Navigating Change: Google Maps, Real-Time Information, and Transit Ridership

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Abstract

We show that the introduction of real-time transit tracking in Google Maps led to higher subway ridership in the United States. Ridership per capita was 10.7% larger 3 years after the staggered rollout of real-time data—an effect similar to much costlier interventions like free transit. Real-time tracking in proprietary agency applications had much smaller impacts, even when the proprietary apps pre-dated Google Maps. Survey data confirms that commuters reduced car trips and opted for transit following the rollout. We see suggestive evidence that air quality improved and estimate that travelers are willing-to-pay around $0.70 per trip for the enhancement from Google Maps.

Keywords : Public Transportation; Travel Behavior; Travel Time

JEL Classification Codes: R42, R41, H44

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1 Introduction

Public spending on urban transit in the United States has more than doubled in the past two decades, to about $42 billion in 2017 (Duranton et al. 2020). Yet, Americans are taking transit less than ever. In 2019, ridership was 34% lower than it was in 2002. This trend extends beyond the last two decades. In 1970, nine percent of workers commuted by transit; today, only five percent do (Freemark 2021). Americans, instead, have overwhelmingly chosen to drive in private cars. The dominance of cars has not only reshaped mobility but also imposed large external costs: traffic congestion alone costs tens of billions annually, and vehicles are among the largest contributors to greenhouse gas emissions and urban air pollution.[1]

In this paper, we examine whether innovations in data-driven navigation technologies have slowed this trend, focusing on GoogleMaps—the most widely used mobile navigation app in the United States. A central innovation of GoogleMaps was integrating real-time transit tracking and user location into its algorithms, enabling routes to be dynamically optimized based on current traffic and service conditions. The convenience of real-time tracking at a user's fingertips may reshape urban travel choices via several channels. First, accurate information may reduce waiting costs, a large share of travel costs that rises with income (Hamermesh 2019, Wang 2024). Second, it may lower the "mental load" of navigating increasingly complex transit systems. New research from Gallotti et al. (2016) shows that the complexity of several modern-day transit networks exceeds human cognitive capacity. This trend may be deterring many potential riders away from transit, even in settings where transit offers shorter or cheaper routes (Larcom et al. 2017). Finally, it may cut travel-time uncertainty by providing real-time updates on congestion and delays.

Beginning in 2011 with several pilot cities, and expanding to at least 43 major U.S. transit systems by 2019, GoogleMaps enabled users to instantly check bus and train arrival times, receive optimized pickup directions, and compare up to date travel times and costs across modes—all from their mobile phones. While this innovation could increase transit ridership, the effect of real-time tracking is theoretically ambiguous. The same information could also *reduce* ridership by revealing just how inefficient or unreliable some transit options are relative to driving or other alternatives like walking or ride-sharing.

[1] Among Americans aged 25-65 that are in the labor force, 66% commute to work via car (Ruggles et al. 2024). Couture et al. (2018) estimate that congestion alone costs more than $30 billion annually. Vehicles account for 17 percent of national CO_2 emissions (EPA 2023), up to 75 percent of carbon monoxide emissions, and 40 percent of nitrogen oxide emissions (United States Environment Protection Agency 2025).

To evaluate these competing possibilities, we assemble new data on the rollout of real-time transit tracking in Google Maps and in agency-specific apps. We link this information to monthly ridership logs from 128 transit systems and to individual-level data on commuting mode choices in major US cities. Our empirical strategy exploits variation in the timing of adoption across transit agencies, using an event study design to estimate how the availability of real-time tracking affected both aggregate ridership and individual travel mode choices.

We find that the introduction of real-time tracking in Google Maps increased monthly transit trips per capita by about 0.6 trips per month, or 10.7% on average in the three years following its rollout. The effects increase over time, starting with an increase of 0.6 trips per capita per month and ending at almost 1.5 trips per capita per month by year ten. These effects are driven by agencies with large operations and subway modes. Our results demonstrate the substantial impact that improvements in information technologies can have on routine behavior, particularly in complex choice environments.

Our main empirical challenge is that Google may have incorporated real-time information into its app in cities where transit ridership was growing more rapidly. In other words, our empirical approach may overestimate the true impact of Google Maps' use of real-time tracking if Google positively selected transit agencies. We address this concern in several ways. First, we test for the existence of pre-treatment trends. Our event studies show that ridership changed only after the rollout of real-time tracking within Google Maps. Second, we test whether other measures of transit agency operations, like total service mileage and operating costs, could explain the observed changes in ridership after real-time tracking became available. We find no evidence to support this. Lastly, we conduct a placebo test where we randomly assign the rollout date across agencies and find no effect on ridership. Together, these factors support our assumption that the implementation of Google Maps' real-time tracking across cities was conditionally uncorrelated with transit ridership. As a result, estimated changes in ridership following the introduction of real-time tracking can be credibly attributed to the treatment.

We next investigate which features of Google Maps were most likely responsible for the observed increase in transit ridership. One possibility is that real-time tracking provided access to *new transit information*: millions of users suddenly had real-time updates across multiple transit agencies without needing to opt in. Alternatively, Google Maps could have increased ridership by presenting existing information more seamlessly than previous navigation tools—either through

improved usability or enhanced predictions and mode comparisons derived from user data. To shed light on the mechanisms behind our result, we examine real-time tracking in proprietary transit agency apps, which often predated Google Maps' integration. These proprietary apps had a substantially smaller impact on ridership, and controlling for their existence does not alter the estimated effect of Google Maps. Taken together, these findings indicate that Google's primary contribution was reducing the informational complexity inherent in urban travel decisions, rather than merely supplying new data. By streamlining information and making it easily interpretable across routes and modes, Google Maps helped travelers navigate a complex choice environment more efficiently, which ultimately encouraged greater use of public transit.

Rising transit use from Google Maps may have generated substantial social benefits. Congestion alone costs the US economy $30 billion annually (Couture et al. 2018), and private vehicles account for over 17% of carbon dioxide emissions in the US.[2] If transit tracking improvements in Google Maps encouraged travelers to switch mode from car to transit, then it may have also reduced congestion and improved local air quality (Anderson 2014, Chen & Whalley 2012, Li et al. 2019, Gendron-Carrier et al. 2022).

We assess whether real-time tracking in Google Maps induced mode switching among urban residents using individual-level data from the American Community Survey. Consistent with our analysis of ridership data, we find the likelihood of commuting on public transit increased by 1.16 percentage points (4.4%) within five years of Google Maps incorporating real-time tracking. The likelihood of commuting via car fell by a similar magnitude of about 1.3 percentage points (2.1%). These findings suggest that real-time tracking induced some mode-switching from cars to public transit and likely generated external benefits via reduced congestion.

The individual-level data also reveal striking heterogeneity in the impact of real-time information across the income distribution. Google's use of real-time information induced above-median-income commuters to increase use of transit, and decrease use of cars, and these effects are even larger for above 90th percentile income commuters. However, real-time information reduced transit use by below-median-income commuters and increased car use. These results are consistent with our finding that agencies with subways experienced a disproportionate increase in ridership once Google Maps incorporated real time information, as subway riders tend to have higher average

[2]The transportation sector comprises 30% of carbon emissions in the US (EPA 2023). Private vehicles comprise 58% of overall carbon dioxide emissions from the transportation sector (Office 2022), thus private vehicles comprise approximately $0.3 \times 0.58 = 0/0.174$ of overall carbon dioxide emissions.

income than other modes (American Public Transportation Association 2017).

To investigate whether the improvement to Google Maps had detectable impacts on air quality, we collect outdoor measures of nitrogen oxides (NOx) and carbon monoxide (CO) from the US Environmental Protection Agency. We focus on these two pollutants as they make up about 80% of on-road vehicle emissions (Industrial Economics, Inc. 2011). We find that real-time tracking reduced CO levels for the average urban resident by about 0.033 parts per million (7%) and NOx levels by approximately 3.9 parts per billion (12.1%), although the later result manifests some pre-trends, thus we interpret the NOx result with caution.

While the public benefits of the Google Maps treatment are potentially large, we quantify a lower bound welfare measure by estimating the private benefits through a discrete choice model.[3] Following Berry (1994), we estimate that consumers are willing to pay about $0.70 per trip to access real-time tracking information. Given total ridership at baseline, and the approximate costs of adopting real-time tracking, our estimates suggest that the private benefits alone likely outweigh the costs to transit agencies of real-time tracking.

To sanity check our result, we compare our willingness-to-pay estimate to exiting literature from in-transit studies on travelers' value of time (Goldszmidt et al. 2020, Buchholz et al. 2020, Wang 2024). Comparing our estimate of the private benefits of real-time tracking with these value of time estimates suggests that real-time tracking is equivalent in value to saving up to 15 minutes of travel or wait time.

Our study extends a large, existing literature on travel behavior and mode choice. We document novel findings that a navigation app can rival large-scale infrastructure policies in terms of its impacts on behavior. Recent studies focused on infrastructure expansion efforts (Gonzalez-Navarro & Turner 2018, Majid & Vyborny 2018, Tsivanidis 2024, Severen 2021) have found that adding train lines or bus rapid transit lines increases within-city public transit ridership by 6 to 16%. Other studies focusing on free fare policies (Cats et al. 2017, Bull et al. 2021) find travel increases by 12 to 14%. We show that the improvement to Google Maps had an effect of a similar magnitude to these much costlier public interventions. These comparisons are important for policy makers considering physical vs. technological investments.

Among existing work specifically exploring the effects of real-time transit tracking on ridership

[3]Real-time transit information could have private benefits even without an increase in ridership if it meant riders saved time or switched to non-transit modes.

(Ferris et al. 2010, Tang & Thakuriah 2012, Chow et al. 2014, Brakewood et al. 2015, Brakewood & Watkins 2019), our paper is the first to employ quasi-experimental methods. These prior studies use survey methods or small samples within a single city over a limited time frame and mostly focus on bus modes and agency-specific apps. They find that real-time tracking either has no impact on ridership or leads to a modest 1-2% increase. Using a staggered roll-out design and a large sample of transit agencies, we find that Google's use of real-time tracking led to economically large and sustained effects on transit ridership.

Lastly, our findings are relevant to behavioral literature that focuses on the role of (in)attention and the limits of an individual's cognitive capacity (Sims 2003, Gabaix 2019). Economists have documented how obstacles to acquiring and processing information lead to sub-optimal choices in many contexts, from which light bulb to buy (Allcott & Taubinsky 2015) to which job to take (Jäger et al. 2024). We show that a technological improvement to a popular decision support tool enabled by real-time information has substantial impacts on travel choices, a setting in which it is known that consumers have sub-optimal habits (Larcom et al. 2017).

Our paper is structured as follows. Section 2 provides background on Google Maps and the incorporation of real-time tracking. Section 3 outlines the data collected for the study. Section 4 describes the empirical strategy to identify the impacts of real-time tracking availability on ridership, and presents these results. Section 5 describes the analysis of the impacts of real-time on mode switching and air quality while Section 6 presents the discrete choice model used to value its private benefits. Finally, Section 7 concludes.

2 Google and Transit Tracking

The history of mass transit tracking is closely linked to Google. In much of the developed world today, transit users can access real-time transit tracking information for their local transit system using their mobile phones through Google Maps or other tracking apps. However, the ubiquity of real-time transit information today is the result of a few key innovations in transit tracking, public dissemination of transit data, and mobile phone technology that transpired over the last 20 to 30 years. Google has played an integral role in developing each of these innovations.

The essential tool that has enabled the dissemination of real-time transit tracking to the general public is a data organization process called General Transit Feed Specifications or "GTFS" feeds. Most transit agencies today utilize GTFS platforms in order to track movement of transit vehicles.

The very first GTFS feed was developed by a Google employee in 2005 for the Portland Trimet transit agency. The "G" of GTFS originally stood for "Google" but was later changed to "General" after GTFS became the *de facto* standard across transit agencies for tracking timetables (Ferris et al. 2010).

The main innovation of the GTFS was in standardizing how transit agencies organized their timetable schedules and in making this information publicly available.[4] Prior to GTFS, there was no industry standard for organizing transit timetables. Many transit applications developed in the early 2000s relied on these open-source GTFS feeds (Wikipedia 2022).

"Real-time" tracking (also called "automatic vehicle location systems") refers to the minute-by-minute tracking of transit vehicles. When transit vehicles run on schedule, static timetable information and real-time information are the same. But when transit vehicles are not on schedule (either running ahead, behind, or not running due to service interruptions), real-time tracking provides a more accurate prediction of transit vehicle arrival time and trip length. In the case of buses or above-ground vehicles, tracking occurs via Global Positioning Systems (GPS). In the case of subways or other right-of-way vehicles tracking occurs via track circuit systems. This tracking data feeds into dispatcher software that is used for operations management.

Public dissemination of transit tracking and trip-planning tools predate Google Maps. Some transit agencies, like King County Metro in Seattle, made their tracking data public through web-based applications as early as the 1990s before the rise of smartphone apps (Ferris et al. 2010, DOT 2025). However, these early tools were often impractical for trip planning. Even if a user had access to a web-application while in transit, users would have to look up their transit stop identifier through a complex menu of options because these tools were unable to integrate the GPS coordinate of a user with that of the transit system. Starting in the early mid-2000s with the advent of GTFS feeds, third-party developers like Google improved the accessibility and usability of timetables and tracking information by developing mobile phone application software and by making the software available through various interfaces like SMS or iPhone (Ferris et al. 2010). Several major transit agencies like the BART in San Francisco, the MBTA in Boston, and the CTA in Chicago developed their own apps as early as 2011 (see Appendix Figure A.12). The availability of these proprietary agency apps and trip-planning tools means that users could access real-time

[4] A GTFS feed is a collection of data files with a particular naming structure. The data files contain information describing a transit schedule and include: identifying information about the agency, distinct routes, trips, scheduled departure and arrival times at stops, stop locations, and a calendar of operation (Wikipedia 2022).

info through their mobile phones prior to Google Maps in some locations.

However, Google Maps' adoption of real-time tracking was particularly influential for several reasons. First, Google Maps was the earliest to map GTFS feed stop identifiers to a user's location (Ferris et al. 2010).[5] Second, the Google Maps app was broadly adopted by cell phone users during the time period of our study. One in two mobile phone users across the globe utilized the Google Maps app as early as 2013 (Smith 2013). Third, unlike agency apps, Google Maps displayed transit information for *several* agencies, meaning users could look up transit information across several agencies within one app. Lastly, Google Maps incorporated real-time tracking into its unique prediction and optimization algorithms. While most agency apps provided onboard travel predictions, Google Maps provided users with travel time predictions inclusive of transfers, switching modes, and walking to and from transit stops.

Figure 1 maps the rollout dates for 42 out of the 128 agencies in our sample that we identified as having real-time tracking prior to 2019. The rollout of real-time tracking does not appear to follow a distinct geographic pattern, nor were early adopters always the largest cities. Smaller metro areas like Madison, WI adopted the same year as major West Coast cities like Portland, San Diego, and San Francisco. New York City, Salt Lake City, Los Angeles, and Tampa followed suit in 2012 and 2013. Among the remaining major US cities, Chicago and Houston adopted in 2014, Seattle and San José in 2015, Denver in 2016, and Austin in 2018. The most recent adopters in our sample include Spokane and Dayton.[6]

Our study tracks ridership from 2002 through 2019. Over this time period, information provided through Google Maps changed in various ways. Mode-specific comparisons improved over time. Google Maps first introduced driving directions in 2007, and subsequently added directions for walking, cycling and transit in 2008, 2010, and 2012, respectively. Access to Google Maps increased due to improvements in cellular data access and compatibility across operating systems.

[5]Because Google had Google Maps at its disposal, they could integrate tracking information within Google Transit directly into their navigation software. Throughout this paper, we refer to "Google Maps" synonymously with "Google Transit", however Google Transit is technically a feature within Google Maps focused on trip planning via public transit.

[6]We empirically test whether the timing of Google real-time tracking adoption is predicted by growth in transit usage, population, or other city attributes in Appendix Figure A.1. Neither measures of city size nor growth rates of population predict adoption time. Real-time tracking did rollout earlier in cities with larger shares in commuting via public transit, and shorter average commute times, although changes in ridership per capita do not predict adoption year. Google Maps real-time tracking also arose about a year following the availability of proprietary apps. This is consistent with anecdotal evidence from Madison's Metro Transit personnel that when deciding on where to implement their GTFS-based real-time tracking, Google tended to choose transit agencies with a track record of sophisticated data management and where they could easily reach legal agreements with transit agencies for data access.

For instance, iPhone users could not use Google Maps on their phones until 2012 and 4G only became readily available in the US after 2013. Accuracy of travel times also improved on the Google Maps app over this time period.[7] Our dynamic-effects specification shows that the impacts of real-time tracking on ridership increased over time, consistent with improvements in smartphone services. Throughout our analysis, our estimation approach adjusts for potential bias stemming from treatment effect heterogeneity over time (De Chaisemartin & d'Haultfoeuille 2020, Borusyak et al. 2024).

3 Data Description

To estimate the effect of Google Maps' real-time tracking on travel behavior, we collect data on real-time adoption dates, transit ridership, air quality, commute mode choices, and a variety of city-level controls spanning 2002 through 2019.

3.1 Transit Agency Ridership and Operations

Our primary data source is the government-sponsored National Transit Database (NTD). The NTD provides data on transit operations back to 2002 for over 600 public transit agencies across the US. We collected information on monthly ridership, and annual-level operating expenses, fare revenues, number of transit vehicles in service, and number of miles in service at the agency–by–mode level. Our unit of observation is a transit agency-by-mode pair where a mode takes on one of four categories: bus, subway, commuter rail, and light rail. Our measure of "ridership" from the NTD is a count of "unlinked passenger trips", which is the number of times a rider steps onto a transit vehicle. Thus, a complete trip from origin to destination that uses multiple transit vehicles counts as multiple "rides" in our data.[8]

3.2 Google Maps & Proprietary App Real-time Data Rollout

We manually gathered information on the availability and rollout date of Google Maps' real-time tracking by transit agency and mode. We determined rollout dates using press releases, blog posts, tweets, and other media posts from Google, transit agencies, and local news sources. Generally,

[7] For instance, predictions on car travel time improved in 2015 to include information on time-specific traffic patterns and, in 2016, Google added ride-hailing services as one of the mode options available in Google Maps.

[8] Any US public transit agency that receives federal funding from the Federal Transit Administration must report their operating information annually to the NTD, except for agencies that operate 30 or fewer vehicles. Consequently, the NTD data are not representative of these smaller agencies. As of 2019, the NTD captured 97.3% of the total number of public transit trips that the American Public Transit Association estimates happened that year. Total unlinked passenger trips in 2019 were 9.66 billion according to the NTD and 9.923 billion according to the American Public Transit Association (American Public Transportation Association 2021).

Google would implement real-time tracking at the same time across modes. For instance, if an agency operated both buses and subways, real-time tracking started at the same time for both modes. We used a similar strategy for collecting information on the availability and rollout of proprietary agency transit tracking apps. In general, agency apps pre-dated Google Maps' provision of real-time tracking by one to five years (see Appendix Figure A.12).

We focused our search efforts on the 128 largest transit agencies based on their annual revenues and ridership in order to increase the likelihood of finding rollout date information and to increase the likelihood that such information was accurate. We found reports of Google real-time tracking for at least one mode among 43 of the 128 largest agencies. Specifically, we found evidence that 53 unique agency-by-mode pairs—comprising 43 agencies—had real-time tracking as of 2019. Appendix Figure A.2 provides details on the rollout date for these 43 treated agencies as well as our sources. We did not find reports of Google real-time tracking for 12 agency-by-mode pairs—typically commuter rail —among these 43 treated agencies. For 85 of the largest 128 agencies, we were unable to find any reports or online discussion of Google real-time tracking adoption as of 2019 for any mode. In total, we use 129 agency-by-mode pairs without reported real-time tracking as controls when estimating changes in ridership. In Section 4.2 we discuss several robustness checks that explore the sensitivity of the results to potential errors of treatment assignment, including using only the 53 treated agency-by-mode pairs, assigning the earliest real-time tracking date to all modes for a given agency, and testing inference after randomizing the rollout dates across agencies.

3.3 Individual-level Commuting Choices and City Characteristics

To investigate the impact of Google's use of real time data on commuting patterns and to investigate income heterogeneity, we obtained individual-level data from the American Community Survey (ACS) for years 2005 through 2018 (Ruggles et al. 2024). These data allow us to observe the primary mode of commute as well as demographics for over 1.2 million individuals across 74 cities in our sample.[9] We also collect city-level demographics from the 2000 and 2010 US Decennial Census, including racial composition, educational attainment, and poverty rate.

[9] ACS data only report the city of residence for individuals living in cities with populations over 250,000, thus some cities are dropped from the commuting choice analysis.

3.4 Air Quality

Our data on air quality come from the EPA Daily Outdoor Air Quality Data. We study carbon monoxide (CO) emissions and nitrogen oxides (NOx) because these two pollutants comprise over 80% of on road vehicle emissions (Industrial Economics, Inc. 2011). These data provide monitor-level readings from 2008 through 2019 for 87 cities in our sample. Each monitor is identified by its latitude and longitude. We assign a monitor to a city if it is located within 25 miles of the city's centroid. We exclude air quality readings from exceptional events, like wildfires or dust storms, from our sample. For CO and NOx, we use readings from a 1-hour sample duration.[10]

3.5 Descriptive Statistics

Table 1 reports mean agency characteristics for agencies that had real-time tracking as of 2019 and agencies that did not. The third column reports the p-value for the significance of the difference in means. Most characteristics are measured as of 2008—prior to the implementation of real-time tracking in any US city—except for some characteristics sourced from ACS for which the earliest observed year is 2013. There are significant level differences across real-time and non-real-time agencies. Google real-time tracking was more likely to roll out in agencies with higher ridership per capita and with larger operations whether measured by service area population, revenues, costs, or number of modes. These differences are consistent with Google's profit incentive to choose locations where they can collect a large amount of data on passenger trips. Real-time cities are also slightly more likely to be in Western states and less likely to be in the South. Because differences in ridership levels may create differential ridership growth across agencies, our empirical design controls for time trends interacted with baseline agencies' ridership levels. We also include agency-by-mode fixed effects and time-varying regional fixed effects in all specifications so that our estimates are conditional on fixed operational differences and any differences in region-specific trends across agencies. Notably, most city-level characteristics shown in Panel B are well-balanced, suggesting that local economic factors and demographics were not significant drivers of Google Maps' real-time rollout.

While our sample of 128 agencies captures just 20% of agencies in the NTD, this sample comprises the vast majority of transit usage: 92% of passenger trips occur within the 128 agencies in our sample. Appendix Figure A.3 compares total annual passenger trips among our sample

[10] NOx readings are only available with a 1-hour sample duration. CO results look very similar for readings from an 8-hour average sample duration.

agencies relative to aggregate trips among all agencies in the NTD. Notably, ridership is quite skewed even within our sample. The majority of all transit rides and transit miles happen on subways. Appendix Figure A.4 shows the composition of transit rides (Panel A) and vehicle revenue miles (Panel B) by mode in each year of our sample. Although most observations in our sample are buses (124 agency-mode pairs), the vast majority of transit rides and mileage occur on one of 12 subway systems in our sample.

4 Agency-Level Ridership & Operations

Our primary goal is to estimate how the availability of real-time transit tracking through Google Maps affected transit ridership. Our research design exploits variation in the timing of real-time tracking availability across transit agencies and modes to compare ridership on agency-modes with real-time tracking to those without real-time tracking in Google Maps. Our identifying assumption is that Google's decision on when and where to integrate real-time tracking was uncorrelated with agency-mode specific trends in travel behavior. Based on Panel A of Table 1, Google appears to have targeted agencies with relatively large operations and high ridership per capita. The rollout could therefore also have occurred in agencies (or for agency-by-mode pairs) where ridership was already growing. We use panel event studies to test for evidence of conditional pre-existing trends and provide supporting evidence by examining trends in other agency operations.

Our baseline econometric model is the following:

$$r_{imt} = \sum_{l=-12}^{12} \delta_l \mathbf{1}\left[q - R_i = l\right] + \eta_{im} + \gamma_{dy} + \tau_{ds} + \boldsymbol{\rho}_{iy} + \varepsilon_{it} \tag{1}$$

where r_{imt} is monthly ridership per capita for agency i and mode m in month-of-sample t. We measure ridership per capita based on the agency's service area population size as of 2002.[11] The parameters of interest δ_l measure the effect of Google real-time information l quarters after it was first made available in quarter $q = R_i$ relative to the reference period. The reference period in our specification includes all quarters more than three years prior to treatment. Equation 1 includes a vector of agency-by-mode fixed effects η_{im} to control for time-invariant unobserved differences in ridership across agency-modes. We also include a vector of region-by-year (e.g. North-East $\times$ 2015) fixed effects γ_{dy} and season-by-region (e.g. North-East $\times$ winter) fixed effects τ_{ds} to account for regional growth trends and geographic-specific seasonal differences in transit ridership (i.e., ridership typically peaks in fall and spring months in northern parts of the US). Finally, $\boldsymbol{\rho}$ includes

[11] In Section 4.2, we show robustness to alternative measures of ridership, including log(total monthly ridership) and ridership per capita based on the agency's service area in 2019.

a vector of agency-mode-specific characteristics interacted with year fixed effects. It includes an interaction of 2002 ridership per capita interacted with year fixed effects to control for differential growth in ridership for agency-modes of different sizes. For 12 agencies in our sample, we were only able to identify a month and year in which real-time tracking in Google Maps was actively *in use*, as opposed to when it first became available. Because such agency-modes likely have differential ridership trends over time, $\boldsymbol{\rho}$ also includes an interaction of an "In Use" dummy with a year fixed effect.

We weight the regression in (1) by vehicle revenue miles in the base year of 2002 to capture the impact of real-time transit on the average service mile and to account for potential heteroskedasticity from agencies of different sizes. We use vehicle revenue miles (miles covered by in-service transit vehicles) to capture the combined size effects of population, service frequency, and geographic service density. Following Solon et al. (2015), we also directly model heterogeneity by agency-mode size in unweighted regressions. To account for arbitrary serial correlation in travel behavior within a given metro area, standard errors ε_{it} in Equation (1) are clustered by urbanized area.[12]

Our preferred estimation strategy is the imputed fixed effect estimator from Borusyak et al. (2024). If treatment effects are homogeneous, exploiting differential timing in a standard two-way fixed effects model results in a valid estimate of the treatment effect. However, in the presence of treatment effect heterogeneity (for example, heterogeneity in effects over time or across units), average treatment effects estimated in models with least squares are weighted averages of individual treatment effects where some may receive negative weights (De Chaisemartin & d'Haultfoeuille 2020, Borusyak et al. 2024, Sun & Abraham 2021). A number of estimators have been developed to deal with the potential bias of heterogeneous treatment effects in staggered adoption designs. Among the various estimators, we select Borusyak et al. (2024) to increase precision (Roth et al. 2023) and because it accommodates designs in which only one panel unit may be treated at a given time (unlike Callaway & Sant'Anna (2021)). In section 4.2, we test the sensitivity of our results to alternative estimators, including traditional least squares and Wooldridge (2021).

4.1 Ridership

Figure 2 shows our main event study results following Eq. 1. Each coefficient estimate gives the difference in monthly transit trips per capita in a particular quarter relative to the reference period.

[12]The NTD defines an "urbanized area" as the primary urbanized area served by the transit agency. Each urbanized area in our sample is served by one or more agencies.

Under the Borusyak et al. (2024) estimator, the reference period includes all quarters in the sample that come before the pre-treatment window. Since we estimate coefficients for 12 pre-treatment quarters (three years before rollout), the reference period spans from the first quarter of 2002 up to the thirteenth pre-treatment quarter. Immediately following Google Maps real-time rollout, we find monthly per capita transit trips increase by approximately 0.5 trips. By quarter three the effect increases to about one additional trip, and increases again by the 11th quarter to nearly 1.5 trips. We find no evidence that ridership was trending differentially between treatment and control agency-mode pairs prior to Google Maps' use of real-time data.

In Table 2 we report the average treatment effect of Google Maps real-time tracking on ridership over all post-treatment periods. Panel A shows results with a time window covering three years pre- and three years post- real-time adoption, consistent with the event study results shown in Figure 2. Panel B shows results over the entire panel from 2002 to 2019. Based on the shorter panel, ridership per capita increased by between 0.552 and 0.625 rides per month. Given that the 2008 weighted average trips per capita per month was approximately 5.841, this result implies an average increase between 9.5 and 10.7%. The results more than double when considering the entire panel, consistent with increasing treatment effects shown in Figure 2. These result are robust to controlling for the rollout of proprietary agency apps and Uber in column (2) and additional city and agency controls in column (3).

Existing literature measuring the effects of improving transit access find substantial differences in the relative impact depending on a city's pre-treatment transit reliance (Tsivanidis 2024, Severen 2021, Gupta et al. 2022). Similarly, Hall et al. (2018) finds Uber entry has distinct impacts on subway ridership relative to bus ridership. And an experiment in Bull et al. (2021) that temporarily makes transit fares free shows that ridership increases only on subways. Motivated by this prior work, we explore how our results differ across transit modes and large relative to small transit systems.

Figure 3 shows our heterogeneity analysis. Each color shows results of estimating Equation 1 without weights across distinct subsamples. In this analysis we drop weights to explore whether heterogeneity in treatment effects is correlated with the weighting variable in our main specification (vehicle revenue miles) as per Solon et al. (2015). Panel A shows heterogeneity by agency operation size as measured by annual vehicle revenue miles as of 2002. Panel B shows heterogeneity by mode, comparing subway to all other modes. Based on Panel A, it is evident that the overall treatment

effect captured in Figure 2 is largely driven by ridership growth among agencies in the top decile of transit operations. Google Maps' adoption of real-time tracking has no impact on agencies in the bottom 90% of service operations.

Although not all top decile agencies are subway systems, Panel B shows that our estimates are overwhelmingly driven by ridership on subway modes.[13] The red squares show that ridership on buses, light rail, and commuter trains does not change following Google's adoption of real-time tracking.[14] However, ridership on subway modes shown in purple circles is significantly more responsive to real-time tracking. Ridership trends upward to 2 additional trips per month per capita by quarter four, and reaches 3 additional trips per capita by quarter 11, with some seasonal fluctuation in between.

We show the average heterogeneous effects by agency size and by mode in Appendix Table A.2. Column (1) replicates Panel B, column(1) of Table 2. The remaining columns use the same specification, but without weights and with different sub-samples. Column (2) uses only agencies with operations in the top decile (based on vehicle revenue miles as of 2002). The treatment effect is very similar to the overall main effect using this limited sample, suggesting most of the effect is coming from the largest agencies. When we further restrict the sample to only subway modes in column (3), the effect nearly doubles to nearly 2.4 additional trips per capita per month.

4.2 Robustness Checks

Robustness to estimator: We test the sensitivity of our results to alternative estimators, including traditional least squares, the Wooldridge (2021) two-way fixed effect (TWFE) method, and a "stacked" TWFE design. The Wooldridge (2021) method provides an alternative way of overcoming the problem of negative weights associated with TWFE regressions by adopting a regression-based solution that relies on a set of saturated interaction effects. That is, the model includes treatment cohort dummies, time period dummies, and a set of cohort-by-time treatment indicators. The "stacked" TWFE approach provides explicit design-based identification, whereby each treated agency is compared to only "pure control" agencies over contemporaneous time periods. The "stacked" approach includes cohort-by-year fixed effects, so that identification comes from within-cohort comparisons across event time.

[13] Appendix Figure A.13 lists all agencies with a subway system as well as all agencies by mode that have operations in the top decile as of 2002.

[14] Commuter train modes serve only as controls in our analysis, as we did not find any Google real-time adoption dates among commuter rail systems prior to 2020.

Results of these alternative estimation methods are shown in Appendix Figure A.5. The main event study results shown by gray dots replicate results of Figure 2. The OLS estimators are smaller in magnitude compared to our main results, suggesting that the "forbidden" comparison of already-treated units to newly-treated units in the OLS estimator creates downward bias in our context (Borusyak et al. 2024). Treatment effects under the "stacked" approach are slightly larger than the traditional least squares, which again suggests that the comparison of already-treated to newly-treated units under OLS creates some downward bias. Standard errors under the "stacked" approach largely overlap that of our main results. These alternative TWFE approaches show no evidence of a pre-trend, but a gradual increase in ridership following the launch of Google real-time.

Robustness to treatment & sampling assumptions: Because the dates for Google Maps' first use of real-time data are based on our own research, and not on administrative data, it is possible that our estimates suffer from bias due to erroneous treatment assignment. We assign agency-by-mode pairs without observed real-time rollout prior to 2020 as "pure controls" in our main specification. However, this may introduce bias if some of those units were in fact treated but not identified due to missing or incomplete online documentation of rollout dates.[15] We may also have mis-specified the exact rollout date of Google Maps for certain modes within treated agencies if some modes were not as well documented as others. We assess sensitivity of our results to the selected sample and treatment assignment in several ways.

First, we estimate treatment effects via traditional least squares using only treated units. This approach excludes "pure controls" and focuses on the 53 agency-by-mode pairs identified as treated during our sample period. In this specification, treatment is identified by comparing outcomes after Google Maps' real-time rollout to outcomes for the same agency-mode pairs prior to treatment, and to not-yet-treated units. Estimation is via traditional least squares because the imputation method requires sufficient data on untreated units (i.e., "pure controls" or never-treated units) to estimate unit and time fixed effects. Second, we exclude agencies for which information on the roll-out date was imprecise. Imprecision arose either because we could not pin down the exact month - but we could observe the year - of initial adoption; or online documentation showed only when real-time tracking was *in use*, but not when it was first implemented. Lastly, we apply the earliest Google Maps real-time tracking date to *all* modes within agency.

[15] For "pure-control" agencies, we checked whether real-time tracking was available in Google Maps as of December 2021 and found that it was not, i.e. agencies that we did not identify a real-time rollout date for in our manual search did not have real-time information as of 2021.

These results are shown in Appendix Figure A.6. The OLS results are, again, smaller than our main results suggesting that the already-treated to newly-treated unit - comparison creates downward bias in our context. Notably, the treated sample OLS results are very similar to the full sample OLS results shown in Appendix Figure A.5. We estimate the other two sub-sample results, "Exclude In Use" and "Min Date", using Borusyak et al. (2024). Both sets of event study estimates are very similar to our main results. In summary, these tests lends confidence to our assignment of treatment and control units.

Robustness to definition of "Ridership": We assess the sensitivity of our results to varying definitions of "ridership". Our main specification measures the outcome as monthly ridership per capita with service area population in 2002 as the denominator—the first year in our sample. We use the base year's population as the denominator rather than a contemporaneous year's population because population could respond to the treatment itself, and because the NTD does not have consistent updates of service area population across agencies across years. However, if Google Maps targeted agencies with growing populations, this definition may overstate the true effect. To address this concern, we employ three alternative measures of the outcome: ridership per capita with service area population in 2011 as the denominator (the first year any agency received Google Maps real time tracking), with service area population in 2019 as the denominator (the last year in our sample), and log(total ridership). Results are shown in Appendix Figure A.7. Using 2011 or 2019 as the base year serves to increase our estimates, suggesting that using 2002 as a base year is a more conservative approach. Magnitudes are very similar using log(total ridership) as compared to our main estimates. On average log(total ridership) increases by about 15% after treatment.

We also employ a propensity score matching approach to limit the sample to treated and control agencies with the greatest overlap in observable characteristics. To carry out this approach, we first assign each treated agency-mode pair to a control agency-mode pair based on a propensity score using nearest-neighbor matching and allowing for up to two neighbors. The propensity score is a function of agency-mode vehicle revenue miles as of 2002, the mode type, whether the agency has a subway mode, the share of city residents that are black as of 2010, and the square mileage of the city. This process leaves a sample of 82 agency-mode pairs (52 treated and 30 control). We then re-estimate the average treatment effect of Equation 1 with matched-group fixed effects and city fixed effects rather than agency-mode fixed effects and employ the traditional least squares estimator. Appendix Table A.3 shows very similar results to our main findings, often with larger

magnitudes.

Randomization Inference: We use randomization inference to provide evidence on the conditional exogeneity of treatment. Specifically, we randomly reassign rollout dates in two steps. In the first step, we randomly assign exactly 43 agencies to the treatment group. In the second step, we randomly draw rollout dates for all agencies in the treatment group. We repeat this exercise 5000 times. For each iteration, we estimate Equation 1 using the (Borusyak et al. 2024) estimator. We display the results of this procedure in Appendix Figure A.9. The gray histograms show the distribution of the coefficients from these 5000 random draws and the red dotted line denotes the real effect using the real treatment assignments. The randomization inference exercise also provides exact p values that are valid for small samples. After conducting the randomization exercise, our p-value is 0.052. The real effect lies to the far-right portion of the distribution, above the 95th percentile—which suggests that our results are not an artifact of random chance.

Rambachan & Roth Parallel Trends Sensitivity: We implement the "honest" approach to parallel trends following Rambachan & Roth (2023). Their approach provides a statistical test for whether secular pre-trends can explain estimated treatment effects in a panel fixed effect framework. We test for the existence of pre-trends against a smoothness restriction as follows:

$$\Delta_{SD} \equiv \{\delta : |(\delta^{t+1} - \delta^{t}) - (\delta^{t} - \delta^{t-1}| \leq M\}$$

where Δ_{SD} measures the "second difference" of the difference in trends δ across pre and post-treatment time periods. M governs the amount by which the slope of δ can change between consecutive periods. In other words, M measures by how much the slope of the pre-trend is allowed to change in post-treatment periods. Appendix Figure A.10 shows the sensitivity of our ridership results under various deviations from the linear extrapolation assumption (where $M = 0$). In red, we show the 95% confidence interval of the treatment effect (averaging all post-treatment periods), while in blue we show the 95% confidence interval when allowing for violations of the pre-period parallel trends up to parameter M. For our outcome of ridership, the coefficient would remain significant up to $M = .0015$, meaning the results remain significant even if post-treatment deviations are allowed to be more than twice the size of the pre-treatment slope (≈ 0.0007).

Leave-one-out Analysis: Finally, we conduct the leave-one-out analysis to show the average treatment effects of each city. An estimate includes a pure treatment of treated city-mode pair and the externality because 16 cities are in the both treatment group and control group.[16] The

[16]These cities are Austin, Baltimore, Boston, Chicago, Denver, Houston, Los Angeles, New York, Oceanside, Philadelphia, Portland, Saint Louis, Salt Lake City, San Francisco, Seattle,Tampa.

exercise also provides a test for whether the baseline results of GoogleMaps on ridership is driven by a specific city. To see this, we estimate Equation 1 using the (Borusyak et al. 2024) estimation by excluding each individual city each time. We plot the largest twenty cities that are different from the beseline estimate in Figure A.11. The full result of each city are shown in Table A.4.

In summary, our findings demonstrate that the availability of real-time tracking through Google Maps increased transit ridership. This effect manifests primarily among large agencies and among subway modes. We speculate that the reason subway modes dominate is related to the demographic differences in average subway riders relative to bus riders. In Section 5, we provide additional analyses to support this hypothesis using micro data on household income from the ACS.

More generally, our results imply that, after three years of implementation, real-time tracking has a similar impact on ridership as making fares free. Bull et al. (2021) find that fare-free passes in Santiago, Chile increased transit trips by 10%. Cats et al. (2017) find a larger impact of 14% when analyzing a policy change to free transit fares in Tallinn, Estonia. Importantly, real-time tracking appears to have a significantly larger ridership impact than policies focused on increasing access to transit. For instance, Baum-Snow & Kahn (2000) find that reducing the average distance from residences to rail transit by one mile increases ridership by 1.2%. Given that real-time tracking is essentially free for transit agencies, our study suggests that providing such information to users can be an inexpensive means to increase ridership.

4.3 Transit Operations

In order to interpret our results as the causal impact of real-time tracking, it must be true that the timing and implementation of Google Maps real-time tracking across transit agencies is uncorrelated with other factors that affect ridership. Visual examination of pretrends in ridership in Section 4 give some credence to this assumption. However, these analyses do not directly rule out that changes to agency operations might spuriously drive our results. We test the validity of our identifying assumption by exploring whether vehicle miles in service (defined by NTD as "vehicle revenue miles"), vehicles in operation, total operating costs, or fares change prior to or after the implementation of real-time tracking. These measures provide a snapshot of transit agency services, operations, or route changes that might impact ridership.

Figure 4 suggests that changes to the total service and route availability cannot explain the change in ridership following real-time tracking. Panel A plots the difference in vehicle revenue miles per capita in each quarter three years before and three years after relative to the quarter

of real-time rollout. Panel B plots the same for vehicles in operation. There is neither evidence of differential growth prior to real-time adoption or evidence that miles traveled or vehicles in operation are affected by real-time implementation in the post period.

We next test for changes in total costs per capita and fares charged by the agency in Panels C and D, respectively. The bottom panels of Figure 4 show no evidence that costs or fares trended differently before the implementation of real-time tracking. This suggests that ridership did not increase after real-time tracking due to cheaper transit fares, for instance. However, we do see some evidence that fares increased after Google Maps real-time tracking. Agencies may have responded strategically to increased willingness to take transit by increasing the fares charged to riders. Notably, the change in fares goes in the opposite direction we would expect if we were concerned that cheaper transit explained our increase in transit ridership.

4.4 Agency Tracking Apps

Google's provision of real-time tracking may have impacted travel decisions through several channels, including: improved accuracy of arrival times, and expected transit duration; improved usability and optimization of alternative routes specific to one's location; and lastly Google Maps may have provided new information on routes for transit users not local to a particular agency, or to users who had not previously utilized an agency's proprietary app. Any combination of these mechanisms could be responsible for the effects on ridership. While it is outside the scope of this study to disentangle each of these effects, we provide evidence to suggest that the second channel is likely an important one.

For each agency, we searched for the availability and rollout date of apps developed by transit agencies. Like Google Maps, these apps enabled users to observe real-time tracking of public transit. However, agency apps —particularly those that pre-dated Google —often did not have the capacity to integrate a user's location in space and suggest customized travel routes. Instead, users would often have to search for a given transit station from a drop-down menu or by looking up the route of a transit line. Use of such apps was not as "user-friendly" as Google's app. Importantly, agency apps rarely provided side-by-side comparisons of alternative modes.

If the main benefit of Google Maps real-time tracking was purely providing new information on arrival times and transit duration, then the treatment from agency apps should look similar to that of Google. However, Figure 5 suggests a much smaller effect. Estimates from the full sample, shown in red, show the availability of real-time tracking through agency apps had little-to-no effect

on ridership. The purple point estimates show there is a significant increase in trips per capita among subway modes of about 0.5 trips per month. This magnitude is about 35% of our main estimate of 1.4 trips per month. These results suggest that the majority of the ridership effect from Google Maps real-time tracking are from some combination of the ease of use, the direct comparisons across modes or the popularity of Google Maps.

5 Individual-Level Commuting Choices & Income Heterogeneity

Our results suggest that real-time tracking had an economically and statistically significant impact on public transit ridership. This increase in ridership could be driven by entirely *new trips* (from existing or new transit users), or it could be driven by people substituting to transit from a private car or taxi for an *existing trip*. Differentiating these channels is important for understanding the broader welfare consequences of real-time transit tracking. Specifically, if it causes substitution from private to public transportation, it could reduce overall congestion and improve air quality, at least in the short run. In this case, real-time tracking provides external benefits. If, on the other hand, real-time tracking leads purely to an increase in transit trips with no offsetting effect on car trips, the benefits of real-time tracking are primarily private. Existing literature on the impact of transit infrastructure improvements on mode switching has mixed findings. Gaduh et al. (2022) find new transit lines in Jakarta had no discernible impact on mode choice or vehicle ownership, in part because the system was not successful in reducing commute times. However, Majid & Vyborny (2018) find that a striking 40% of transit riders on a new rapid transit system in Lahore switched from private transport.

As the NTD does not provide information on individual trips or transit riders, we leverage microdata from the American Community Survey (ACS) to better understand how Google Maps influenced the mode-specific composition of commuting trips. We also use data on household income in the ACS to explore whether higher-income commuters respond differently to the treatment than lower-income commuters.

First, we explore how the adoption of real-time tracking in Google Maps impacts the likelihood of urban residents to commute using public transit versus a car. The ACS is an annual survey that includes a question on what mode respondents use to commute to work. Respondents may commute by means other than transit or car (for example, walking, biking, or working from home), thus the likelihood of commuting via car or transit are not mechanically inverse). The ACS only reports responses for individuals living in identifiable cities—populations over 25,000—thus our sample of

cities and transit agencies is smaller for this analysis than the prior ridership analyses. We estimate an event study of the following form:

$$\Pr(c_{njt}) = \sum_{l=-5(\ni-1)}^{5} \kappa_l \mathbf{1}\left[y - R_i = l\right] + X_{it}\theta + \alpha_i + \gamma_{dy} + \rho_{iy} + \varepsilon_{it} \tag{2}$$

where $\Pr(c_{njt})$ is an indicator for whether any individual in household n in city j in year t reports commuting by mode c where c is either car or public transit. The parameters of interest κ_l measure the effect of Google Maps with real-time information l years after it was first made available in year $y = R_i$. We include X_{it}, a vector of household-specific controls related to the highest education level in the household, the household income, and indicators for the household income decile. The specification also includes a vector of city fixed effects α_i, region-by-year fixed effects γ_{dy}, and an interaction of year fixed effects with year 2002 city-level ridership per capita ρ_{iy} to control for differential trends in commuting across cities. We cluster standard errors by urbanized area and weight the regression by the household n survey weight. For computational tractability and the importance of including household-level controls, we estimate Equation 2 via traditional least squares.[17]

Figure 6 shows estimates of κ_l from Equation 2. Panel A shows an increase in commuting via transit. The effect increases with time from about 1.2 percentage points to nearly 4 percentage points by year 5. The average effect size over the entire panel—shown in Table 3—is approximately 1.16 percentage points, or about 4% of the baseline mean. Panel B of Figure 6 shows a decline of a similar magnitude in propensity for urban residents to commute by car. The likelihood of commuting by car falls by 1.3 to 1.5 percentage points, as shown in Panel B of Table 3. These results from the ACS sample corroborate our main findings from the NTD —real-time tracking increased usage of public transit. The ACS sample further shows that real-time tracking in Google Maps increased public transit commuting trips at the same time that it decreased commutes in private vehicles. This suggests that at least some of the increase in transit ridership was the result of substitution away from cars. This is important as it indicates real-time information likely generated external benefits.

Next, we explore whether there is heterogeneity in responses to real-time transit based on household income. Such heterogeneity could help explain the large estimated effects for subway

[17] We show that results are qualitatively similar under the imputed fixed effect estimator after aggregating the ACS data to the city-year-level, and measuring c_{jt} using city-level shares of commute mode choice. The event study point estimates, shown in Appendix Figure A.8, are not statistically significant after the city-level aggregation, but show a very similar pattern to Figure 6.

ridership (as shown in Figure 3) as subway riders, on average, have higher income (American Public Transportation Association 2017) and a higher opportunity cost of wait time (Small 2012, Goldszmidt et al. 2020). To test for differential treatment effects, we use data on household income from the ACS. We explore heterogeneity under traditional least squares in order to interact the Google Maps treatment indicator with indicators for the distribution of household income. Our heterogeneity specification is as follows:

$$\Pr(c_{njt}) = \beta_1 R_{jt} + \beta_2 (R_{jt} \times I_{50-90,nj}) + \beta_3 (R_{jt} \times I_{90-100,nj}) + \eta I_{nj} + \alpha_i + \gamma_{dy} + \rho_{iy} + \varepsilon_{it} \quad (3)$$

where the outcome is an indicator for whether an individual in household n in city j in year t chooses to commute with mode c, where c is either public transit or car. R_{jt} takes the value one if city j has Google real-time tracking in year t. We distinguish three categories of household income: below the 50th percentile, between the 50th and 90th percentile, and above the 90th percentile. β_1 gives the effect of the treatment for households with incomes below the 50th percentile. The parameters β_2 through β_3 are coefficients on the interaction of higher income categories with R_{jt} —they thus give the differential effect of the treatment for households in those income categories. We additionally control for the log of household income, I_{nj}. All other fixed effects and controls in Equation 3 follow that of Equation 2. We cluster standard errors ε_{it} by urbanized area.

The point estimates above the dashed line in Figure 7 show the average treatment effect β_1 from Equation 3 estimated *without* the interaction terms (β_2, β_3, and β_4). The blue diamonds and black circles show, respectively, β_1 when the outcome is whether the respondent uses public transit to commute or a car to commute.

Figure 7 provides two findings. First, higher-income households are substantially more likely to commute via transit following Google Maps real-time tracking and less likely to commute via car. Second, lower-income households are *less* likely to commute via transit, and may increase commutes by car. Majid & Vyborny (2018) also find that new high-speed transit lines in Lahore disproportionately attracted ridership among highly educated riders. Because high-income individuals are most likely to take the subway, this pattern may explain why most of our overall treatment effect manifests among subway modes.

6 City-Level Air Quality

We next test whether changes in travel behavior induced by the introduction of real-time transit tracking in Google Maps had a detectable impact on air quality. We estimate the following equation:

$$q_{it} = \sum_{l=-12(\ni-1)}^{12} \theta_l \mathbf{1}\left[q - R_i = l\right] + \alpha_i + \gamma_{dy} + \tau_{ds} + \rho_{iy} + \varepsilon_{it} \tag{4}$$

where q_{it} is the average air quality for city i in month t. We measure air quality using carbon monoxide and nitrogen oxides. The parameters of interest θ_l give the effect of Google Maps real-time information l quarters after its rollout. We include a vector of city fixed effects α_i, region-by-year fixed effects γ_{dy}, season-by-region fixed effects τ_{ds}, and a control for 2002 ridership per capita interacted with year fixed effects, ρ_{iy}. To account for the large differences in population across cities with a monitor, we weight by city population as of 2010.

Figure 8 shows results of estimating the parameters in Equation 4, while Table 4 reports average treatment effects. We find that air quality improved following Google Maps real-time tracking. In particular, carbon monoxide concentrations (Panel A of Figure 8) fell by about 0.043 parts per million for the average city resident, or about 10%, in the first three years following real-time adoption. These effects are stable across specifications with additional controls accounting for the arrival of Uber, the existence of a proprietary agency app, non-attainment status, and temperature (columns (1) - (3) of Table 4). To put the magnitude of the effect in context, recall that real-time tracking led to a 13% increase in public transit ridership within three years. Motor vehicles are the dominant source of carbon monoxide in most cities, comprising up to 75% of emissions (United States Environment Protection Agency 2025). As a back-of-the-envelope comparison, if the entire increase in ridership came from reductions in car trips, then an upper bound on the decrease in carbon monoxide would be approximately 10% (0.75*0.13). In fact, our estimated per-person reduction in carbon monoxide could be higher than this for several reasons. First, if real-time transit reduced congestion and not just car trips, then emissions from residual traffic would also be lower, particularly if reductions occurred at peak hour. Further, our regression is weighted by population. This gives greater weight to treatment effects in larger cities - those that are more likely to have subways and experienced a substantially larger impact on ridership. Indeed, in Appendix Table A.5, we show that unweighted estimates of the impact of real-time transit on the average monitor are smaller and less precisely estimated than our estimates weighted by population.

Panel B of Figure 8 and Table 4 also show evidence of reductions in nitrogen oxides. The estimates indicate that nitrogen oxides fell by 3.9 parts per billion (or about 12%) for the average

city resident. However, we interpret this result as suggestive, as Panel B of Figure 8 shows that nitrogen oxide concentrations may have been falling in advance of real-time tracking becoming available. Because traffic emissions are a lower overall share of nitrogen oxides than carbon monoxide (United States Environment Protection Agency 2025), they vary more substantially across cities with comparable traffic emissions due to differences in industrial pollution, which may have been trending differently across cities.

7 Welfare

We next investigate how much consumers value the technological improvement to Google Maps. Using a random-utility model, we obtain a revealed-preference estimate of willingness to pay for Google Maps with real-time tracking. Following Berry (1994), we employ market shares of transit trips as a sufficient statistic for the utility consumers obtain from their chosen mode. When a passenger chooses to take public transit, they consider the utility from each mode's attributes and the disutility from its price.

Consider a traveler i in city c choosing mode $m \in \{0, 1\}$ for their trip. Let $m = 1$ represent public transit modes including light rail (LR), heavy rail (HR), commuter rail (CR) and metro bus (MB), and $m = 0$ represent the outside option of private transportation such as driving or walking. The conditional indirect utility of traveler i taking mode m in city c and region r at time t for a given trip is:

$$u_{icmt} = \beta X_{cmt} + \delta R_{cmt} + \alpha p_{cmt} + \lambda_c + \Phi_{rq} + \nu_{cmt} + \epsilon_{icmt} \tag{5}$$

where R_{cmt} represents whether Google Maps had real-time tracking information in city c at period t, p_{cmt} represents the one-time cost of that mode[18], λ_c are city fixed effects, Φ_{rq} are region-quarter-year fixed effects, and ϵ_{icmt} is a mean-zero stochastic term, which is assumed to follow the type I extreme-value distribution. The parameter δ indicates the marginal utility of Google Maps with real-time tracking, and α indicates the marginal utility of price. We assume preference parameters do not vary by individual i.

Traveler i chooses mode m if $u_{icmt} > u_{ickt}$ for $\forall k \neq m$. Following Berry (1994), if the error term is type I extreme-value, the market share of trips (s_{cmt}) for mode m in city c can then be characterized by:

$$s_{cmt} = \frac{exp(\beta X_{cmt} + \delta R_{cmt} + \alpha p_{cmt} + \lambda_c + \Phi_{rq} + \nu_{cmt})}{\sum_{k=0}^{1} exp(\beta X_{ckt} + \delta R_{ckt} + \alpha p_{ckt} + \lambda_c + \Phi_{rq} + \nu_{ckt})} \tag{6}$$

[18]In Table 6, we use monthly cost as a robustness check.

Then normalizing the utility of the outside option ($m = 0$, private transportation) to 0, equation 6 implies that $ln(s_{c0t}) = -ln(\sum_{k=0}^{1} exp(\beta X_{ckt} + \delta R_{ckt} + \alpha p_{ckt} + \lambda_c + \gamma_t + \Phi_{rq} + \nu_{cmt})$. The difference between the log market share for taking transit ($ln(s_{c1t})$) and the log market share for the outside option ($ln(s_{c0t})$) is then:

$$ln(s_{c1t}) - ln(s_{c0t}) = \beta X_{c1t} + \delta R_{c1t} + \alpha p_{c1t} + \lambda_c + \Phi_{rq} + \nu_{c1t}, \tag{7}$$

Which can be estimated using standard least squares. The willingness to pay (WTP) per trip for Google Maps with real-time tracking is then given by $-\delta/\alpha$.

Empirically, we construct the market shares for public transportation s_{c1t} as follows. Let P_{ct} be the population of city c in year t. We assume that the number of individuals in city c represents potential travelers and that each individual takes T_c city-average trips daily[19]. We then convert the number of daily trips to monthly trips by multiplying by 20 (we assume people travel 20 days out of the month, on average). To convert the number of rides reported in the NTD to the number of potential trips, we assume 1 ride is equivalent to 1 trip. In sum, the share of public transit usage is $s_{c1t} = Ridership_{ct}/(20P_{ct}T_c)$.

To identify δ, we leverage variation in the use of real-time information in Google Maps across cities as in our earlier analysis. To identify α, we leverage changes in fares across agencies. The main empirical concern in the literature is that market-level prices are simultaneously determined by supply and demand, rendering them endogenous and necessitating the use of instruments (Berry 1994, Nevo 2001, Ito & Zhang 2020). In our context, however, public transit fares are not the outcome of a market equilibrium and change slowly —oftentimes through political and bureaucratic processes.[20] Furthermore, transit agencies are highly subsidized, largely operate on "soft" budgets, and prioritize lower-income and non-White populations in their decisions (Huang & Kahn 2023, Wang 2024). For example, when considering price changes, public transit agency boards cite equity and affordability as key criteria.[21] Combined this evidence suggests fares are not the outcome of a competitive market and are uncorrelated with shocks to ridership.

[19] Based on 2017 National Household Travel Survey (NHTS) data, each individual takes 4 trips on average in any mode of transportation, including walking, biking, car, bus, and subway. A trip is defined as any movement from one address to another within a 24-hour period. We further compute this number by state. Table 6 shows that our results are not sensitive to the choice of rides per trip.

[20] In some localities, fare changes are constrained by legislation, for example in Boston, see https://boston.curbed.com/2019/1/28/18200348/t-fare-hike-2018.

[21] In recent years some major transit agencies including Boston's MBTA and Denver's RTD have adopted zero fares, see https://www.mbta.com/projects/fare-free-program-routes-23-28-and-29 and https://www.cnbc.com/2023/01/14/zero-fare-public-transit-movement-gains-momentum.html for details. Further, the FTA provides service and fare equity guidance to transit agencies through Circular 4702.1B for all agencies with 50 or more fixed route vehicles in peak service in large urbanized areas (over 200,000 in population).

The estimated coefficients are shown in Table 5. The estimation sample is smaller than our main sample because adult fare data from APTA for specific agencies and modes were only available from 2008. The first column shows results with city and region-by-quarter-by-year fixed effects, the second column adds average household income for cities in the ACS as a control, the last column adds the log of population as a control. Column (1) includes 120 agencies, Columns (2) and (3) have a smaller sample because household income is sourced from the ACS, which is a subsample of cities (sample includes 82 agencies). The willingness-to-pay estimate increases with additional controls and in the smaller sample.

Our estimates indicate that the willingness-to-pay for Google Maps with real-time tracking is between \$0.73 and \$1.3 per trip. For context, value-of-time estimates from the literature indicate that individuals are willing to pay between \$5 and \$19 to reduce wait or travel time by one hour (Buchholz et al. 2020, Goldszmidt et al. 2020, Wang 2024). Re-scaling our willingness to pay measure using these value of time estimates suggests that real-time tracking is roughly equivalent in value to saving 2-15 minutes in travel time.

8 Conclusion

This paper estimates that Google's incorporation of real-time transit tracking into its navigation application Google Maps led to a substantial increase in public transit ridership. In the three years following the rollout of real-time data in Google Maps, ridership on public transit increased by 10.7%, with most of the effect coming from increased ridership on subways. The results cannot be explained by changes in agency operations. We have also shown that the increase in ridership occurred because commuters reduced car use, and find suggestive evidence that the rollout led to improvements in local air quality.

We find that incorporating real-time information into Google Maps had an effect of similar magnitude to much costlier public interventions such as lowering fares and increasing routes. Our analysis suggests that travelers are willing-to-pay a substantial \$0.70 per trip for Google Maps with real-time tracking. What generates this value? The introduction of real-time tracking could have impacted travel behavior purely by providing new information on the arrival and departure times of vehicles. However, controlling for agency applications that incorporated real-time information prior to Google Maps does not change our estimate of Google's impact. Therefore the treatment effect is largely due to Google's value add to this data - its popularity meant the information was widely accessible, and its use of the data to improve the estimation of travel times and optimization

of travel routes credibly reduces the indirect costs of transit use including psychological, cognitive, and time costs.

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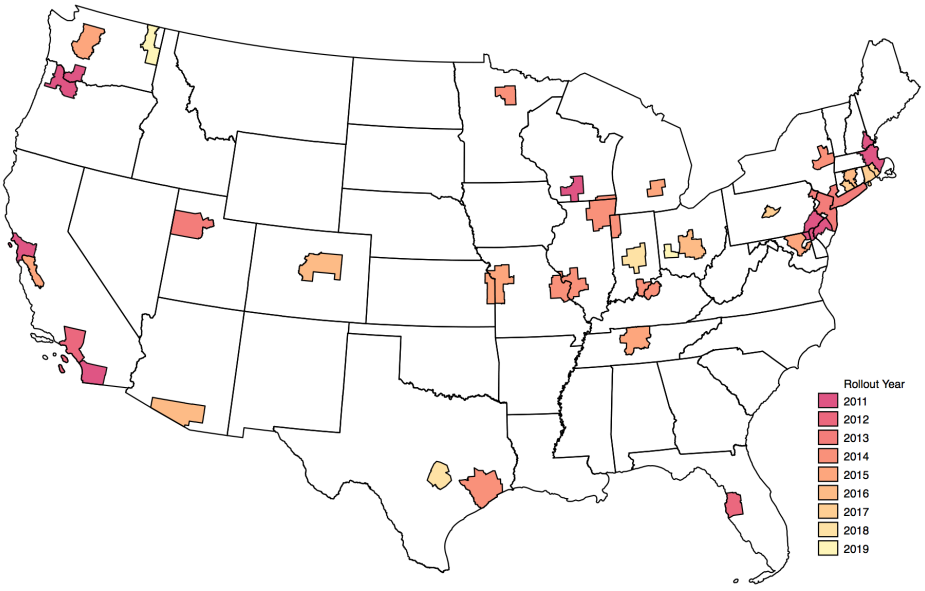


Figure 1: Year that Google Maps implemented Real-time Tracking by Sample Metro Area

Note: Map shows the year when Google Maps made real-time transit tracking available within each of our sample metro areas.

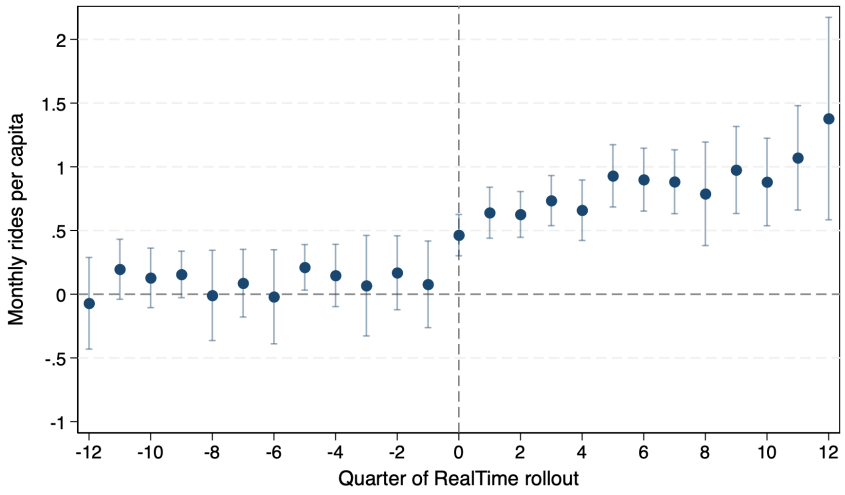
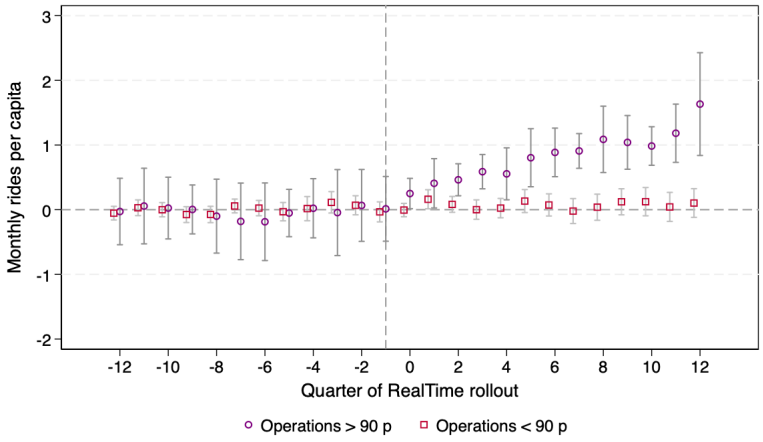
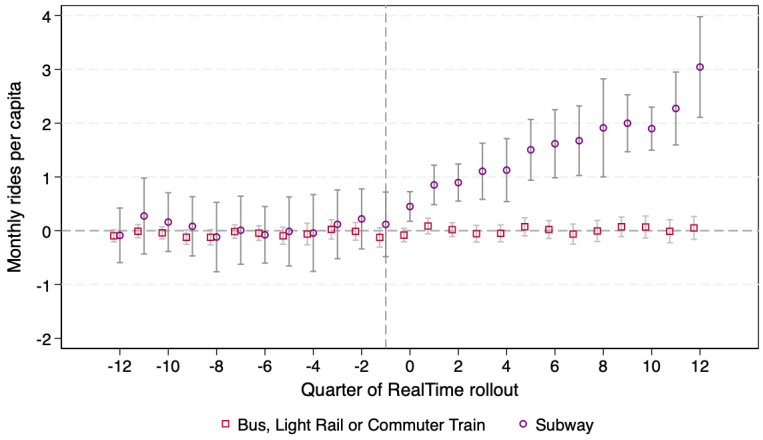


Figure 2: Effect of Real-time Information on Public Transit Ridership

Note: Figure plots the estimates and 95% confidence intervals of δ_l using Eq. 1. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether Google Maps real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area. Parameters estimated using the imputation method (Borusyak et al. 2024).



(a) Real-time Effect by Agency-Mode Operations Size



(b) Real-time Effect by Mode

Figure 3: Heterogeneity of Real-time Information Effect on Ridership

Note: Figure plots the estimates and 95% confidence intervals of δ_l using Eq. 1. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether Google Maps real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Standard errors clustered by urbanized area. Observations are unweighted. Parameters estimated using the imputation method (Borusyak et al. 2024). The red squares and purple circles indicate estimates from distinct samples. Panel A shows results of Eq. 1 for agencies with operations below versus above the 90th percentile, as measured by annual vehicle revenue miles as of 2002. Panel B shows results of Eq. 1 for subway modes relative to all other modes (bus, light rail, and commuter rail.)

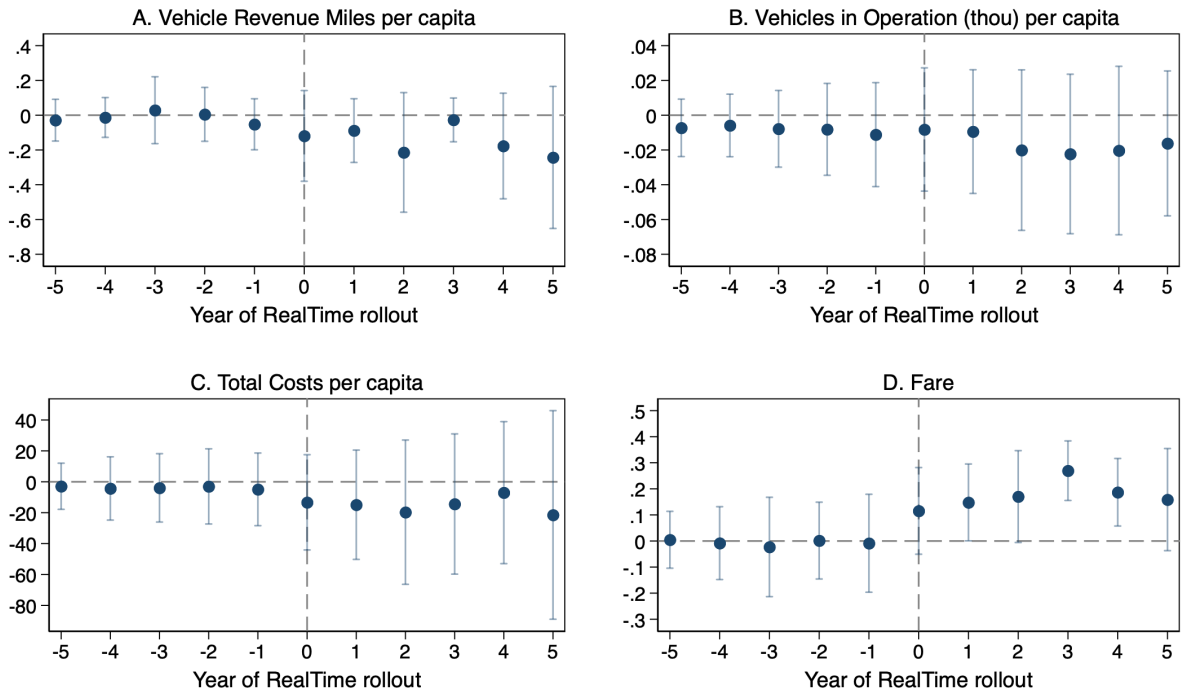


Figure 4: Transit Agency Operations and Google Real-time Rollout

Note: Figure plots the estimates and 95% confidence intervals δ_l from a version of 1 where time t is indexed by year rather than month and event time l is indexed by years since treatment rather than quarter. Each panel is one of four agency operational outcomes: Panel A is annual vehicle revenue miles per capita. Panel B is vehicles in operation ('000s) per capita. Panel C is total annual costs per capita. Panel D is the average single-ride adult fare sourced from the APTA. Because these operational outcomes vary by year (not month, like the ridership outcome), data used to produce these estimates are aggregated to agency-mode-year level. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether Google Maps real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered at by urbanized area. Parameters estimated using the imputation method (Borusyak et al. 2024).

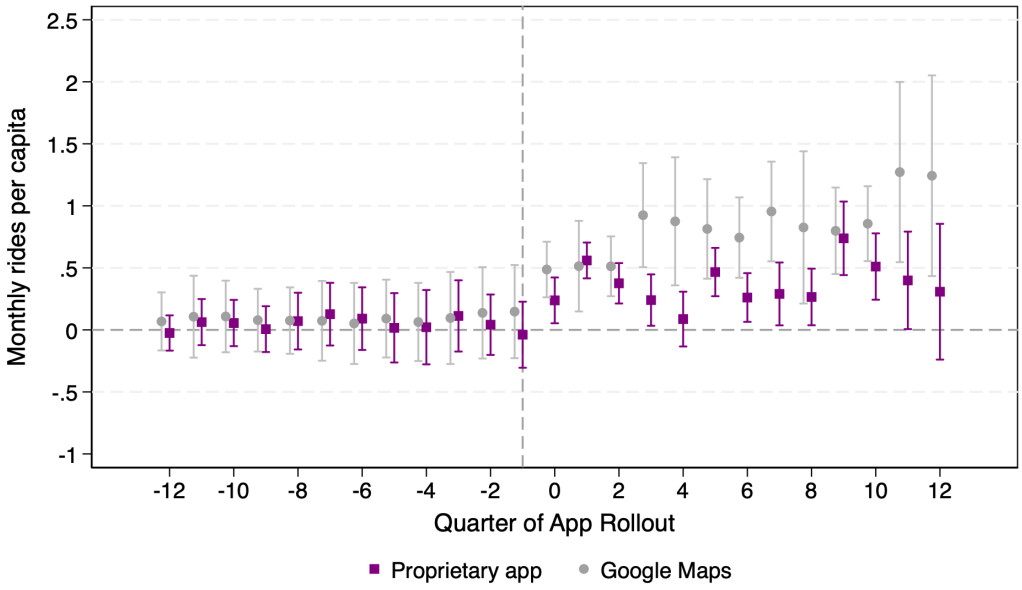


Figure 5: Effect of Agency Tracking Apps on Public Transit Ridership

Note: Figure plots the estimates and 95% confidence intervals of δ_l using a version of Eq. 1. For the purple squares, R_i is the quarter when an agency's proprietary app was introduced. For the gray circles, R_i is Google Maps real time tracking, and exactly replicates teh specificaiton shown in Figure 2. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership-by-year fixed effects. For the proprietary app specification, we also control for an indicator for Google Maps real-time rollout. Standard errors clustered by urbanized area. Observations weighted by 2002 vehicle revenue miles. Parameters estimated using the imputation method (Borusyak et al. 2024).

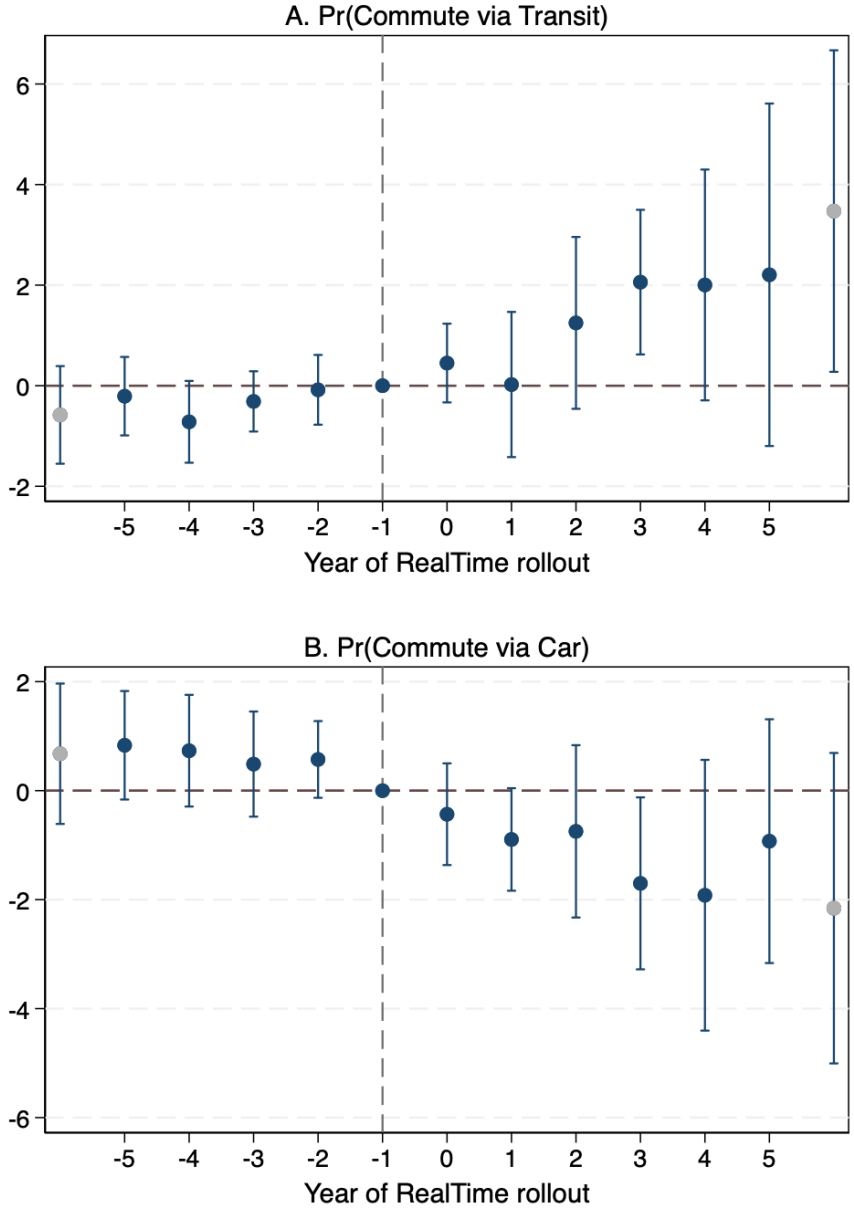


Figure 6: Effect of Real-time Information on Commute Mode Choice

Note: Figure plots the estimates and 95% confidence intervals of κ_l using Eq. 2. The outcome is the probability that anyone in a household commutes via public transit in Panel A; and the probability that anyone in a household commutes via car in Panel B. Estimates based on traditional least squares. Controls include city fixed effects, region-by-year fixed effects, 2002 ridership-by-year fixed effects, 2002 vehicle revenue miles-by-year fixed effects, an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect, indicators for the household's highest level of education, indicators for the household income levels at below the 50th percentile, between the 50th and 90th, and above the 90th percentile, and log of household income. Observations are weighted by the ACS household sampling weight. Standard errors clustered by urbanized area.

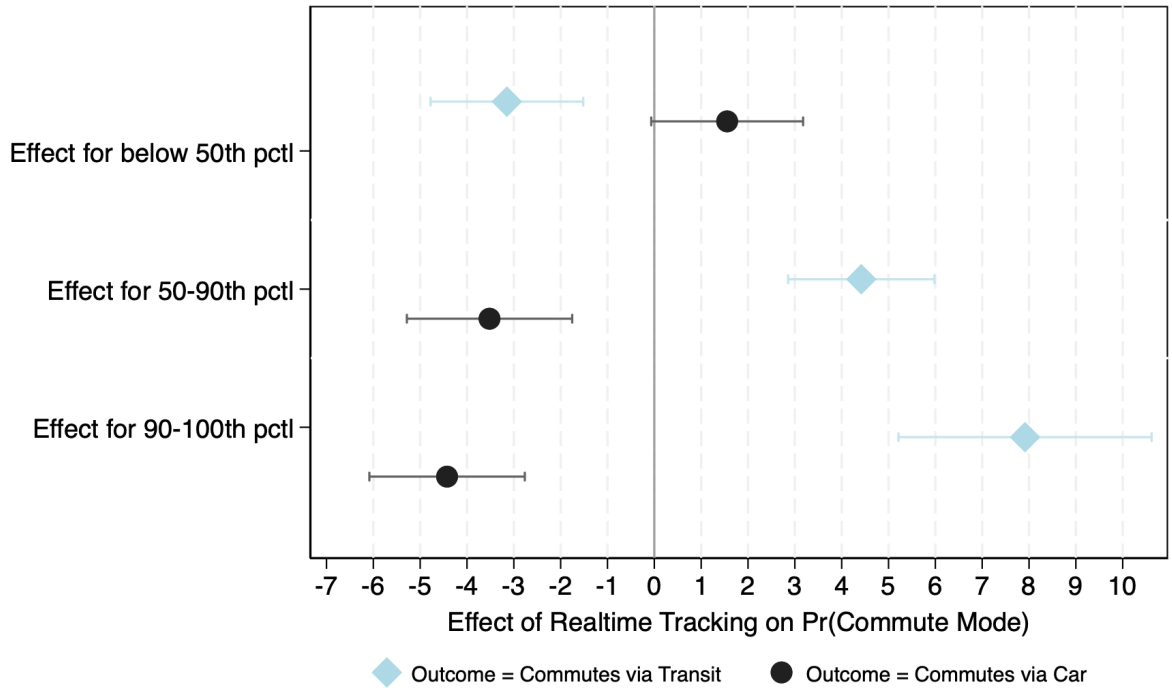


Figure 7: Real-time Information, Commute Mode Choice, and Household Income

Note: Figure shows the effect of real-time tracking on commute mode choice, and the heterogeneous effect by household income bin following Equation 3. The top row shows the estimate for β_1, the effect for households with income below the 50th percentile. The middle row shows the total effect $(\beta_1 + \beta_2)$ for households with income between the 50th and 90th percentiles; and the bottom row shows the total effect $(\beta_1 + \beta_3)$ for households with income above the 90th percentile. Diamonds indicate estimates from a regression where the outcome is whether any respondent in a household uses public transit to commute; and circles indicate estimates from a regression where the outcome is whether any respondent in a household uses a car to commute. Both regressions estimated using traditional least squares. Controls include city fixed effects, region-by-year fixed effects, 2002 ridership-by-year fixed effects, 2002 vehicle revenue miles-by-year fixed effects, an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect, indicators for whether anyone in the household is in the labor force, indicators for the household's highest level of education, indicators for the household income levels at below the 50th percentile, between the 50th and 90th, and above the 90th percentile, and log of household income. Observations are weighted by the ACS household sampling weight. Standard errors clustered by urbanized area.

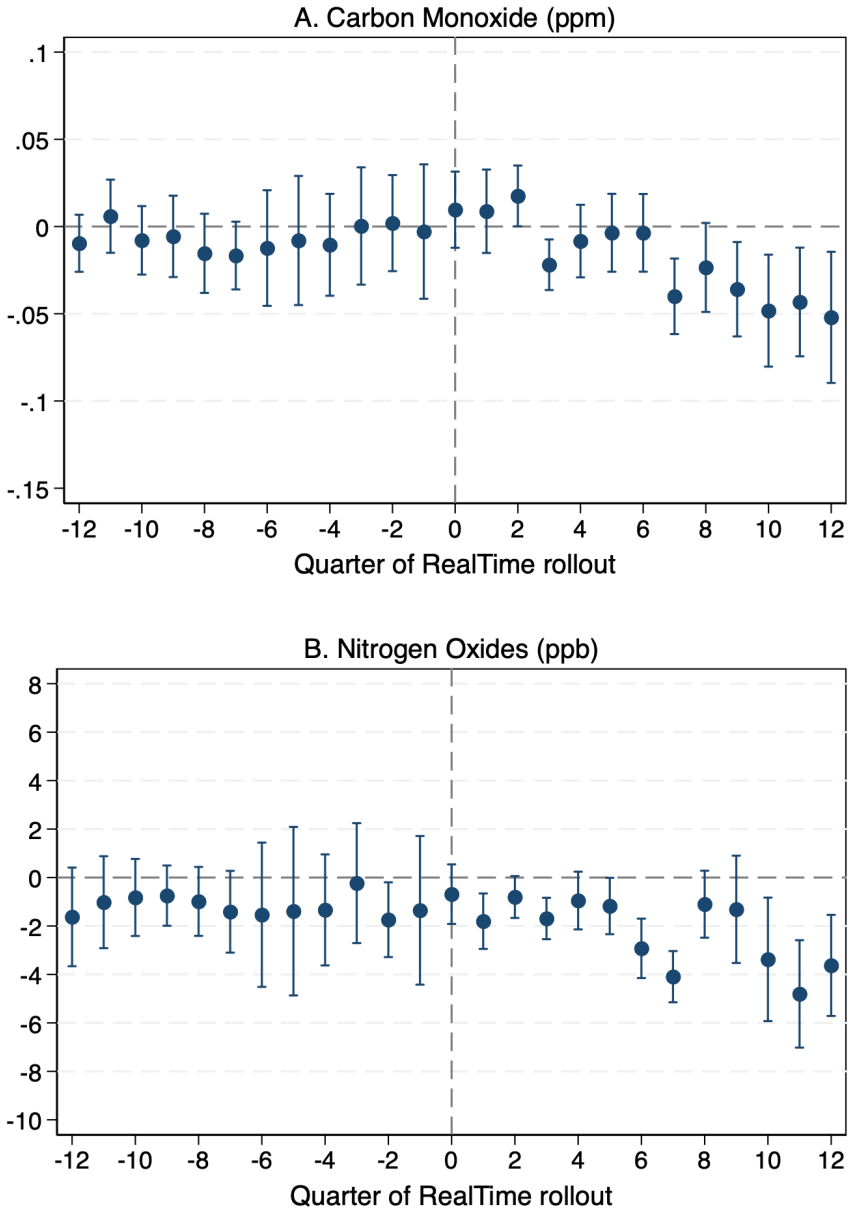


Figure 8: Effect of Real-time Information on Air Quality

Note: Figure plots the estimates and 95% confidence intervals of θ_l using Eq. 4. All estimates based on the imputation method (Borusyak et al. 2024). The outcome in Panel A is carbon monoxide (ppm). The outcome in Panel B is nitrogen oxides (ppb). Controls include city fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Standard errors clustered by urbanized area. Air quality data sourced from the EPA. Estimates are weighted by the 2010 city population.

Table 1: Summary Statistics

	RealTime	Non-RealTime	P-val
Panel A: 2008 Agency Characteristics			
Ridership per capita	9.044	4.459	0.000
Service Area population (thou)	10,743.215	10,298.217	0.842
Service Area sq. mi.	2,304.384	2,303.206	0.998
Fare Revenues ($ mn)	1,302.953	280.947	0.000
Base Adult Fare ($)	1.929	1.857	0.653
Vehicle Revenue Miles (thou)	15,341.155	4,258.301	0.000
Operating Vehicles	3,772.717	948.460	0.000
Total Cost ($ mn)	2,576.366	649.909	0.000
Share of operations privatized	0.038	0.190	0.000
Number of modes	2.265	1.757	0.001
Pr(Subway)	0.680	0.162	0.000
Pr(Proprietary App by 2019)	0.953	0.826	0.018
Panel B: 2008 City Characteristics			
Population (2010)	3,789,053	3,499,278	0.757
Area (sq.mi.)	984.977	815.518	0.321
Pr(Northeast)	0.209	0.200	0.903
Pr(South)	0.163	0.353	0.025
Pr(West)	0.395	0.271	0.153
Share black	0.211	0.220	0.801
Share of commutes by car	0.359	0.351	0.696
Share of commutes by public transit	0.083	0.071	0.478
Average commute time (min.)	24.134	24.779	0.601
Share below poverty line	0.208	0.213	0.704
Share with bachelor's degree	0.224	0.193	0.169
Share of households with internet (2013)	0.778	0.748	0.128
Share of households with cellular data (2013)	0.358	0.317	0.118
Share of households with highspeed internet (2013)	0.658	0.627	0.175
Average Daily NOx (ppb)	40.234	37.141	0.477
Average Daily CO (ppm)	0.589	0.567	0.565
Number of Agencies	43	85	

Note: Panels A data sourced from National Transit Database (NTD). Means weighted by agency vehicle revenue miles as of 2002. Panel B data sourced from the US Decennial Census and the American Community Survey (ACS). Because ACS data is only reported for cities with populations over 250,000; Panel B outcomes measured in 2008 cover 74 agencies (22 realtime, 52 non-realtime), and outcomes measured in 2013 cover 55 agencies (22 realtime, 33 non-realtime).

Table 2: Average Effects of Real-time Transit Tracking on Ridership

A. Dep. Var: Trips per capita per month - 3 Years Pre/Post	(1)	(2)	(3)
Realtime (=1)	0.557***	0.552***	0.625***
	(0.180)	(0.180)	(0.209)
OwnApp (=1)		0.037	0.077
		(0.057)	(0.054)
Uber (=1)		0.043	0.030
		(0.059)	(0.070)
Controls			Y
Dep. Var. Mean	5.841	5.841	5.841
Weights	BaseVRM	BaseVRM	BaseVRM
Observations	29058	29058	28718

B. Dep. Var: Trips per capita per month - Full Panel	(1)	(2)	(3)
Realtime (=1)	1.328***	1.323***	1.447***
	(0.301)	(0.305)	(0.273)
OwnApp (=1)		0.078	0.101**
		(0.055)	(0.047)
Uber (=1)		0.060	0.046
		(0.063)	(0.080)
Controls			Y
Dep. Var. Mean	5.841	5.841	5.841
Weights	BaseVRM	BaseVRM	BaseVRM
Observations	36657	36657	36149

Note: All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcome varies by agency-mode-month and is sourced from the NTD. Additional fixed effects include agency-by-mode and season-by-region. "Controls" include the 2010 share of city population that is black interacted with a year fixed effect; and the agency-mode share of operations that are privatized. All parameters estimated using the imputation method (Borusyak et al. 2024). Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated agency-modes and is weighted by 2002 VRM. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 3: Average Effects of Real-time Transit Tracking on Commute Modes

A. Dep. Var: Pr(Commute on Transit)	(1)	(2)	(3)
Realtime(=1)	1.186**	1.173**	1.159**
	(0.558)	(0.561)	(0.559)
Ln(Income)	0.176	0.175	0.693
	(1.333)	(1.333)	(1.279)
OwnApp (=1)		0.036	0.040
		(0.344)	(0.343)
Uber (=1)		-1.150	-1.133
		(0.927)	(0.904)
HH Income<p50			1.206
			(0.829)
p50>HH Income<p90			-0.143
			(0.593)
Controls			Y
Dep. Var. Mean	29.167	29.167	29.167
Weights	ACS Survey Weight	ACS Survey Weight	ACS Survey Weight
Adjusted R^2	0.250	0.250	0.251
Observations	1262691	1262691	1262691

B. Dep. Var: Pr(Commute in Car)	(1)	(2)	(3)
Realtime(=1)	-1.488**	-1.428*	-1.330**
	(0.692)	(0.716)	(0.655)
Ln(Income)	10.543***	10.544***	13.119***
	(0.885)	(0.886)	(1.161)
OwnApp (=1)		-0.247	-0.227
		(0.438)	(0.404)
Uber (=1)		1.055	0.826
		(0.858)	(0.722)
HH Income<p50			12.883***
			(1.934)
p50>HH Income<p90			13.496***
			(1.162)
Controls			Y
Dep. Var. Mean	62.980	62.980	62.980
Weights	ACS Survey Weight	ACS Survey Weight	ACS Survey Weight
Adjusted R^2	0.238	0.238	0.247
Observations	1262691	1262691	1262691

Note: All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, 2002 vehicle revenue miles-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcomes vary by household-year and are sourced from the ACS. "Controls" include indicators for the household's highest level of education. Parameters estimated using standard two-way fixed effects. Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities and is weighted by the household survey weight. *$p < 0.10$, *$p < 0.05$, *$p < 0.01$

Table 4: Average Effects of Real-time Transit Tracking on Air Quality

A. Dep. Var: CO (ppm)	(1)	(2)	(3)
Realtime (=1)	-0.025*	-0.025*	-0.033**
	(0.013)	(0.013)	(0.015)
OwnApp (=1)		0.000	-0.001
		(0.007)	(0.006)
Uber (=1)		-0.003	-0.003
		(0.020)	(0.020)
Temperature (degF)			-0.002***
			(0.001)
Nonattainment (=1)			-0.010
			(0.021)
Dep. Var. Mean	0.425	0.425	0.425
Weights	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)
Observations	13139	13139	10174

B. Dep. Var: NOx (ppb)	(1)	(2)	(3)
tau	-3.212***	-3.210***	-3.927***
	(0.852)	(0.846)	(1.021)
OwnApp (=1)		-0.062	-0.125
		(0.369)	(0.365)
Uber (=1)		0.422	0.289
		(0.732)	(0.803)
Temperature (degF)			-0.357***
			(0.076)
Nonattainment (=1)			-1.895
			(1.318)
Dep. Var. Mean	32.226	32.226	32.226
Weights	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)
Observations	11823	11823	9623

Note: All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcomes vary by city-month and are sourced from the EPA. Additional fixed effects include season-by-region. "Nonattainment" equals 1 if the county is in nonattainment for any criteria pollutant in a given year. All parameters estimated using the imputation method (Borusyak et al. 2024). Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities and is weighted by 2010 city population. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 5: Welfare Analysis of Real-time Transit Tracking

	(1)	(2)	(3)
Realtime (δ)	0.601***	0.969***	1.064***
	(0.155)	(0.222)	(0.211)
Fare (α)	-0.814***	-0.887***	-0.774***
	(0.134)	(0.126)	(0.149)
Ln(Service Area Population)			-0.996**
			(0.407)
Ave Household Income(x 10^4)		0.007	0.219*
		(0.115)	(0.122)
Observations	11,944	5,561	5,561
Region-by-quarter-by-Year FE	Y	Y	Y
City FE	Y	Y	Y
$WTP = -\frac{\delta}{\alpha}$ per trip	0.738	1.092	1.375

Note: Observations in the table are aggregated at the agency-city-month-year level after 2008. All regressions include region fixed effects interacted with quarter interacted with year fixed effects and city fixed effects. Standard errors are clustered by urbanized area. Parameters estimated using Borusyak et al. (2024) Regressions weighted by agency-mode vehicle revenue miles as of 2002. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. In column (1), 38 (82) agencies are included in the treatment (control) group. In columns (2) and (3), 28 (54) agencies are included in the treatment (control) group.

A Additional Figures

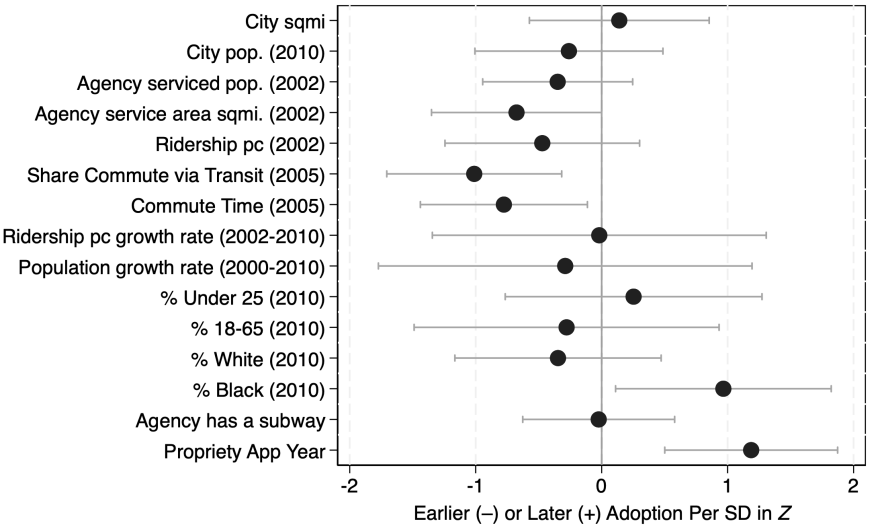


Figure A.1: Predictors of Google Real-time Tracking adoption year

Note: Figure shows estimates of β from the regression: $AdoptionYear_{im} = \beta(Z_{im})$ where Z is the standardized Z-score of one of 15 agency or city characteristics. Agencies with higher values of Z adopted real-time tracking roughly β years later.

Table 6: Welfare Analysis of Real-time Transit Tracking - Robustness Checks

	(1) 1.5 trips/ride	(2) 2 trips/ride	(3) 2.5 trips/ride	(4) 3 trips	(5) 4 trips
Google (β)	1.104^***	1.027^***	0.928^***	0.954^***	0.981^***
	(0.223)	(0.234)	(0.231)	(0.224)	(0.239)
Fare	-0.775^***	-0.995^***	-0.914^***	-0.897^***	-0.882^***
	(0.157)	(0.273)	(0.132)	(0.137)	(0.138)
Observations	5519	5519	5519	5519	5519
Adjusted R^2	0.788	0.789	0.789	0.735	0.788
Quarter-by-Year FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
$WTP = -\frac{\beta}{\alpha}$	1.425		2.095	2.062	2.072

Note: Observations in the table are aggregated at the agency-city-month-year level. Sample spans three years prior and three years after real-time rollout. All regressions include region fixed effects interacted with quarter interacted with year fixed effects and city fixed effects. Standard errors are clustered by urbanized area. Regressions weighted by agency-mode vehicle revenue miles as of 2002. Column (1) - (3) assume various number of trips per ride. Column (4) uses monthly fare and assumes that each rider takes 30 trips per month. Column (5) - (6) report the estimation by varying the number of trips per day for each individual. *$p < 0.10$, **$p < 0.05$, ***< 0.01

Figure A.2: Sources of Google Real-time Tracking Start Date by City

	Metro Area	National Transit Database ID	Transit Agency Name	Start of Realtime Tracking	"In Use"	Unreported Month	2002 Service Population	Source
1	Madison, WI	5005	Metro Transit	May 2011	X		219,185	https://twitter.com/search?q=%40mymetrobus%20real%20time&src=typed_query
2	Boston, MA	1003	MBTA	June 2011			4,510,400	https://betanews.com/2011/06/08/google-maps-can-now-track-buses-and-trains-in-real-time/
3	Philadelphia, PA	3019	SEPTA	June 2011			3,728,909	https://technical.ly/philly/2011/06/01/transitview-septa/
4	San Diego, CA	9026	MTS	June 2011			2,674,436	https://www.sandiegouniontribune.com/news/sdut-google-mts-team-real-time-bus-maps-2011jun08-story.html
5	Tampa, FL	4027	PSTA	June 2012	X		862,076	https://twitter.com/search?q=%40ridePSTA%20google%20real&src=typed_query&f=live
6	Long Beach, CA	9023	LBT	September 2012	X		573,734	https://la.streetsblog.org/2012/09/04/major-changes-at-long-beach-transit/
7	New York City, NY	2008	MTA	March 2013			17,799,861	https://www.theverge.com/2013/3/27/4153064/google-adds-real-time-nyc-transit-tracking-google-maps
8	Salt Lake City, UT	8001	UTA	March 2013			1,744,417	https://maps.googleblog.com/2013/03/live-transit-information-in-more-cities.html
9	Santa Monica, CA	9008	BigBlueBus	March 2013			458,506	http://www.santamonicanext.org/2015/06/big-blue-bus-real-time-arrival-info-is-here/
10	Tampa, FL	4041	HART	October 2013			578,252	http://gohart.blogspot.com/2013/10/google-trip-planner-now-uses-real-time.html
11	Chicago, IL	5113	Pace	January 2014			4,468,180	https://www.chicagotribune.com/news/ct-google-maps-real-time-met-20150603-story.html
12	Louisville, KY	4018	TARC	January 2014			754,756	https://www.wdrb.com/news/tarc-real-time-bus-arrivals-now-available-on-google-maps/article_352aa54f-b570-5f3d-bd84-abea924120ad.html
13	St Louis, MO	7006	St Louis Metro	January 2014	X	X	1,562,961	https://www.metrostlouis.org/nextstop/metro-adds-real-time-data-to-trip-planner/
14	Chicago, IL	5066	CTA	March 2014			3,708,773	https://www.chicagotribune.com/news/ct-google-maps-real-time-met-20150603-story.html
15	Houston, TX	6008	Metro	April 2014			2,796,994	https://www.metro-magazine.com/bus/news/291959/houston-metro-google-partner-for-real-time-info
16	Grand Rapids, MI	5033	The Rapid	June 2014			539,080	http://blog.ridetherapid.org/rapid-google-maps/
17	Albany, NY	2002	CDTA	October 2014			678,394	http://alloveralbany.com/archive/2014/10/29/cdta-now-offering-realtime-bus-info
18	Baltimore, MD	3034	MTA	January 2015	X	X	2,077,667	https://medium.com/transit-app/how-we-saved-baltimore-600-000-in-one-day-f8311e487e58
19	Santa Clara, CA	9013	VTA	January 2015	X	X	1,719,600	https://www.mercurynews.com/2014/02/19/vta-apps-offer-real-time-arrival-info-for-light-rail/
20	Kansas City, MO	7005	KCATA	April 2015			756,557	http://www.kcata.org/news/kcata_now_offering_live_transit_information_in_google_maps
21	San Francisco, CA	9003	BART	June 2015			741,774	https://www.bart.gov/news/articles/2011/news20110608
22	San Francisco, CA	9015	MUNI	June 2015			793,600	https://www.theverge.com/2015/6/2/8712771/google-maps-real-time-transit-updates-san-francisco-chicago-UK
23	Seattle, WA	0001	King County Metro	June 2015			1,774,300	https://seattletransitblog.com/2015/06/03/real-time-transit-in-google-maps/
24	Seattle, WA	0003	Pierce Transit	June 2015			670,820	https://seattletransitblog.com/2015/06/03/real-time-transit-in-google-maps/
25	Oakland, CA	9014	AC Transit	July 2015			1,415,129	https://abc7news.com/traffic/ac-transit-partners-with-google-maps-to-give-riders-real-time-bus-data/840473/
26	San Diego, CA	9030	NCTD	October 2015			821,380	https://timesofsandiego.com/politics/2015/10/19/real-time-schedules-for-nctd-buses-now-available-in-google-maps/
27	Lansing, MI	5036	CATA	November 2015	X		300,032	https://www.reddit.com/r/msu/comments/3taln1/lpt_google_maps_will_give_you_cata_routes_and/
28	Los Angeles, CA	9154	LA Metro	December 2015			11,789,487	https://la.curbed.com/2015/12/11/10621598/los-angeles-metro-realtime-arrival-information
29	Nashville, TN	4004	MTA	December 2015			573,294	https://www.nashville.gov/News-Media/News-Article/ID/4779/Nashville-MTA-unveils-new-tracking-technology-for-bus-system
30	Denver, CO	8006	RTD	January 2016		X	2,400,000	http://www.dailycamera.com/boulder-county-news/ci_29355106/rtd-releases-data-real-time-app-tracking-denver
31	Hartford, CT	1048	CTTRANSIT	February 2016		X	851,535	https://twitter.com/CTTRANSIT/status/697417846704488449
32	Anchorage , AK	0012	PTD	July 2016			218,145	https://www.muni.org/Departments/Mayor/PressReleases/Pages/PeopleMoverTeamswithGoogleandCodeforAnchoragetoImprovetheRiderExperience.aspx
33	Colombus, OH	5016	COTA	December 2016			11,331,963	https://columbus.org/2016/12/live-transit-updates-cota-buses-now-available-google-maps/
34	New Haven, CT	1055	CTTRANSIT	January 2017		X	531,314	https://www.cttransit.com/news/real-time-information-new-haven-cttransit-buses-now-available
35	Providence, RI	1001	RIPTA	January 2017		X	920,310	https://www.ripta.com/popular-transit-app-is-now-offering-real-time-information-for-ripta-passengers
36	State College, PA	3054	CATA	January 2017	X		83,444	https://twitter.com/search?q=%40CATABUS%20google&src=typed_query&f=live
37	Portland, OR	0008	TriMet	July 2017			1,253,502	https://www.inquirer.com/philly/business/transportation/dude-wheres-my-ride-septa-invests-in-real-time-data-20170705.html
38	Westchester, NY	2076	Bee Line Bus	September 2017			923,459	https://nyc.streetsblog.org/2017/09/14/real-time-westchester-bus-info-mysteriously-appears-on-google-maps/
39	Indianapolis, IN	5050	IndyGo	January 2018			1,218,919	https://twitter.com/IndyGoBus/status/958785475405328384
40	Austin, TX	6048	CMTA	June 2018			901,920	https://www.reddit.com/r/Austin/comments/8skaoh/google_maps_now_showing_realtime_updates_for_some/
41	Portland, OR	0024	C-Tran	October 2018	X		304,455	https://twitter.com/search?q=%40ctranvancouver%20google&src=typed_query&f=live
42	Dayton, OH	5017	RTA	January 2019	X	X	559,062	https://www.facebook.com/iriderta/posts/1697774993686538?comment_id=1697849840345720
43	Spokane, WA	0002	STA Transit	September 2019	X		371,055	https://twitter.com/search?q=%40spokanetransit%20google%20real%20time&src=typed_query&f=live

Note: "In Use" denotes that the transit agency had already adopted real-time tracking by the source date. Unreported Month denotes that the source provided the year, but not the month, of adoption of real-time tracking. In these instances, the authors assign January as the effective start month. 2002 Service Population sourced from the National Transit Database.

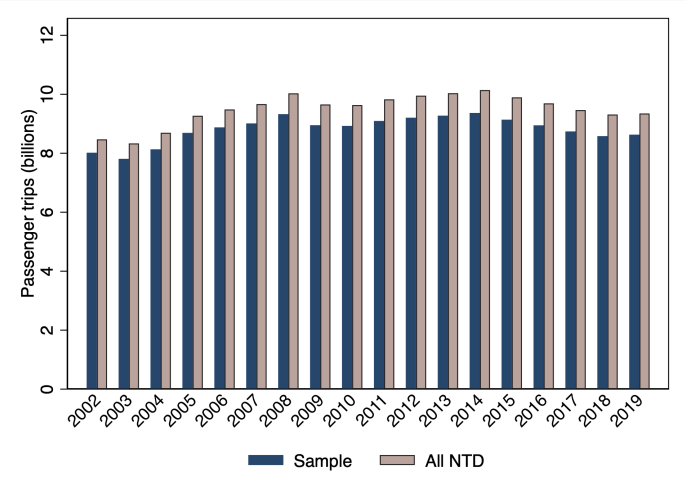


Figure A.3: Annual Passenger Trips for Sample vs Population of Transit Agencies

Note: Figure plots the aggregate passenger trips among the 128 transit agencies in our sample in blue and aggregate passenger trips of all 634 transit agencies in pink. Source: NTD & the American Public Transit Association.

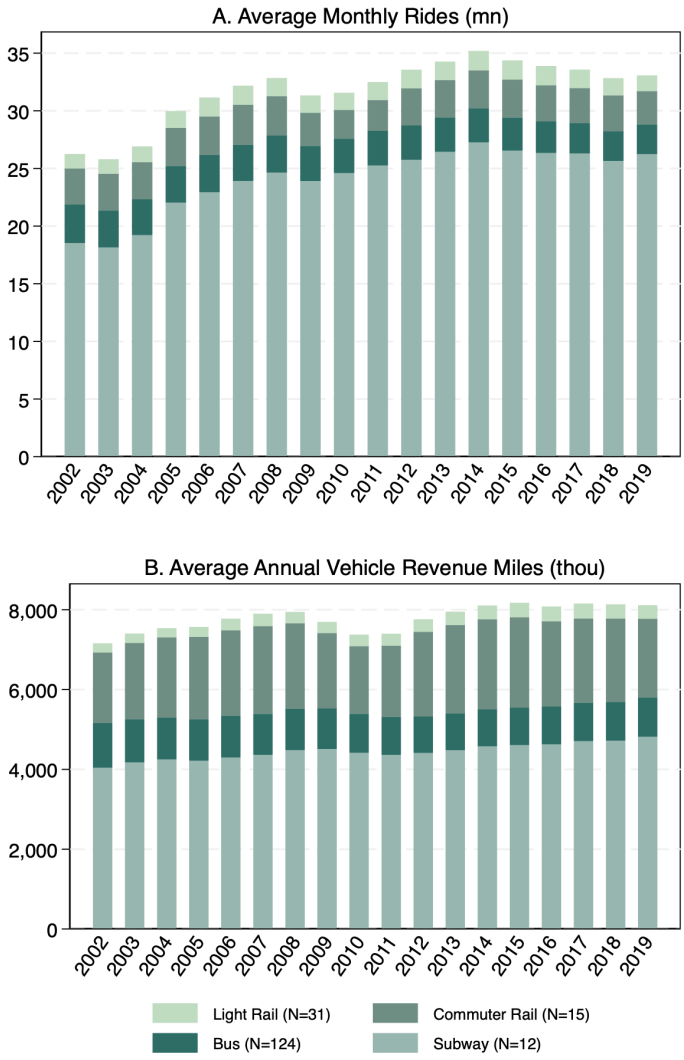


Figure A.4: Composition of Public Transit Operations

Note: Figure plots the composition of public transit operations by mode among the 128 transit agencies in our sample. Panel A shows the mode-specific composition by average monthly rides, and Panel B shows the mode-specific composition by average annual vehicle revenue (vrm) miles. Note that ridership and vrm occur mainly on subways, but there are comparatively few subway agencies relative to bus agencies (12 agencies with a subway system relative to 124 agencies with a bus system). Source: NTD & the American Public Transit Association.

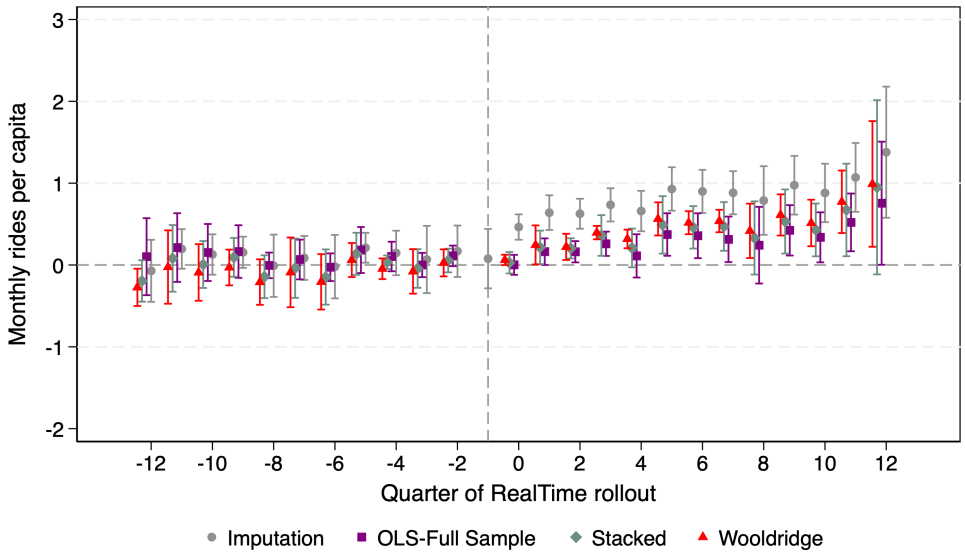


Figure A.5: Sensitivity to Estimation Method: Effect of Real-time Information on Ridership

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1. Each dot shows the change in monthly trips per capita in quarter q relative to the omitted quarter (under all estimation methods, the omitted $q = -1$, the quarter prior to Google Maps' real-time implementation. Under Borusyak et al. (2024), the omitted quarter is all quarters prior to $q = -12$.) Each color dot uses different estimation methods as follows: gray is the imputation method (Borusyak et al. 2024); purple is traditional least squares with the full sample; teal is a "stacked" TWFE approach, and red is **??**. All specifications include agency-by-mode fixed effects, season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcome varies by agency-mode-month and is sourced from the NTD. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area.

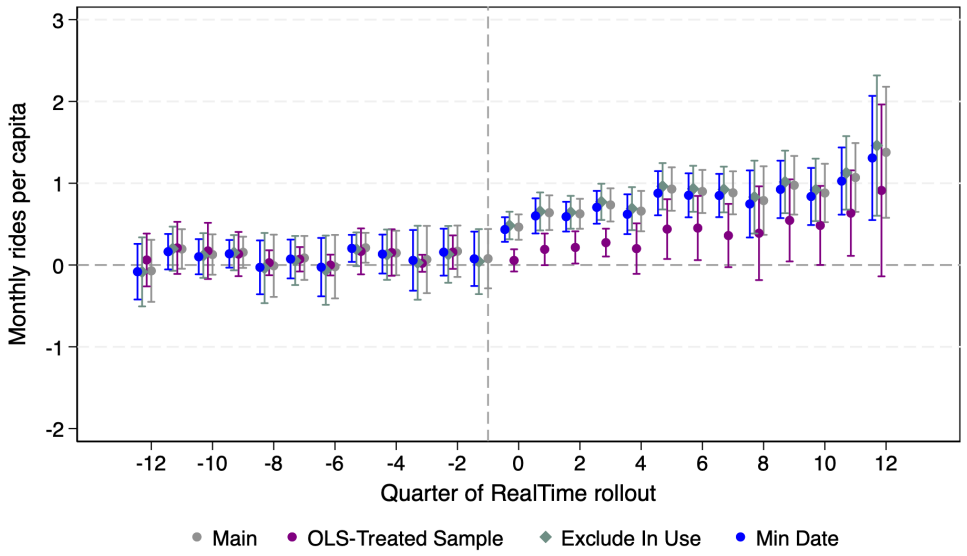


Figure A.6: Sensitivity to Roll-Out Date Definition: Effect of Real-time Information on Ridership

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1. Each dot shows the change in monthly trips per capita in quarter q relative to quarter $q = -1$, the quarter prior to Google Maps' real-time implementation. Each color dote uses different estimation methods as follows: gray employ the imputation method (Borusyak et al. 2024); purple uses traditional least squares with the full sample; red uses traditional least squares with only treated units in the sample; and light green uses a "stacked" TWFE approach. All specifications include agency-by-mode fixed effects, season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcome varies by agency-mode-month and is sourced from the NTD. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area.

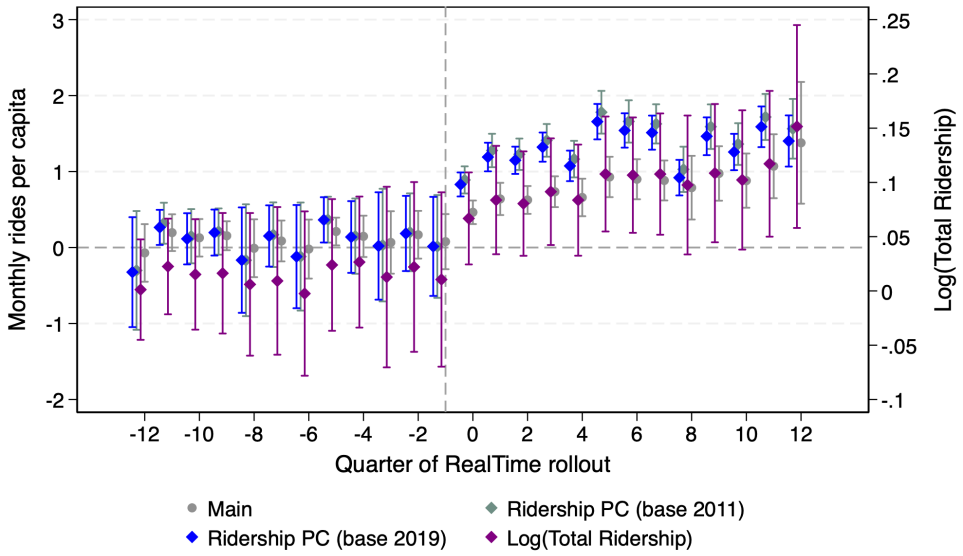


Figure A.7: Sensitivity to Outcome Definition: Effect of Real-time Information on Ridership

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1 where y is one of three alternative definitions of ridership: ridership per capita with 2011 population as the base; and ridership per capita with 2019 population as the base, and log(total ridership). Each dot shows the change in monthly trips per capita in quarter q relative to quarter $q = -1$, the quarter prior to Google Maps' real-time implementation. All parameters estimated using the imputation method (Borusyak et al. 2024). All specifications include agency-by-mode fixed effects, season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area.

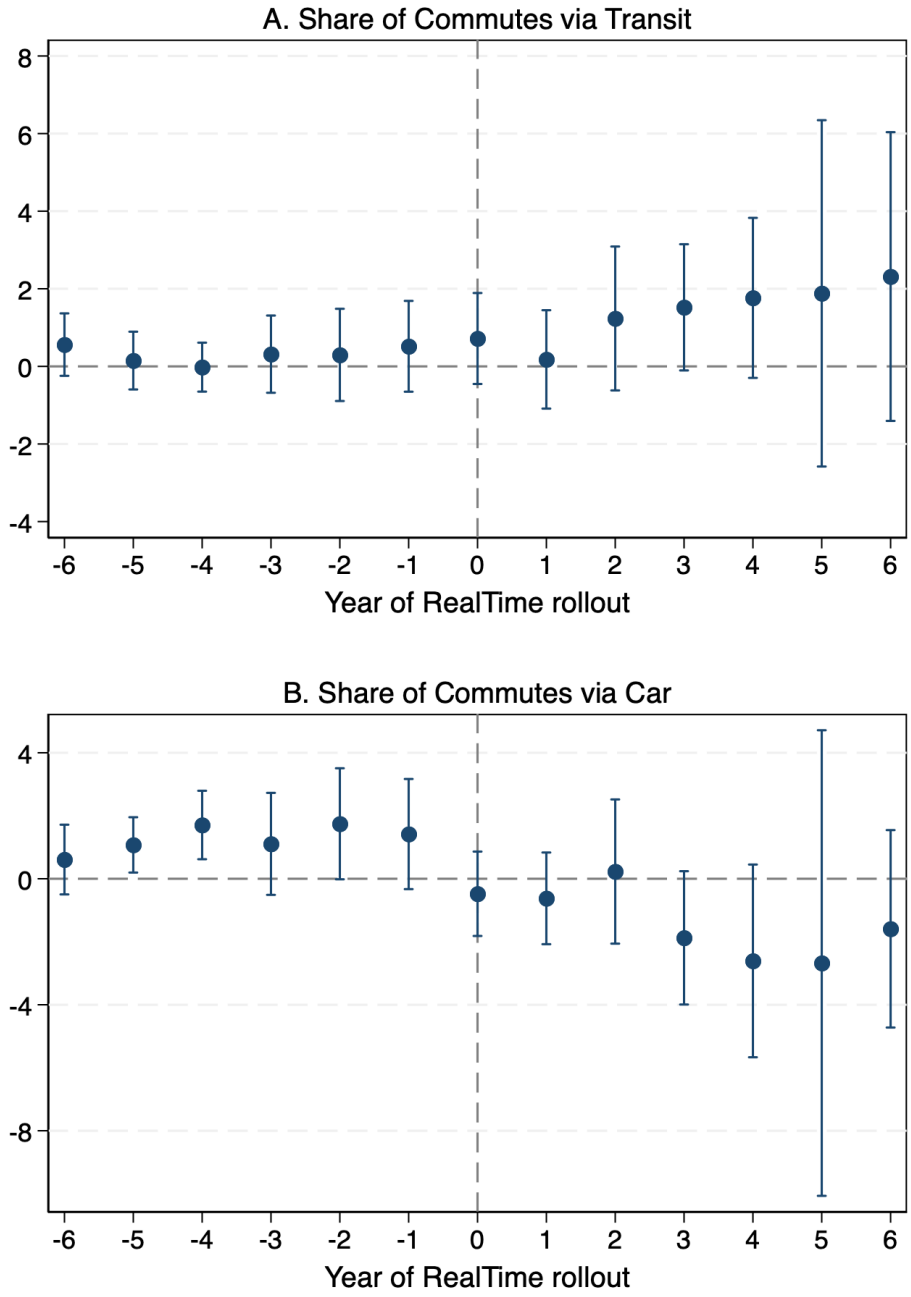


Figure A.8: Real-time Information and Commute Mode Choice at City Level

Note: Figure shows the effect of real-time tracking on average city-level commute mode choice following Equation 3. Controls include city fixed effects, region-by-year fixed effects, 2002 ridership-by-year fixed effects, 2002 vehicle revenue miles-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Standard errors clustered by urbanized area. Parameters estimated using the imputation method (Borusyak et al. 2024).

Table A.1: Average Effects of Real-time Transit Tracking on City-Level Commute Modes

A. Dep. Var: City-Level Share of Commutes on Transit (%)	(1)	(2)	(3)
Realtime(=1)	1.099*	1.065	1.073*
	(0.659)	(0.671)	(0.590)
OwnApp (=1)		0.273	0.278
		(0.310)	(0.332)
Uber (=1)			-0.322
			(0.607)
Dep. Var. Mean	16.611	16.611	16.611
Observations	781	781	781

B. Dep. Var: City-Level Share of Commutes in Car (%)	(1)	(2)	(3)
Realtime(=1)	-1.038	-1.018	-1.018
	(0.751)	(0.764)	(0.766)
OwnApp (=1)		-0.162	-0.162
		(0.582)	(0.585)
Uber (=1)			0.042
			(1.045)
Dep. Var. Mean	69.643	69.643	69.643
Observations	781	781	781

Note: All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcomes vary by city-year and are sourced from the ACS. Parameters estimated using the imputation method (Borusyak et al. 2024). Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities. *$p < 0.10$, *$p < 0.05$, *$p < 0.01$

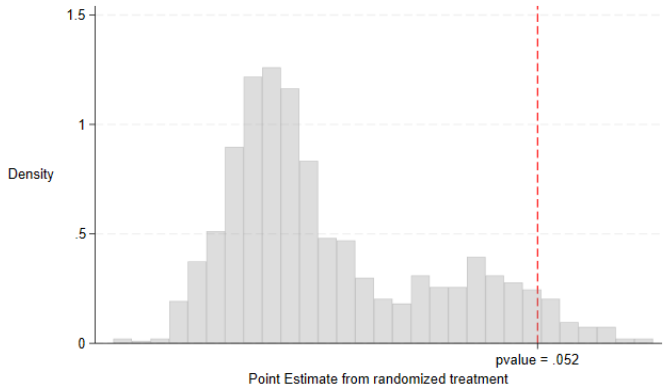


Figure A.9: Randomization Inference

Note: Figure plots the distribution of point estimators utilize the randomization inference (Horowitz (2019)). Each estimator is estimated using Eq. 1 by randomly assign the treatment time for all agencies. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, and base ridership-by-year fixed effects. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area. Parameters estimated using the imputation method (Borusyak et al. 2024).

Table A.2: Effects of Real-time Transit Tracking on Ridership by Mode and Agency Size

	(1)	(2)	(3)
Realtime (=1)	1.328***	1.217***	2.381***
	(0.301)	(0.243)	(0.259)
Sample	Full	Top 10	Subways
Observations	36657	3912	2496
Dep. Var. Mean	5.8419	5.6674	6.243
Weights	BaseVRM	None	None

Note: The "Top 10" sample includes only agency-by-mode pairs with 2002 vehicle revenue miles in the top 10th percentile. "Subways" sample includes only subway modes. All specifications include agency-by-mode fixed effects, season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcome varies by agency-mode-month and is sourced from the NTD. All parameters estimated using the imputation method (Borusyak et al. 2024). Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated agency-modes. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

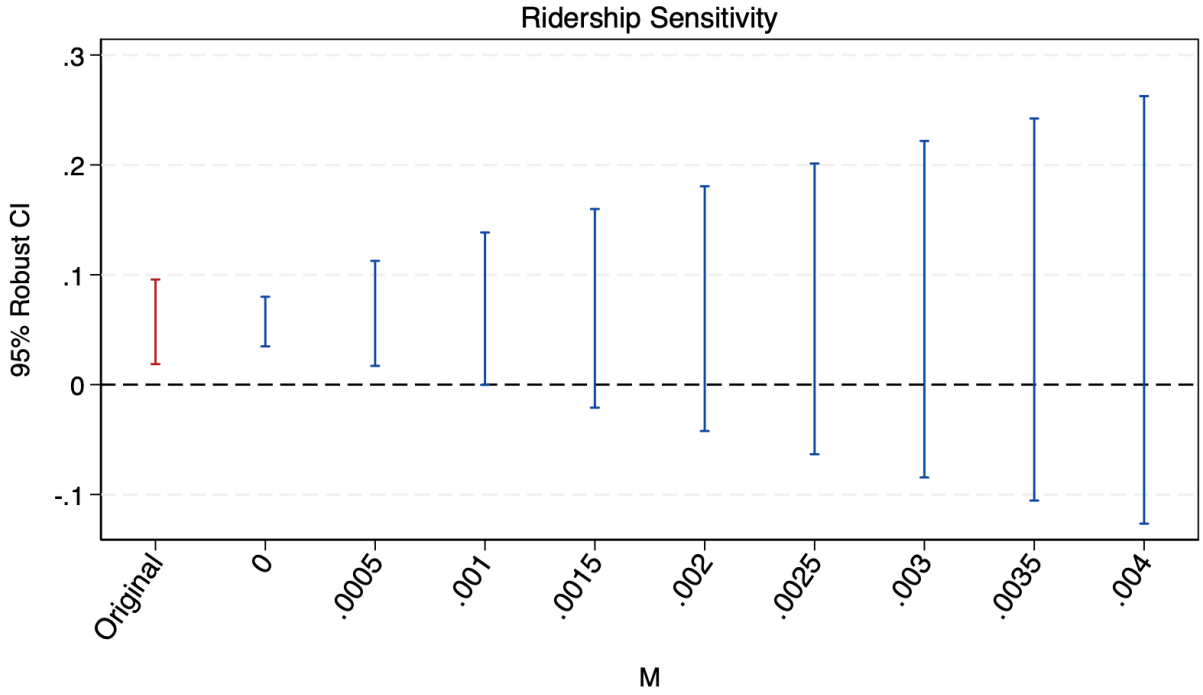


Figure A.10: Parallel Trends Sensitivity Analysis for Ridership Effect

Note: This figure assesses the plausibility of the parallel trends assumption when interpreting the impact of Google Maps' real-time tracking on transit ridership. The figure shows the sensitivity of our results to a linear extrapolation of pre-event coefficients using the honest approach to parallel trends from Rambachan & Roth (2023). The figure reports 95% confidence intervals for the average of all post-CWA coefficients when we allow the slope of the pre-trend coefficients to change by no more than M across consecutive periods.

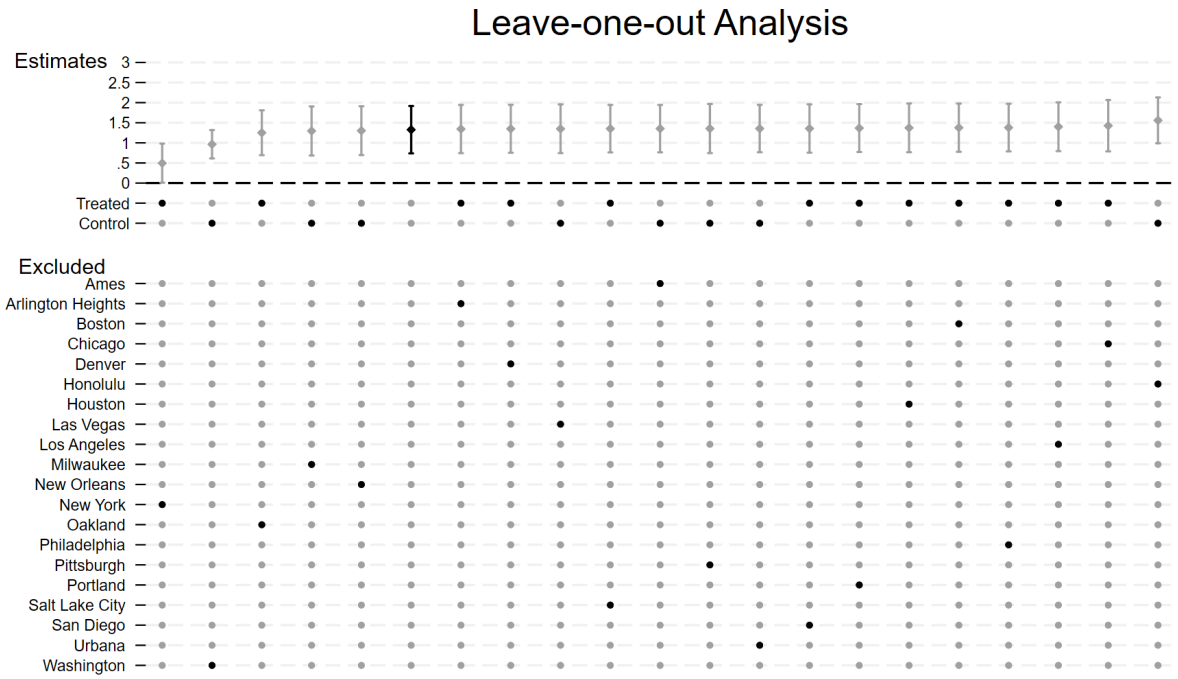


Figure A.11: Leave-one-out Analysis

Note: This figure shows the estimates and 95% confidence interval of cities that generate the largest twenty treatment effects. All parameters estimated using the imputation method (Borusyak et al. 2024). *$p < 0.10$, *$p < 0.05$, *$p < 0.01$

Table A.3: Real-time Tracking Effects Under A Propensity Score Matching Approach

	Monthly Trips PC	Ln(Monthly Trips)	CO (ppm)	NOx (ppb)	Transit Share	Car Share
Realtime (=1)	0.320***	0.087***	-0.046	-3.559**	3.819**	-2.810**
	(0.103)	(0.028)	(0.036)	(1.454)	(1.705)	(1.112)
Observations	17288	17288	5216	4258	490	490
Adjusted R^2	0.911	0.977	0.465	0.597	0.624	0.799
City FE	Y	Y				
Year x Region FE	Y	Y	Y	Y	Y	Y
Quarter x Region FE	Y	Y	Y	Y		
Match Group FE	Y	Y	Y	Y	Y	Y
Panel Unit FE	Agency-Mode	Agency-Mode	City	City	City	City

Note: This table shows estimates on the impact of Google Realtime tracking on each outcome listed in the top row using a propensity score matching design. The propensity score predicts the likelihood of an agency-mode ever having their realtime tracking integrated into GoogleMaps as of 2019. The propensity score is based on a logit regression with the the following covariates: agency-mode vehicle revenue miles as of 2002, the mode type, whether the agency has a subway mode, the share of city residents that are black as of 2010, and the square mileage of the city. We also include matched-group fixed effects and city fixed effects. We employ nearest-neighbor matching allowing for up to two neighbors. This process leaves a sample of 82 agency-mode pairs (52 treated and 30 control). Parameters estimated using standard least squares. Standard errors are clustered by urbanized area.

Table A.4: Leave-one-out Analysis (Full Sample)

Excluded City	Estimate	95% Confidence Interval	Difference (%)
Akron	1.328	[.739, 1.918]	.014
Albany	1.332	[.741, 1.922]	.29
Allentown	1.328	[.738, 1.918]	0
Ames	1.354	[.764, 1.944]	1.975
Anaheim	1.328	[.738, 1.918]	-.009
Anchorage	1.329	[.739, 1.92]	.098
Ann Arbor	1.33	[.74 , 1.919]	.123
Arlington He	1.345	[.744 , 1.945]	1.245
Athens	1.322	[.731 . 1.914]	-.452
Atlanta	1.317	[.73 , 1.904]	-.865
Austin	1.331	[.735 , 1.926]	.206
Bakersfield	1.328	[.738 , 1.918]	-.002
Baltimore	1.333	[.724 , 1.943]	.404
Baton Rouge	1.328	[.738 , 1.918]	.003
Bellingham	1.329	[.739 , 1.92]	.087
Boston	1.378	[.778 , 1.978]	3.752
Bridgeport	1.328	[.739 , 1.918]	.002
Buffalo	1.332	[.742 , 1.921]	.267
Chapel Hill	1.328	[.738 , 1.918]	0
Charlotte	1.328	[.738 , 1.918]	-.007
Chicago	1.427	[.789 , 2.066]	7.478
Cincinnati	1.326	[.737 , 1.916]	-.123
Cleveland	1.312	[.718 , 1.907]	-1.184
Columbus	1.332	[.74 , 1.924]	.295
Corpus Chris	1.329	[.739 , 1.918]	.034
Culver City	1.328	[.739 , 1.917]	-.023
Dallas	1.327	[.737 , 1.918]	-.05
Dayton	1.329	[.739 , 1.919]	.091
Denver	1.351	[.755 , 1.947]	1.711

Continuation of Table A.4			
Detroit	1.328	[.738 , 1.917]	-.042
Dover	1.328	[.738 , 1.918]	.017
Durham	1.328	[.738 , 1.918]	.001
El Paso	1.328	[.739 , 1.918]	.021
Eugene	1.324	[.732 , 1.917]	-.281
Everett	1.329	[.742 , 1.916]	.073
Fairfax	1.328	[.738 , 1.918]	-.033
Flint	1.328	[.739 , 1.918]	.023
Fort Lauderd	1.329	[.739 , 1.919]	.078
Fort Myers	1.328	[.738 , 1.918]	-.03
Fort Worth	1.328	[.737 , 1.918]	-.042
Fresno	1.328	[.738 , 1.917]	-.032
Gainesville	1.337	[.746 , 1.928]	.659
Garden City	1.329	[.737 , 1.921]	.076
Grand Rapids	1.33	[.738 , 1.922]	.142
Greensboro	1.328	[.738 , 1.918]	-.012
Hampton	1.328	[.737 , 1.918]	-.044
Hartford	1.332	[.741 , 1.923]	.291
Houston	1.374	[.767 , 1.98]	3.429
Indianapolis	1.33	[.738 , 1.921]	.109
Iowa City	1.329	[.739 , 1.919]	.072
Ithaca	1.338	[.748 , 1.928]	.746
Jacksonville	1.327	[.737 , 1.917]	-.065
Kansas City	1.334	[.742 , 1.927]	.462
Lafayette	1.329	[.74 , 1.919]	.098
Lansing	1.33	[.739 , 1.92]	.122
Las Vegas	1.351	[.746 , 1.956]	1.711
Lexington	1.328	[.738 , 1.918]	.002
Long Beach	1.338	[.743 , 1.933]	.731
Los Angeles	1.401	[.795 , 2.007]	5.507
Louisville	1.336	[.743 , 1.929]	.569

Continuation of Table A.4			
Madison	1.329	[.737 , 1.922]	.096
Memphis	1.328	[.739 , 1.918]	.004
Miami	1.326	[.736 , 1.917]	-.123
Milwaukee	1.296	[.687 , 1.906]	-2.403
Minneapolis	1.336	[.742 , 1.93]	.59
Montebello	1.328	[.741 , 1.915]	.01
Nashville	1.33	[.739 , 1.921]	.135
New Haven	1.33	[.74 , 1.92]	.147
New Orleans	1.304	[.697 , 1.911]	-1.849
New York	.496	[.009 , .982]	-62.683
Newark	1.33	[.748 , 1.911]	.105
North Charle	1.328	[.738 , 1.918]	-.017
Oakland	1.252	[.694 , 1.81]	-5.733
Oceanside	1.337	[.744 , 1.929]	.64
Olympia	1.328	[.738 , 1.919]	.018
Orange	1.325	[.75 , 1.9]	-.244
Orlando	1.329	[.739 , 1.919]	.064
Philadelphia	1.381	[.789 , 1.973]	3.969
Phoenix	1.328	[.738 , 1.918]	-.001
Portland	1.368	[.773 , 1.964]	3.023
Providence	1.332	[.741 , 1.923]	.276
Raleigh	1.328	[.738 , 1.918]	-.034
Reno	1.328	[.738 , 1.919]	.013
Richmond	1.328	[.738 , 1.918]	-.002
Riverside	1.328	[.738 , 1.917]	-.025
Rochester	1.33	[.74 , 1.919]	.129
Sacramento	1.326	[.739 , 1.914]	-.134
Saint Louis	1.343	[.744 , 1.942]	1.11
Saint Peters	1.335	[.739 , 1.93]	.496
Salt Lake Ci	1.354	[.763 , 1.944]	1.92
San Antonio	1.333	[.742 , 1.924]	.354

Continuation of Table A.4			
San Bernardi	1.327	[.739 , 1.915]	-.089
San Carlos	1.327	[.741 , 1.914]	-.056
San Diego	1.357	[.756 , 1.959]	2.185
San Francisc	1.326	[.741 , 1.911]	-.153
San Jose	1.344	[.747 , 1.94]	1.177
Santa Barbar	1.328	[.737 , 1.919]	-.008
Santa Cruz	1.331	[.736 , 1.926]	.214
Santa Monica	1.337	[.746 , 1.929]	.7
Seattle	1.34	[.74 , 1.941]	.93
Spokane	1.331	[.739 , 1.923]	.21
Springfield	1.331	[.742 , 1.919]	.183
State Colleg	1.338	[.747 , 1.93]	.757
Syracuse	1.328	[.739 , 1.917]	-.031
Tacoma	1.34	[.75 , 1.93]	.898
Tallahassee	1.328	[.738 , 1.918]	-.004
Tampa	1.333	[.74 , 1.927]	.38
Thousand Pal	1.328	[.738 , 1.918]	.001
Tucson	1.329	[.739 , 1.919]	.042
Vancouver	1.329	[.74 , 1.918]	.087
Washington	.966	[.614 , 1.318]	-27.264
West Covina	1.328	[.74 , 1.915]	-.038
West Palm Be	1.327	[.737 , 1.918]	-.062
White Plains	1.332	[.741 , 1.924]	.325
Yaphank	1.328	[.738 , 1.919]	.023

Note: All parameters estimated using the imputation method (Borusyak et al. 2024). Each row shows the point estimate in column 1, 95% confidence interval in column 2, and the percentage difference compared to the beseline estimate. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table A.5: Average Effects of Real-time Transit Tracking on Air Quality: Unweighted

A. Dep. Var: CO (ppm)	(1)	(2)	(3)
Realtime (=1)	-0.021	-0.022	-0.031
	(0.015)	(0.015)	(0.019)
OwnApp (=1)		0.005	0.003
		(0.011)	(0.011)
Uber (=1)		-0.004	0.006
		(0.016)	(0.017)
Temperature (degF)			-0.002***
			(0.000)
Nonattainment (=1)			-0.003
			(0.018)
Dep. Var. Mean	0.421	0.421	0.421
Observations	13139	13139	10174

B. Dep. Var: NOx (ppb)	(1)	(2)	(3)
Realtime (=1)	-1.633	-1.676	-2.923*
	(1.119)	(1.102)	(1.538)
OwnApp (=1)		0.216	-0.410
		(0.538)	(0.605)
Uber (=1)		0.479	0.516
		(0.654)	(0.702)
Temperature (degF)			-0.258***
			(0.044)
Nonattainment (=1)			-0.729
			(1.100)
Dep. Var. Mean	24.885	24.885	24.885
Observations	11823	11823	9623

Note: All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). Outcomes vary by city-month and are sourced from the EPA. Additional fixed effects include season-by-region. "Nonattainment" equals 1 if the county is in nonattainment for any criteria pollutant in a given year. All parameters estimated using the imputation method (Borusyak et al. 2024). Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities. *$p < 0.10$, *$p < 0.05$, *$p < 0.01$



Figure A.12: Rollout of Agency Apps relative to Google Maps Real-time Tracking

Figure A.13: List of Agencies with Subways and in Top Decile of Operations

	Agency	City	State	Mode	GoogleMaps Realtime Rollout	Vehicle Revenue Miles, 2002	Top 10th percentile	Subway Mode
1	Chicago Transit Authority	Chicago	IL	Subway	2014m3	5,185,313	1	1
2	Chicago Transit Authority	Chicago	IL	Bus	2014m3	5,496,788	1	0
3	County of Miami-Dade	Miami	FL	Subway		615,253	0	1
4	Dallas Area Rapid Transit	Dallas	TX	Bus		2,629,263	1	0
5	Denver Regional Transportation District	Denver	CO	Bus	2016m1	3,153,129	1	0
6	King County Department of Metro Transit	Seattle	WA	Bus	2015m6	2,878,549	1	0
7	Los Angeles County Metropolitan Transportation Authority	Los Angeles	CA	Subway	2015m12	511,198	0	1
8	Los Angeles County Metropolitan Transportation Authority	Los Angeles	CA	Bus	2015m12	7,686,857	1	0
9	MTA Long Island Rail Road	New York	NY	Commuter Rail		4,878,600	1	0
10	MTA New York City Transit	New York	NY	Bus	2013m3	10,203,970	1	0
11	MTA New York City Transit	New York	NY	Subway	2013m3	28,478,348	1	1
12	Maryland Transit Administration	Baltimore	MD	Subway		391,881	0	1
13	Massachusetts Bay Transportation Authority	Boston	MA	Subway	2011m6	1,654,277	0	1
14	Metro-North Commuter Railroad Company, dba: MTA Metro-North Railroad	New York	NY	Commuter Rail		4,294,208	1	0
15	Metropolitan Atlanta Rapid Transit Authority	Atlanta	GA	Subway	2021m12	1,963,738	0	1
16	Metropolitan Transit Authority of Harris County, Texas	Houston	TX	Bus	2014m4	3,767,766	1	0
17	New Jersey Transit Corporation	Newark	NJ	Commuter Rail		4,068,045	1	0
18	New Jersey Transit Corporation	Newark	NJ	Bus		6,691,666	1	0
19	Northeast Illinois Regional Commuter Railroad Corporation	Chicago	IL	Commuter Rail		2,935,389	1	0
20	Port Authority Trans-Hudson Corporation	New York	NY	Subway		951,859	0	1
21	Port Authority of Allegheny County	Pittsburgh	PA	Bus		2,468,264	1	0
22	San Francisco Bay Area Rapid Transit District	Oakland	CA	Subway	2011m6	4,933,648	1	1
23	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	Subway		1,183,813	0	1
24	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	Bus	2011m6	2,955,322	1	0
25	The Greater Cleveland Regional Transit Authority	Cleveland	OH	Subway		147,356	0	1
26	Washington Metropolitan Area Transit Authority	Washington	DC	Bus		3,181,468	1	0
27	Washington Metropolitan Area Transit Authority	Washington	DC	Subway		4,419,340	1	1

Note: This Figure lists all agencies in our sample that either have a subway mode or have annual vehicle revenue miles as of 2002 in the top decile of the sample. Source: National Transit Database.

Timeline of Google Maps

- 2005: GTFS feed for static timetables: (TriMet, Portland)
- 2011: GTFS extended for real-time tracking in Boston, San Diego, San Francisco, Portland, Madrid, & Torino (only available on Androids or desktops) https://maps.googleblog.com/2011/06/know-when-your-bus-is-late-with-live.html
- 2011: Side-by-side comparison of driving, walking, biking, or transit was available at this time (again, only on Android or desktop) https://blog.google/outreach-initiatives/sustainability/take-green-route-in-google-maps/
- 2012: Google Maps app was available for iPhone https://blog.google/products/maps/google-maps-is-now-available-for-iphone/
- 2013: "Enhanced navigation" for driving: Maps would tell you if there is a traffic delay and could suggest an alternative route https://blog.google/products/maps/a-new-google-maps-app-for-smartphones/
- 2015: Predicts car travel time, taking into account traffic patterns based on time of day/day of week (only on desktop) https://snowdropsolutions.co.uk/google-releases-predictive-travel-time/
- March 2016: Ridehailing services available on Maps https://blog.google/products/maps/a-new-google-maps-app-for-smartphones/
- 2019: Can select arrival/departure times on phone app https://smartphones.gadgethacks.com/how-to/see-what-traffic-will-be-like-specific-time-with-google-maps-0193097/