_{it}$), minimum temperature (denoted by $MinTemperature_{it}$), and precipitation (denoted by $Precipitation_{it}$) in county i on day t as additional independent variables.

Another important factor that can affect both mobility and immunization is holidays. For example, residents are more likely to travel during holidays to gather with family and friends. On the other hand, residents are less likely to be vaccinated during holidays for two reasons. First, residents are more likely to have other plans during the holidays. Second, vaccination sites may be closed or partially closed during holidays (see, e.g., Florida Department of Public Health in Orange County 2021). To control for the effect of holidays, we include a vector of holidays (denoted by $Holiday_t$) as additional independent variables.[13]

The relationship between the dependent and independent variables can be described as

$$\begin{aligned} Mobility_{it} =& \beta_0 + \beta_1 Vaccination_{it-1} + \beta_2 Weather_{it} + \beta_3 Holiday_t \\ &+ \beta_4 County_i + \beta_5 Day_t + \epsilon_{it}, \end{aligned} \tag{1}$$

where $Weather_{it} = \{MaxTemperature_{it}, MinTemperature_{it}, Precipitation_{it}\}$ and ϵ_{it} denotes an error term. Note we include county fixed effects (denoted by $County_i$) to capture the systematic differences across counties and day fixed effects (denoted by Day_t) to capture the time trends of mobility over different days of a week.

We are particularly interested in the coefficient β_1, because it describes the relationship between vaccination and mobility. A positive coefficient indicates an increase in vaccination increases mobility, whereas a negative coefficient indicates otherwise. Note our estimation will be biased if the error term (i.e., ϵ_{it}) correlates with both the dependent variable (i.e., $Mobility_{it}$) and the independent variable of interest (i.e., $Vaccination_{it-1}$). The coefficient β_2 indicates the correlation between weather and mobility, and β_3 indicates the correlation between holiday and mobility. Finally, β_4 and β_5 indicate the differences in mobility across counties and over time, respectively.

[13] Holidays include Christmas Eve, Christmas Day, New Year's Eve, Martin Luther King Day, President's Day, Memorial Day, and Juneteenth.

4.2. Identification Strategy

Using (1) to estimate the effect of vaccine rollouts on mobility presents an endogeneity issue when the error term, ϵ_{it}, correlates with both the dependent variable, $Mobility_{it}$, and the independent variable of interest, $Vaccination_{it-1}$. For example, an increase in COVID-19 infection may reduce mobility, because residents are worried about being infected while traveling. At the same time, an increase in COVID-19 infection may increase vaccination, because residents are more aware of the risks of COVID-19 and the benefits of vaccination. Although controlling for observable features such as COVID-19 infection is possible (see Section 5.3.2), we cannot control for unobservable features (e.g., health consciousness) that affect both mobility and vaccination. To address the endogeneity issue, we consider three alternative approaches: difference-in-differences, regression discontinuity, and IV.

First, a difference-in-differences approach requires a control group that does not have vaccination. However, in the case of the COVID-19 vaccine rollout, all states started vaccination around mid-December 2020, immediately after the Pfizer/BioNTech vaccine was approved for emergency use (Gee 2021). For this reason, a control group required by the difference-in-differences approach does not exist. Even if such a control group exists, the difference-in-differences approach would not be suitable, because the treatment is a continuous instead of a binary variable.

Second, a regression discontinuity approach requires a cutoff to assign the intervention. Some might suggest using the vaccination start date (December 14, 2020) as the cutoff date, because vaccination is zero before the cutoff date and a positive number after the cutoff date. This approach is not plausible, because the change in mobility around the cutoff date could be due to time trends. Others may consider the age of 65 as a cutoff, because residents aged 65 and above were prioritized for vaccination in the initial months of the vaccine rollout. This approach is plausible but requires individual-level data about vaccination and mobility. Yet, our publicly available data are aggregated at the county—as opposed to individual—level. For this reason, the regression discontinuity approach is not suitable for addressing our issues either.

Third, an IV approach requires an exogenous variable that correlates with the variable of interest but does not correlate with the error term. Identifying a good IV to assess the impact of vaccination is a daunting task. Classes of medication, facility prescribing patterns, physician patterns, and patient characteristics have been considered as IVs but proven to fail to meet the necessary IV criteria (Chen and Briesacher 2011, Groenwold et al. 2010). Potential IVs in our setting include the closeness to vaccination facilities, age groups of the vaccinated people, and characteristics of vaccination facilities. However, these IVs require vaccination records at the individual or vaccination-site level. Due to limitations in the publicly available data, these potential IVs are infeasible for our analysis.

In this study, we propose using the percentage of the population eligible for vaccination in county i on the day before day t (denoted as $VaccineEligibility_{it-1}$) as an IV for vaccination (i.e., $Vaccination_{it-1}$). Previous studies, such as those by Agrawal et al. (2021) and Aslim et al. (2022), have used vaccine eligibility as an IV to examine the relationship between vaccine administration and health outcomes at the individual level.

Our study extends this approach by focusing on vaccine eligibility at the population level. The motivation for this approach is that during the COVID-19 vaccine rollout, states made vaccines available based on factors such as age, underlying health conditions, and occupation. Consequently, the proportion of the eligible population would have a direct impact on the number of doses administered, thus meeting the relevance criterion of a valid IV. Consistent with previous studies, we calculate vaccine eligibility primarily based on age (Agrawal et al. 2021, Aslim et al. 2022). In addition, our study differs from previous studies by calculating the percentage of essential healthcare workers eligible for vaccine during the initial phase, providing a more comprehensive representation of the initially eligible population.

To determine the vaccine eligibility variable, we obtained data on the age and occupational distribution of the population from the 2015-2019 American Community Survey (ACS) conducted by the U.S. Census Bureau (Census Bureau 2022a) and matched it with the categorization of healthcare workers based on the CDC guideline (Centers for Diseases Control and Prevention 2021). We test the relevance criterion through a first-stage regression in which the dependent variable is vaccination and the independent variables are vaccine eligibility and other control variables.

Our proposed IV is likely to meet the exogeneity criterion because the process of phasing in the vaccine based on eligibility criteria does not directly affect mobility in each county. State administrators determine the population eligible for vaccine primarily based on age group, so the percentage of the eligible population does not affect mobility. To account for the possibility that older individuals, who are more likely to be eligible for the vaccine in the earlier phase, may have reduced mobility regardless of the administration process, we include county fixed effects in our analysis. These fixed effects account for county-level characteristics, such as the percentage of elderly individuals and transportation infrastructure, that may directly affect mobility.

4.3. IV Regression

In the main analysis, we use the two-stage least squares (2SLS) approach to estimate the effect of vaccine rollouts. In the first stage, we regress the endogenous variable, $Vaccination_{it-1}$, over the IV and other exogenous variables:

$$\begin{aligned} Vaccination_{it-1} =& \alpha_0 + \alpha_1 VaccineEligibility_{it-1} + \alpha_2 Weather_{it} + \alpha_3 Holiday_t \\ & + \alpha_4 County_i + \alpha_5 Day_t + \xi_{it}, \end{aligned} \tag{2}$$

where the coefficient α_1 indicates the relation between $Vaccination_{it-1}$ and $VaccineEligibility_{it-1}$. A statistically significant coefficient would suggest our IV has a strong first stage. We use the first-stage regression model to predict the endogenous variable (denoted by $\widehat{Vaccination}_{it-1}$).

In the second stage, we regress the dependent variable, $Mobility_{it}$, over the predicted endogenous variable, $\widehat{Vaccination}_{it-1}$, from the first stage and other exogeneous variables:

$$\begin{aligned} Mobility_{it} =& \beta_0 + \beta_{IV} \widehat{Vaccination}_{it-1} + \beta_2 Weather_{it} + \beta_3 Holiday_t \\ &+ \beta_4 County_i + \beta_5 Day_t + \zeta_{it}, \end{aligned} \tag{3}$$

where the coefficient of interest is β_{IV}. A positive coefficient indicates an increase in vaccination leads to increased mobility, whereas a negative coefficient indicates otherwise. Comparing β_1 in equation (1) and β_{IV} in equation (3) allows us to understand whether our proposed IV effectively addresses potential endogeneity issues.

5. Results and Discussion

In this section, we first provide summary statistics of our data in Section 5.1. We then present the results from our proposed IV regression in Section 5.2. Finally, we perform extensive robustness checks in Section 5.3.

5.1. Summary Statistics

Our dataset covers 658 counties from December 16, 2020, to April 30, 2021. Table 1 provides the definition and summary statistics of the dependent and key independent variables. For ease of interpretation, we have multiplied the variable, $Vaccination$, by 100. The dependent variable, $Mobility$, has a mean of -8.53 with a standard deviation of 30.72. Because the dependent variable measures mobility relative to baseline days, the negative mean of this variable suggests the average mobility during our study period has not recovered to the baseline mobility yet. The main independent variable of interest, $Vaccination$, has a mean of 15.87 and a standard deviation of 15.61. This variable has a wide variation for two reasons. First, the percentage of the fully vaccinated population differs across counties on a given day. Second, the percentage of the population that is fully vaccinated increases over time in a given county.

5.2. Main Results

We start with assessing the relevance condition of the IV by conducting the first-stage regression as specified by (2) and summarizing the results in Table 2. The positive coefficient of the variable, $VaccineEligibility$, confirms the positive relationship between the percentage of the population eligible for the COVID-19 vaccine and the percentage of the population being fully vaccinated. The coefficient of the variable is significantly different from zero at the 1% significance level, which

Table 1 Definition and Summary Statistics

Variable	Definition	Mean	Std. Dev.
Dependent			
Mobility	Mobility in transit stations relative to baseline days	−8.53	30.72
Independent			
Vaccination	Percentage of the population that are fully vaccinated	15.87	15.61
Observations		129,626	

Note: This table provides the definition and summary statistics of the dependent and key independent variables. For ease of interpretation, we have multiplied the variable, $Vaccination$, by 100.

Table 2 Results from the First-Stage Regression

Variable	Coefficient	Standard Error
Vaccine Eligibility	0.319 * **	0.010
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.832	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the first-stage regression. The dependent variable is vaccination. Independent variables are vaccine eligibility, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

suggests our IV has a strong first stage. The coefficient of 0.319 means a one-percentage-point increase in vaccine eligibility increases vaccination coverage by 0.319 percentage points.

Next, we formally analyze the effect of vaccine rollouts on mobility by using the 2SLS regression (see Section 4.3). Table 3 summarizes the results from the IV regression. The coefficient of the variable, $Vaccination$, is positive and significantly different from zero at the 1% significance level, which suggests an increase in vaccination increases mobility. Because our dependent variable measures residents' mobility relative to the baseline days, the coefficient of 0.435 means a one-percentage-point increase in vaccination increases mobility by 0.435 percentage points.

As a comparison, we conduct the OLS regression specified by equation (1). The results are summarized in Table 4. We see the coefficient of $Vaccination$ is positive and significantly different from zero at the 1% significance level, which suggests an increase in vaccination increases mobility. However, the coefficient in the OLS regression has a smaller magnitude than that in the IV regression, which suggests one might underestimate the effect of vaccine rollouts by ignoring potential endogeneity issues.

5.3. Robustness Checks

We perform extensive robustness checks to analyze the sensitivity of our results. First, Sections 5.3.1 and 5.3.2 control for statewide COVID-19 policies and COVID-19 infection, both of which may

Table 3 Results from the IV Regression

Variable	Coefficient	Standard Error
Vaccination	0.435 * **	0.022
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.816	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

Table 4 Results from the OLS Regression

Variable	Coefficient	Standard Error
Vaccination	0.295 * **	0.024
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.818	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the OLS regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

affect both vaccination and mobility. Next, we test two alternative models: Section 5.3.3 analyzes the effect of first-dose vaccination; Section 5.3.4 uses the log-transformed percentage of the population that is fully vaccinated as an alternative independent variable, and Section 5.3.5 includes a quadratic term of vaccination to examine the non-linear effect. Sections 5.3.6 and 5.3.7 address the potential concern that our estimation may be driven by a particular state or week, and Section 5.3.8 uses lagged versions of vaccination as the independent variable.

5.3.1. Controlling for Statewide COVID-19 Policies. A potential concern is that statewide COVID-19 policies affect both vaccination and mobility. For example, statewide stay-at-home orders can reduce mobility because people are required to stay at their homes. At the same time, they can increase vaccination coverage because people are more likely to receive vaccines if they are not traveling or engaging in other activities. To address this potential concern, we first identify relevant statewide policies from Boston University's COVID-19 US State Policy Database and then include these policies as additional independent variables (Raifman et al. 2020). Table 5 summarizes the results when we include stay-at-home orders, business closures, and reopenings as additional independent variables. The results from this robustness check are not significantly different from those in the main analysis, which suggests omitting statewide COVID-19 policies does not drive our results.

Table 5 Results from the IV Regression (Control for Statewide COVID-19 Policies)

Variable	Coefficient	Standard Error
Vaccination	$0.439***$	0.022
Statewide COVID-19 Policies	Included	
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.816	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, statewide COVID-19 policies, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

5.3.2. Controlling for COVID-19 Infection. As mentioned in Section 4.1, COVID-19 infection may affect both mobility and vaccination. For instance, a high rate of infection in an area makes people more cautious and reduces their mobility. At the same time, the fear of getting infected increases the number of people willing to get vaccinated. To address this concern, we include the seven-day rolling average of daily newly reported cases in county i on day t (denoted by $Infection_{it}$) as an additional independent variable. The results from this robustness check are summarized in Table 6. We observe from the table that the coefficient of $Vaccination$ is positive and significantly different from zero at the 1% significance level. The results of this robustness check are not significantly different from those of the main analysis, indicating whether we consider COVID-19 infection does not drive our results.

5.3.3. First-Dose Vaccination. Our main analysis uses the percentage of the fully vaccinated population as an independent variable. Note Pfizer/BioNTech and Moderna recommend three- and four-week gaps, respectively, between the first and second doses of the vaccine. Because existing studies (see, e.g., Lovelace 2021, Gorvett 2021) report high efficacy of the first dose, residents may start changing their mobility patterns after the first dose. In this robustness check, we use the percentage of the population that receives at least the first dose (denoted by $FirstDoseVaccination$) as an alternative independent variable.

The results from this robustness check are summarized in Table 7. We observe from the table that the coefficient of $FirstDoseVaccination$ is positive and significantly different from zero at

Table 6 Results from the IV Regression (Control for COVID-19 Infection)

Variable	Coefficient	Standard Error
Vaccination	0.457∗∗∗	0.023
COVID-19 Infection	Included	
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.815	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, COVID-19 infection level, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

the 1% significance level, which suggests an increase in first-dose vaccination increases mobility. More specifically, the coefficient of 0.361 suggests a one-percentage-point increase in first-dose vaccination increases mobility by 0.361 percentage points. Note the coefficient in this robustness check is smaller than that in the main analysis, because the mean of $FirstDoseVaccination$ is larger than that of $Vaccination$.

Table 7 Results from the IV Regression (First-Dose Vaccination)

Variable	Coefficient	Standard Error
First-Dose Vaccination	0.361∗∗∗	0.018
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.815	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable ismobility in transit stations. Independent variables are first-dose vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

5.3.4. Alternative Model with Log-Transformed Term. In the main analysis, we use $Vaccination$ as an independent variable, because it follows a normal distribution. As a robustness check, we use the log-transformed percentage of the fully vaccinated population, denoted by $\ln(Vaccination)$, as an alternative independent variable. The results from this robustness check are shown in Table 8. We observe from the table that the coefficient of $\ln(Vaccination)$ is positive and significantly different from zero at the 1% significance level, indicating an increase in vaccination increases mobility. The coefficient of 4.473 suggests a one-fold increase in vaccination coverage increase mobility by $4.473 \times (\ln(Mobility \times 2) - \ln(Mobility)) = 3.100$ percentage points.

Table 8 Results from the IV Regression (Linear-Log Model)

Variable	Coefficient	Standard Error
ln(Vaccination)	$4.473{*}{*}{*}$	0.212
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.821	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are log-transformed vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

5.3.5. Alternative Model with Quadratic Term. In the main analysis, we use $Vaccination$ as an independent variable. However, a potential concern is that the impact of vaccination on mobility might be non-linear. In this robustness check, we expand our analysis by constructing an additional 2SLS regression model that includes a quadratic term of the vaccination variable, denoted by $Vaccination^2$, to examine the non-linear effect of vaccination on public transportation mobility. Our analysis finds the coefficient of $Vaccination$ is 0.803 and is statistically different from zero, indicating vaccination has a significant impact on public transportation mobility. The coefficient of $Vaccination^2$ is negative and statistically significant at the 1% significance level, which suggests the marginal effect of vaccination on public transportation mobility diminishes as vaccination coverage increases. The magnitude of the first-order effect is almost two times larger than that estimated in the main analysis without the quadratic term, indicating a large initial boost in public transportation use following vaccination.

5.3.6. Leave-State-Out Analysis. To address a potential concern that our results are driven by a particular state, we perform a leave-state-out analysis by leaving out one state at a time and re-estimate the effect of vaccine rollouts; we summarize the results in Table 10. As the table shows, all the coefficients are positive and significantly different from zero, which suggests an increase in vaccination increases mobility. These coefficients are not significantly different from each other or those in the main analysis, which suggests our results are not driven by a particular state.

Table 9 Results from the IV Regression (Quadratic Model)

Variable	Coefficient	Standard Error
Vaccination	0.803 ***	0.052
Vaccination^2	−0.011 ***	0.001
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.822	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination and its quadratic term, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

Table 10 Results from the IV Regression (Leave-State-Out Analysis)

Left-Out State	Coefficient	Standard Error	Left-Out State	Coefficient	Standard Error
AL	0.424 ***	0.022	MT	0.432 ***	0.022
AZ	0.435 ***	0.022	NE	0.433 ***	0.022
AR	0.440 ***	0.022	NV	0.430 ***	0.022
CA	0.462 ***	0.024	NH	0.433 ***	0.022
CO	0.429 ***	0.022	NJ	0.441 ***	0.023
CT	0.434 ***	0.022	NM	0.441 ***	0.023
DE	0.435 ***	0.022	NY	0.438 ***	0.023
DC	0.436 ***	0.022	NC	0.437 ***	0.023
FL	0.453 ***	0.023	ND	0.433 ***	0.022
GA	0.421 ***	0.022	OH	0.432 ***	0.023
ID	0.429 ***	0.022	OK	0.444 ***	0.023
IL	0.433 ***	0.023	OR	0.432 ***	0.023
IN	0.432 ***	0.023	PA	0.431 ***	0.022
IA	0.431 ***	0.022	RI	0.435 ***	0.022
KS	0.434 ***	0.022	SC	0.418 ***	0.021
KY	0.440 ***	0.023	SD	0.433 ***	0.022
LA	0.447 ***	0.023	TN	0.435 ***	0.023
ME	0.435 ***	0.022	UT	0.431 ***	0.022
MD	0.439 ***	0.022	VT	0.435 ***	0.022
MA	0.437 ***	0.022	VA	0.435 ***	0.022
MI	0.434 ***	0.022	WA	0.433 ***	0.023
MN	0.431 ***	0.022	WV	0.433 ***	0.022
MS	0.431 ***	0.022	WI	0.433 ***	0.022
MO	0.439 ***	0.023	WY	0.434 ***	0.022

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the leave-state-out analysis. We leave out one state at a time and perform IV regression with the newly constructed data. The dependent variable is mobility in transit stations. The independent variables are vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

5.3.7. Leave-Week-Out Analysis. To address a potential concern that our results are driven by a particular period, we perform a leave-week-out analysis by leaving out one week at a time and re-estimate the effect of vaccine rollouts; we summarize the results in Table 11. As the table shows, all the coefficients are positive and significantly different from zero, which suggests an increase in vaccination increases mobility.

Table 11 Results from the IV Regression (Leave-Week-Out Analysis)

Index	Left-Out Week	Coefficient	Standard Error
1	2020-12-16 to 2020-12-21	0.460 ***	0.022
2	2020-12-22 to 2020-12-28	0.445 ***	0.022
3	2020-12-29 to 2021-01-04	0.434 ***	0.022
4	2021-01-05 to 2021-01-11	0.429 ***	0.022
5	2021-01-12 to 2021-01-18	0.417 ***	0.022
6	2021-01-19 to 2021-01-25	0.417 ***	0.022
7	2021-01-26 to 2021-02-01	0.423 ***	0.022
8	2021-02-02 to 2021-02-08	0.428 ***	0.022
9	2021-02-09 to 2021-02-15	0.439 ***	0.022
10	2021-02-16 to 2021-02-22	0.452 ***	0.022
11	2021-02-23 to 2021-03-01	0.428 ***	0.022
12	2021-03-02 to 2021-03-08	0.435 ***	0.022
13	2021-03-09 to 2021-03-15	0.444 ***	0.023
14	2021-03-16 to 2021-03-22	0.459 ***	0.022
15	2021-03-23 to 2021-03-29	0.447 ***	0.023
16	2021-03-30 to 2021-04-05	0.420 ***	0.022
17	2021-04-06 to 2021-04-12	0.427 ***	0.022
18	2021-04-13 to 2021-04-19	0.425 ***	0.022
19	2021-04-20 to 2021-04-26	0.426 ***	0.023
20	2021-04-27 to 2021-05-03	0.437 ***	0.022
21	2021-05-04 to 2021-05-10	0.440 ***	0.023
22	2021-05-11 to 2021-05-17	0.428 ***	0.022
23	2021-05-18 to 2021-05-24	0.441 ***	0.022
24	2021-05-25 to 2021-05-31	0.429 ***	0.022
25	2021-06-01 to 2021-06-07	0.437 ***	0.022
26	2021-06-08 to 2021-06-14	0.434 ***	0.022
27	2021-06-15 to 2021-06-21	0.437 ***	0.022
28	2021-06-22 to 2021-06-28	0.443 ***	0.022
29	2021-06-29 to 2021-06-30	0.433 ***	0.022

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the leave-week-out analysis. We leave out one week at a time and perform IV regression with the newly constructed data. The dependent variable is mobility in transit stations. The independent variables are vaccination, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

5.3.8. Lag between Vaccination and Mobility. In the main analysis, we use a one-day lag to examine the relationship between vaccination and mobility. In this robustness check, we examine the potential influence of different lags between vaccination and mobility on the overall effect size. More specifically, we modify equation (1) by replacing $Vaccination_{it-1}$ with $Vaccination_{it-k}$, where k is the length of the lag. The results of the analysis are summarized in Table 12 for lag lengths of 0, 7, and 14. Regardless of the lag length, the results indicate that the coefficient of $Vaccination$ is positive and significantly different from zero at the 1% significance level, implying that an increase in the lagged version of vaccination increases mobility.

Table 12 Results from the IV Regression (Different Lags)

Variable	0-Day Lag		7-Day Lag		14-Day Lag	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Vaccination	0.431***	0.022	0.488***	0.024	0.543***	0.026
Weather	Included		Included		Included	
Holiday	Included		Included		Included	
County Fixed Effects	Included		Included		Included	
Day Fixed Effects	Included		Included		Included	
Number of Observations	129,626		125,678		121,072	
Adjusted R-Squared	0.816		0.817		0.819	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination (with different lags), weather, holidays, county fixed effects, day of week fixed effects, and month of year fixed effects. Robust standard errors are clustered by county.

6. Heterogeneous Impacts of Vaccination

In this section, we examine the heterogeneous impacts of vaccination on demand for public transportation, with a particular focus on vulnerable populations. The COVID-19 pandemic has exacerbated socioeconomic inequalities and exposed the issue of vaccine inequality, making it critical to understand how vaccination affects mobility in light of such inequalities.

A recent cross-sectional study, analyzing over 4 million COVID-19 cases and 150,000 COVID-19 deaths, shows socioeconomic risk factors are linked with elevated COVID-19 incidence and mortality rates (Karmakar et al. 2021). The disparity in vaccine coverage is also more pronounced for COVID-19 vaccines than for seasonal influenza vaccines, and socioeconomic factors, such as education level, play a significant role in vaccine disparities (Agarwal et al. 2021). Moreover, socioeconomic factors influence mobility patterns and transportation choices, with disadvantaged populations relying heavily on public transportation (Glaeser et al. 2008, Perchoux et al. 2014).

Given these complex relationships, considering the heterogeneity in treatment effects by incorporating key features of vulnerable populations, such as the percentage of the uninsured population and the percentage of the population without a college degree, is important. These two features signify socioeconomic disadvantages that may have far-reaching consequences, including, but not limited to, affecting access to healthcare and accurate information, leading to differential vaccine behaviors and transportation patterns. For example, research has demonstrated that individuals with these disadvantages are less likely to follow vaccine recommendations and are more likely to disobey stay-at-home orders (Lazarus et al. 2022, Lu et al. 2015, Wang 2022). To analyze these impacts, we employ an IV regression, which considers the two aforementioned key features of the vulnerable population. By incorporating these factors, we can gain a more comprehensive understanding of the heterogeneous impacts of vaccination on mobility, particularly among vulnerable populations.

In our analysis, we use the modified 2SLS approach to examine the heterogeneous effects of vaccination on mobility in the context of socioeconomic factors. This method allows us not only to quantify the direct effect of vaccination on mobility, but also to gain a comprehensive understanding of how the interaction between vaccination and the socioeconomic factors of the county affects mobility. We chose this approach because it provides a more complete picture of the effect of socioeconomic variables on the relationship between vaccination and mobility, which is essential for understanding the heterogeneous effects of vaccination on mobility, especially among vulnerable populations.[14]

To construct the socioeconomic indicator variable ($SocioeconomicIndicator$), we follow a two-step process. First, we rank the counties based on certain socioeconomic variables, namely the percentage of the uninsured population ($PercentUninsured$) and the percentage of the population without a college degree ($PercentNoCollegeDegree$). Second, we divide the counties into two groups using the medians of the socioeconomic variables to create the indicator variable $SocioeconomicIndicator$.

Our modified 2SLS approach allows us to estimate the effects of vaccination and the interaction between vaccination ($Vaccination$) and the socioeconomic indicator ($SocioeconomicIndicator$). To address potential endogeneity concerns, we introduce an additional IV: the interaction between our baseline instrument ($VaccineEligibility$) and the socioeconomic indicator ($SocioeconomicIndicator$). This modified approach allows us to estimate the impact of vaccination on mobility while accounting for heterogeneity in treatment effects.

6.1. Heterogeneity across Insurance

In this section, we analyze the heterogeneous impacts of vaccination on public transportation mobility across different health insurance groups. We used county-level data on the percentage of the uninsured population, represented by $PercentUninsured_i$, and created a binary indicator, $HighPercentUninsured_i$, based on the abovementioned methods. The results of this new

[14] Another method for analyzing heterogeneous effects is to divide counties into two groups based on socioeconomic factors and then run separate 2SLS regressions for each group. This alternative method allows one to compare the coefficients of interest from each regression to identify heterogeneity across population groups. Using this aternative method does not change the main conclusion of this analysis.

IV regression are presented in Table 13. Our analysis shows the coefficient of $Vaccination \times HighPercentUninsured$ is positive and statistically significant at the 1% significance level, suggesting counties with higher percentages of the uninsured population see a larger effect of vaccination on mobility. A one-percentage-point increase in vaccination coverage in counties with lower percentages of the uninsured population increases mobility in public transit stations by 0.366 percentage points, whereas counties with higher percentages of the uninsured population experience an additional 0.139-percentage-point increase in mobility. The ratio of these coefficients reveals that the effect of vaccination on mobility in public transit stations is approximately $0.139/0.366 = 40\%$ greater in counties with higher percentages of the uninsured population.

The uninsured population is of particular interest in our study because it faces numerous challenges, including limited access to healthcare and an increased risk of high medical costs due to COVID-19 hospitalization (Ellingjord-Dale et al. 2022). These factors increase their vulnerability to COVID-19 and decrease their confidence in using public transportation, which affects their mobility. For example, in Collier County, Florida, a wealthy county with a high per-capita income, the uninsured rate for people under 65 is estimated to be about 17.8%, significantly higher than the national average of 9.8% (Census Bureau 2022b). Despite the county's economic prosperity, a significant segment of the population remains uninsured. These workers, who constitute a socioeconomically disadvantaged demographic, rely heavily on public transportation. Therefore, understanding the impact of vaccination progress on their mobility becomes critical.

Our findings have important implications for policymakers and public health officials, who can use these results to develop targeted interventions to improve the accessibility of COVID-19 vaccine to the uninsured population and their demand for public transportation. Our results suggest that focusing vaccination efforts on counties with higher percentages of the uninsured population may lead to a greater reduction in the negative impact of the COVID-19 pandemic on public transportation and, in turn, improve access to employment and overall quality of life for this population.

6.2. Heterogeneity across Education

To examine the relationship between educational attainment and the effect of vaccination on mobility, we examine the percentage of the population in county i who have not completed a college degree, denoted by $PercentNoCollegeDegree_i$. We then create a binary indicator, $HighPercentNoCollegeDegree_i$, based on the abovementioned methods. The results of our IV regression analysis, presented in Table 14, indicate the effect of vaccination on public transportation mobility is affected by the percentage of the population without a college degree in a county. Specifically, the coefficient of $Vaccination \times HighPercentNoCollegeDegree$ is positive and statistically significant at the 1% significance level, indicating that an increase in the percentage of the

Table 13 Results from the IV Regression for Heterogeneous Effect Analysis (Health Insurance)

Variable	Coefficient	Standard Error
Vaccination	0.366 * **	0.026
Vaccination × HighPercentUninsured	0.139 * **	0.043
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.816	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the modified IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, vaccination times the indicator variable for counties with higher percentages of the uninsured population, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

population without a college degree in a county leads to an increase in the impact of vaccination on mobility. After controlling for other variables, our analysis suggests that a one-percentage-point increase in vaccination coverage in counties with lower percentages of the population without a college degree would correspond to a 0.334-percentage-point increase in mobility in public transit stations, whereas it would result in an additional 0.226-percentage-point increase in mobility in counties with higher percentages of the population without a college degree. Specifically, by calculating the ratio of the two effect, we find that the impact of vaccination is approximately $0.266/0.344 = 70\%$ greater in counties with higher percentages of the population without a college degree.

Our analysis provides a compelling narrative of the nuanced effect of COVID-19 vaccination on mobility at public transit stations. We find that this effect is most pronounced in counties with higher percentages of the population without a college degree, a finding with rich policy implications. To explore this phenomenon, one must consider the diverse occupational landscape across educational attainment levels. The U.S. Bureau of Labor Statistics sheds light on this disparity, noting that only 24% of individuals without a bachelor's degree are employed in white-collar occupations, including management, business, and financial operations. By contrast, that figure is 76% for those with a bachelor's degree or higher (Bureau of Labor Statistics 2022). The bifurcation in the occupational distribution has implications for the ability to work from home, a critical factor in the COVID-19 era. The Bureau's survey data underscore this divide, showing that 69% of those with a bachelor's degree or higher enjoy the flexibility to work remotely, compared with 23% of those without a college degree (Dey et al. 2020). The intertwined disparities in occupational distribution and telecommuting opportunities likely shape the mobility differences we observe across counties with different educational profiles.

Despite the widespread use of vaccines, those with a college degree may continue to shun public transportation for their commutes. This is especially true during the period of our analysis, which was marked by numerous work-from-home orders. Conversely, those without a college degree, who often work in essential roles that require their physical presence, would experience a notable increase in health confidence following vaccination.

The increased confidence could bolster confidence in public transport, which prior to the pandemic served as a vital link for socioeconomically disadvantaged communities. The transformative potential of the vaccine, therefore, extends beyond its primary function of reducing the risk of infection and hospitalization. It could foster increased demand for public transportation, a consequential but often underappreciated benefit. Thus, the vaccine functions not only as a tool to improve individual health, but also as a driver of change at the community level, particularly in terms of increased use of public transportation systems.

Table 14 Results from the IV Regression for Heterogeneous Effect Analysis (Education)

Variable	Coefficient	Standard Error
Vaccination	0.334***	0.026
Vaccination × HighPercentNoCollegeDegree	0.226***	0.043
Weather	Included	
Holiday	Included	
County Fixed Effects	Included	
Day Fixed Effects	Included	
Number of Observations	129,626	
Adjusted R-Squared	0.817	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table summarizes the results from the modified IV regression. The dependent variable is mobility in transit stations. Independent variables are vaccination, vaccination times the indicator variable for counties with higher percentages of the population without college degrees, weather, holidays, county fixed effect, and day fixed effect. Robust standard errors are clustered by county.

7. Concluding Remarks

The COVID-19 pandemic instigated a marked decline in demand for public transportation in the U.S., leading to financial distress for governments and public transit agencies. This situation led to corresponding measures, including limited service availability and route elimination. Such changes pose significant challenges to a comprehensive and equitable recovery, most notably affecting socioeconomically disadvantaged groups and low-income workers who heavily rely on public transportation for both mobility and sustenance (Yen and Weber 2021).

Our study addresses potential endogeneity concerns in estimating the impact of COVID-19 vaccination on public transportation demand by using an IV and incorporating data from multiple sources. We find a one-percentage-point increase in the vaccination rate leads to a 0.435-percentage-point increase in mobility at public transportation centers. Although this figure may appear modest, it underscores the notion that vaccination alone cannot restore public transportation demand to pre-pandemic levels. Additional measures such as increased route frequency, expansion of public transit, and phased removal of work-from-home mandates may be required to further boost mobility within the public transportation sector. Furthermore, our subsequent analysis reveals a nonlinear and diminishing effect of vaccination on public transit mobility. This observation further emphasizes that the influence of vaccination in isolation is limited.

Our heterogeneous effect analysis underscores the greater impact of vaccination on public transit mobility in counties with higher percentages of the uninsured population and those with lower levels of education. These findings highlight the need to address vaccine disparities among the socioeconomically disadvantaged population. Our study provides a compelling argument for targeted efforts to increase vaccination coverage in these communities and highlights the potential spillover benefits of such efforts in increasing demand for public transportation among key populations.

We emphasize the importance of rejuvenating public transportation options in sync with vaccine rollouts, even before demand fully recovers. A paucity of public transit options could suppress demand, potentially instigating long-term shifts toward private vehicle usage. Our research contributes to better pandemic preparedness and response by highlighting the relationship between vaccination and demand for public transportation. This understanding can guide policymakers and public transportation agencies to devise strategies to cushion public transit systems from pandemic impacts and ensure a more robust future response. This, in turn, safeguards the well-being of socioeconomically disadvantaged communities heavily dependent on public transportation.

Although vaccination contributes to the recovery of public transport, it is not sufficient on its own to fully restore ridership to pre-COVID levels. Additional policies or interventions are needed to complement vaccination efforts and maximize the potential for public transport recovery. These interventions may include lifting work-from-home orders, investing in public transportation infrastructure, and implementing other demand or supply-side measures.

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