Navigating Change: GoogleMaps, Real-Time Information, and Transit Ridership

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Abstract

We show that an improvement to Google Maps enabled by real-time transit tracking increased public transit ridership, particularly on subways. Our findings are based on panel data combining information on public transit utilization with information on Google Maps' staggered adoption of real-time tracking across transit agencies in the United States. Ridership per capita is 13% larger 3 years after the rollout of real-time information in Google Maps. Agency specific applications that use real-time information have a smaller impact on ridership and do not reduce the estimated effect of Google's adoption of real-time. Using independent data, we verify that city residents reduce car trips and opt for transit during their daily commutes, indicating significant external benefits. We see suggestive evidence of improved air quality and estimate that travelers are willing-to-pay around $0.70 per trip for the improvement. These results suggest that increases in the salience and convenience of public transit can have substantial impacts on welfare.

Keywords : Public Transportation; Travel Behavior; Travel Time

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1 Introduction

Making decisions is hard, especially when the stakes involve complex, evolving choices. Yet, humans are creatures of habit. According to psychologists, between 35 and 45% of daily behavior is repetitive and considered habitual (Wood et al. 2002). Humans may have developed habits to reduce the mental strain of complex choices and to make decision-making more efficient (Wood & Neal 2009). In dynamic environments with many options and fluctuating conditions, however, it is unlikely that habitual behaviors dominate the alternatives. In these settings, technology may substantially improve daily decisions. By curtailing the cost of accessing relevant information, simplifying complex information, and solving costly optimization problems, technology may reduce dependence on habits and facilitate better choices. One context in which this dynamic is particularly relevant is urban travel decisions in the U.S.

In this paper, we study whether improvements in technology impact travel behavior. We focus on an improvement to Google Maps, the most popular cell phone navigation application in the United States (US). Commuting habits are a prime example of a shortcut behavioral response to a complex daily decision problem. In their choice of daily travel, individuals are presented with many alternatives whose relative benefits are a function of real-time conditions that are difficult to observe and predict (Larcom et al. 2017). Google Maps simplifies travel choices by predicting travel times and optimal travel routes. In 2011, Google Maps began incorporating real-time tracking of public transit vehicles into its estimation of travel times and optimal travel routes in a handful of cities. By 2019, at least 43 of the largest 128 transit systems in the US had real-time tracking enabled.

We study whether the technological improvement enabled by real-time tracking in Google Maps impacted behavior by analyzing public transit ridership. With real-time tracking, commuters can instantaneously use their phones to look up precise arrival times of buses or trains, follow directions on when to depart, and compare accurate commute times and costs across modes. Ex ante, it is not obvious what impact Google's incorporation of real-time tracking would have on public transit usage. The more accurate information presented by Google Maps with real-time updates could have *increased* ridership by lowering the psychological and time costs of accessing transit services, however it could equally have *reduced* public transit ridership if users became aware of the relative efficiency of driving routes, for example, if buses were delayed.

To measure the impact of this technological improvement on travel behavior, we compile a

new dataset on the location and timing of publicly-available transit tracking within the Google Maps application. We match this dataset to monthly ridership and transit operations data from the US federal government's National Transit Database (NTD). Our empirical approach compares ridership with and without the availability of Google real-time tracking in an event study design.

We find that the introduction of real-time tracking in Google Maps increased monthly transit trips per capita by about 1 trip per month, or about 13% on average in the three years following its rollout. The effects increase over time, starting with an increase of 0.5 trips per capita per month and ending at almost 1.5 trips per capita per month by year three. Most of these effects are driven by agencies with large operations and subway modes. Our results demonstrate the substantial impact that improvements in decision support tools and technology can have on travel behavior.

Our main empirical challenge is that Google may have incorporated real-time information into it's app for cities where transit ridership was already 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 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. 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. These collectively help support our assumption that the timing and locations of real-time tracking are conditionally uncorrelated with transit ridership, thus changes in ridership following Google Map's real-time tracking are credibly attributable to the treatment.

The improvement to Google Maps enabled by real-time tracking could affect travel behavior purely by providing new information on transit arrival and departure times. It could also impact transit choices via improved predictions and comparisons across modes. Or because the information was made accessible to a wider audience of existing Google Maps users. To explore which mechanism explains our ridership result, we show that real-time tracking information provided in proprietary agency applications—which often predated its incorporation into Google Maps—had a substantially smaller impact on transit ridership. Further, controlling for the pre-existence of real-time information in proprietary applications does not affect the estimated impact of Google using real-time tracking. It was Google's use and dissemination of the new data that primarily led

to changed travel behavior.

The increase in ridership caused by the improvement in Google Maps could have substantial external welfare implications. Congestion costs the US economy 30 billion annually (Couture et al. 2018). Further, the transportation sector accounts for approximately 30% of carbon emissions (EPA 2023), and 40% of nitrogen dioxide emissions (EPA 2024). Public transit can reduce these externalities (Anderson 2014, Chen & Whalley 2012, Li et al. 2019, Gendron-Carrier et al. 2022). US travel, however, is overwhelmingly dominated by cars. In 2017, Americans opted to use a car in over 85% of trips (Wang 2024). The dominance of car travel today is the outcome of a decades-long trend: while nine percent of US workers traveled to work on public transit in 1970, today, that rate is only five percent (Freemark 2021). If improving Google Maps encourages travelers to switch mode from car to transit, then it may also reduce congestion and improve local air quality.

We use a dataset on commuting from the American Community Survey to assess whether Google Maps induced mode switching. Consistent with our analysis of ridership data, we find the share of commutes within a city taken on public transit increases by 1 to 2 percentage points (10%) within four years of Google Maps incorporating real-time tracking. The share of commutes via car falls by a similar magnitude of about 1 percentage point (3%). These findings suggest that real-time tracking induced commuters to switch from cars to public transit and likely generated external benefits via reduced congestion.

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 Environment 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 led to a reduction of NOx by about 2.2 parts per billion (8.5%) after Google real-time tracking, while CO fell by about 0.013 parts per million (3.5%), though these estimates are noisy.

In addition to these public benefits, we quantify a lower bound of the private benefits of Google Maps real-time tracking using a discrete choice model.[1] 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

[1]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.

tracking.

Our paper is the first to evaluate the impacts of real-time transit tracking using quasi-experimental methods. A small interdisciplinary literature explores the effects of real-time transit tracking on ridership (Ferris et al. 2010, Tang & Thakuriah 2012, Chow et al. 2014, Brakewood et al. 2015, Brakewood & Watkins 2019). These studies use survey methods or small samples within a single city over a limited time frame and mostly focus on bus modes and proprietary apps. They find that real-time tracking either has no impact on ridership or leads to a modest 1-2% increase. Using a credible identification strategy and a large sample of transit agencies we find that the use of real-time tracking by Google led to economically large and sustained effects on transit ridership. Using data across modes, we also show that the effects are largest in large agencies (based on service mileage) and on subway modes. As a further contribution, we quantify the willingness-to-pay for this improvement using a discrete choice model.

Our paper contributes 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). We also provide evidence that the effects were not purely informational. Google's adoption of tracking information which in several cases was already publicly available —impacted travel behavior beyond the direct informational content, either through Google's popularity or through improvements to its optimization algorithms.

We also contribute to the literature studying travel behavior and mode choice. Recent studies that have focused on infrastructure expansion efforts (Gonzalez-Navarro & Turner 2018, Majid & Vyborny 2018, Tsivanidis 2024, Severen 2021) have found adding train lines or bus rapid transit lines increase 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 investments in physical vs non-physical transit infrastructure.

A related literature studies the impacts of wait time on travel choices to estimate the value

of time (Goldszmidt et al. 2020, Buchholz et al. 2020, Wang 2024). We document the ridership impacts of real-time tracking, which effectively reduced the psychological, logistical, and time costs of transit.

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 Google and mass transit tracking are closely linked. In much of the developed world today, transit users can access real-time transit tracking information for their local transit system using their smartphones 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 smartphone 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.[2] Prior to GTFS, there was no industry standard for organizing transit timetables. Many transit applications developed in the early 2000's relied on these open-source GTFS feeds (Wikipedia 2022).

"Real-time" tracking (also called "automatic vehicle location systems") refers to the minute-by-

[2] 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).

minute tracking of transit vehicles. When transit vehicles run on time, static timetable information and real-time information are the same. But when transit vehicles are not on time (either running ahead of schedule, behind, or not running due to service interruptions); real-time tracking provides a more accurate method of following the specific location of transit vehicles. 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. Depending on the software capabilities of agencies, the tracking data used by operations management can be re-organized, simplified, and shared with riders through an application program, like Google Maps (Brakewood & Watkins 2019).

While some transit agencies, like King County Metro in Seattle had the capacity to share real-time tracking information with users since the late 1990s, most of these tools (like web-based applications) were often difficult for users to access, particularly when waiting at transit stops and looking for up-to-date information on arrival times. Third-party app developers, like Google, helped to make timetables and tracking information quickly accessible, established mechanisms to map GTFS feed stop identifiers with a user's location, and made information available through multiple interfaces, like SMS or iPhone (Ferris et al. 2010).

As of 2011, some transit agencies like the BART in San Francisco, the MBTA in Boston, and the CTA in Chicago developed their own proprietary apps (see Appendix Figure A.10). While the availability of these proprietary apps means that users could access real-time info through their smartphones prior to Google Maps in some locations, two features of Google Maps mean that its adoption of real-time tracking was particularly noteworthy. First, the Google Maps app was broadly adopted by cell phone users during our time period of study. One in two smartphone users across the globe utilized the Google Maps app as early as 2013 (Smith 2013). Second, unlike proprietary apps, Google Maps displayed transit information for several agencies. This means that users could look up transit information across several agencies within one app. Third, Google Maps incorporated real-time tracking into its unique prediction and optimization algorithms. While most proprietary apps just displayed travel predictions while on board a vehicle, Google Maps provided users with travel time predictions inclusive of transfers, switching modes, and walking to and from transit stops.

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. 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 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.

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. 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.[3] 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.

3 Data Description

To estimate the effect of Google's real-time tracking on public transit use, we collect data on transit ridership, real-time rollout dates, air quality, and a variety of city-level controls spanning 2002 through 2019.

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 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

[3]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.

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.[4]

City Characteristics: We supplement the NTD data with city-level demographics from the 2000 and 2010 US Decennial Census, including racial composition, educational attainment, and poverty rate. In order to capture variation across cities related to commuting patterns and income, we obtained additional data from the American Community Survey (ACS) from 2005 through 2018 (Ruggles et al. 2024).

Google Maps Real-time Rollout: We 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 itself, transit agencies, and local news sources. Generally, 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 transit tracking apps. In general, proprietary apps pre-dated Google Maps provision of real-time tracking by one to five years (see Appendix Figure A.10).

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 were able to find reports of Google real-time tracking for at least one mode among 43 of these 128 largest agencies. Appendix Figure A.1 provides details on the rollout date for these 43 agencies as well as our sources. We did not find reports of Google real-time tracking for some modes—typically commuter rail modes—among 12 of these 43 treated agencies. For the remaining 85 agencies, we were unable to find any reports or online discussion of Google real-time tracking adoption prior to 2019. We use these 97 agency-mode pairs without reported real-time tracking as counterfactuals when estimating changes in ridership.

Transit ridership in the US is heavily skewed across agencies and across modes. While our

[4] 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 was 9.66 billion according to the NTD and 9.923 billion according to the American Public Transit Association (American Public Transportation Association 2021).

sample captures just 20% of all agencies in the NTD, 92% of all passenger trips occur within the 128 agencies in our sample in any given year. Appendix Figure A.2 compares total annual passenger trips among our sample agencies relative to aggregate trips among all agencies in the NTD.

Notably, ridership is quite skewed even among our sample of 128 agencies. The majority of all transit rides and the majority of transit miles happen on subways. Appendix Figure A.3 shows the composition of transit rides (panel A) and vehicle revenue miles (panel B) by mode in each year of our sample. Despite the fact that the majority of observations in our sample are buses (124 agency-mode pairs are buses), the vast majority of transit rides and mileage occur on one of 12 subway systems in our sample.

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 over 300 cities across the US. Each monitor is identified by its latitude and longitude. I 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.

Table 1 reports mean agency characteristics for agencies that had real-time tracking as of 2019 and for agencies that did not. The third column reports the p-value for significance of difference in means across treatment status. All characteristics are measured as of a baseline year 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 more likely to be located in Western states and less likely to be located in the South. Given these initial differences across treated and control units, we include agency-by-mode fixed effects and time-varying regional fixed effects in all specifications so that our estimates are conditional on observable baseline differences. We also estimate dynamic effects to test whether such baseline differences create differential pre-treatment trends, which would invalidate our empirical design. 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.

4 Google Real-time Tracking, Ridership, & Transit 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. 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 rates of ridership per capita. The rollout could therefore also have occurred in agencies, or for agency-modes, where ridership was already growing. We use panel event studies to test for evidence of pre-existing trends and provide supporting evidence by examining trends in other agency operations.

Our baseline econometric model is the following:

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

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. 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). To control for differential growth in ridership for agency-modes of different sizes, we also include an interaction of year fixed effects with year 2002 ridership per capita ρ_{iy}.

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 ser-

vice 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 city.

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).

To employ the imputation method we require sufficient data on untreated units to estimate both unit and time fixed effects. In practice, it is very difficult to estimate the imputation method without the use of "pure control" or never treated units.[5] Hence, our preferred model uses agency-mode pairs that did not receive real-time tracking during our sample period as "pure-controls". As a robustness exercise, we restrict the sample to the 43 agencies identified as "treated" in our sample and estimate the dynamic treatment effect parameters using traditional least-squares. In this model, treatment effects are identified by comparing outcomes for agencies after Google Maps rollout relative to not-yet-treated agencies. Our rationale for restricting the sample to this group is that we remove bias that could arise from mis-specifying the remaining 83 agencies as "controls" when they may, in fact, be treated. This may occur, for example, if we were unable to find online references to the launch of real-time tracking.[6]

4.1 Main Results

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. Under the Borusyak et al. (2024) estimator, the reference period is all quarters in the sample prior to any estimated pre-treatment coefficients. As we estimate pre-treatment coefficients

[5] Intuitively, in a sample with no pure control and staggered adoption, the number of available untreated observations to estimate time fixed effects is decreasing over time as more units become treated.

[6] To manage this risk, we check the presence of real-time tracking using Google Maps as of December 2021.

for 12 pre-treatment quarters, the reference period includes all quarters at least three years prior to the rollout.

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 1 additional trip, and increases again by the eleventh 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 rollout.

In Panel A of Table 2 we report the average treatment effect of Google Maps real-time tracking on ridership over all post-treatment periods. On average, ridership per capita increased by 1.328 rides per month. Given that the weighted average trips per capita as of 2010 was approximately 9.96 trips per month, this result implies an average increase of about 13%. This result is robust to controlling for the rollout of proprietary apps in column (2) and Uber in column (3), neither of which significantly explain ridership in our model.

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 across 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.[7] The red squares show that ridership on bus, light rail, and commuter trains does not change following real-time tracking.[8] However, ridership on subway modes shown in purple circles responds at significantly higher rates 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 eleven, with some seasonal fluctuation in between.

We show the average heterogeneous effects by agency size and by mode in columns (4) and (5) in Panel A of Table 2 using subsamples. Column (4) 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 (5), the effect nearly doubles to 2.8 additional trips per capita per month.

4.2 Robustness Checks

For robustness, we show the traditional least squares event study results in Appendix Figure A.4 as well as average treatment effect results under OLS in Appendix Table A.1. In all cases, the OLS results are smaller in magnitude compared to our main imputation method results, suggesting that the "forbidden" comparison (Borusyak et al. 2024) of already-treated units to newly-treated units in the OLS estimator creates downward bias. Like our main result, the two-way fixed effect event study (Appendix Figure A.4) shows no evidence of a pre-trend, but a gradual increase in ridership following the launch of Google real-time. The average treatment effect estimate from OLS is an additional 0.267 rides per capita per month, as shown in Appendix Table A.1, Panel A column 2. The patterns of heterogeneity are very similar under OLS (shown in columns 3 and 4), although the magnitudes are attenuated and less precisely estimated relative to the subsample analysis under the imputation method. In Panel B, we show OLS results using a smaller panel —3 years before and after rollout—in order to provide consistency with the event study figures. The average and heterogeneous effects are more precisely estimated with this smaller panel, relative to Panel A.

We undertake a number of additional robustness checks for our event study results, which are summarized here:

Robustness to treatment & sampling assumptions: We assess sensitivity to our selected sam-

[7] Appendix Figure A.11 lists all agencies with a subway system as well as all agencies by mode that have operations in the top decile as of 2002.

[8] 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.

ple. Because the rollout dates for Googlemaps are based on our own research, and not based on administrative data, it is possible that our estimates suffer from bias due to erroneous treatment assignment. While we believe the parallel trends assumption holds in our case, it is possible that our results have limited external validity if agencies that we assign as controls are poor representatives of the average non-treated agency in the US. We test the robustness of our results to the selected sample in two ways. First, we employ a propensity score matching approach. We 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 66 agencies (51 treated and 33 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 employing the traditional least squares estimator. Appendix Table A.2 shows very similar results to our main findings, often with larger magnitudes.

Randomization Inference: To test the hypothesis of random assignment of treatments to agencies, we use a non-parameteric approach - randomization inference - to provide evidence of the validity of our results. Specifically, we randomly reassign rollout dates in two steps. In the first step, we randomly assign exactly 43 agencies to 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 (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 the exact p-value 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.

Alternative Specifications: In Appendix Figure A.5, we show our results are robust to measuring the outcome using log monthly transit trips rather than transit trips per month per capita. This suggests that our estimates are not driven by tail effects.

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 test 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 Trends in 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 costs of operating, or fares change prior to 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 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 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. While this is evidence of another margin of treatment from Google Maps real-time tracking, 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 Proprietary Tracking Apps

Google's provision of real-time tracking may have impacted travel decisions through several channels, including: improved accuracy on arrival times and transit times; improved usability and ease of comparing travel choices, costs, and times across travel options 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 three treatments 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 may dominate.

For each agency, we searched for the availability and rollout date of a proprietary app. Like Google Maps, these apps enabled users to observe real-time tracking of public transit. However, proprietary apps —particularly those that pre-dated Google —did not have the capacity to integrate a users 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. And importantly, proprietary apps rarely provided side-by-side comparisons of alternative modes.

If the main benefit of Google Maps real-time tracking was purely about providing new information, then the treatment from proprietary apps should look similar to that of Google. However, Figure 8 suggests a much smaller effect. When considering the full sample which are shown by the red estimates, availability of real-time tracking through proprietary 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 0.2 trips per month. This magnitude is about 15% of our main estimate of 1.3 trips per month. These results are suggestive that the majority of the ridership effect from Google Maps real-time tracking are a result of ease of use and direct comparisons across modes. However, this is largely speculative, since we lack detailed information on city-specific

usage of proprietary apps relative to Google. We leave it to future research to better isolate the mechanisms.

5 Who is Influenced by Google Maps? Composition of Commutes & 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 towards 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 real-time tracking 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. Prior work on transit infrastructure improvements and 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.

While the NTD does not provide information on individual trips or transit riders, we leverage micro data from the American Community Survey (ACS) to better understand how Google Maps influenced the mode-specific composition of commuting trips. We also use the ACS to inform who is most influenced by Google Maps real-time tracking. Specifically, we use data on household income to test our hypothesis that higher-income individuals are more responsive to the treatment relative to lower income people.

First, we explore how adoption of real-time tracking impacts the share of urban residents who use public transit versus cars. The ACS is an annual survey that includes a question on whether respondents commute to work via transit or private vehicle. For each identifiable city in the ACS (includes cities with populations over 25,000), we use responses to this question (weighted by the respondent's survey weight) as well as city population values to create city-level shares of residents who either commute via transit or commute via car. Respondents may commute by means other than transit or car (for example, walking, biking, or working from home), thus these shares do not

mechanically add to one. We then estimate an event study of the following form:

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

where c_{jt} is the share of individuals living in city j in year t that report commuting by a given mode. We show results where c_{jt} is the share of commutes via public transit as well as via car. The parameters of interest κ_l measure the effect of Google real-time information l years after it was first made available in year $y = R_i$. The specification 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 ridership across cities. We cluster standard errors by city.

Figure 5 shows estimates of κ_l from Equation 2. Panel A shows an increase in commuting via transit. The average effect size is approximately 1.2 percentage points, or about 10% from the baseline mean —similar to our main ridership results. The effect increases with time. Panel B shows a decline of a similar magnitude in the share of city residents who report commuting by car. These results provide external validity on our main results —real-time tracking does influence travel behavior, it affects travel behavior of commuters, and it appears to induce switching out of cars and into transit, atleast among commuting trips.

Next, we use data on household income from the ACS to explore whether subway rides comprise the majority of our estimated treatment effect (as shown in Figure 3) due to the demographics of the average subway rider. Subway riders, on average, have higher income (American Public Transportation Association 2017). Therefore, they likely have a higher opportunity cost of wait time (Small 2012, Goldszmidt et al. 2020) and may be more influenced by the Google Maps tracking technology than lower income individuals. To test this hypothesis, we use household-level data on household income from the ACS and estimate a version of Equation 2 weighted by the respondent's household survey weight. 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:

$$\Pr(c_{njt}) = \beta_1 R_{jt} + \beta_2(R_{jt} \times I_{25-50,nj}) + \beta_3(R_{jt} \times I_{50-90,nj}) + \beta_4(R_{jt} \times I_{90,nj}) + \eta I_{nj} + \alpha_i + \gamma_{dy} + \rho_{iy} + \varepsilon_{it} \tag{3}$$

where the outcome is an indicator for whether 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: between

the 25th and 50th percentile, between the 50th and 90th percentile, and above the 90th percentile. The parameters β_2 through β_4 interact indicators for these income categories with R_{jt}, thus give the differential effect of the treatment for households in those income categories. We additionally control for the level of household income, I_{nj}. All other fixed effects in Equation 3 follow that of Equation 2. We cluster standard errors ε_{it} by city.

The point estimates above the dashed line in Figure 6 show the average treatment effect β_1 from Equation 3 estimated *without* the interaction terms (β_2, β_3, and β_4). The diamonds and circles show, respectively β_1 when the outcome is whether the respondent uses public transit to commute or a car to commute. The black color shows results using the imputed fixed effect estimator while the gray color shows results using traditional least squares. Below the dashed line. point estimates in blue show estimates of β_1 through β_4 from Equation 3 estimated using traditional least squares.

Figure 6 provides two findings. First, our commuting composition results using the individual-level data replicate our main results on commuting modes from Table 2 panels B and C; the estimates above the dashed line show that the likelihood of commuting via transit increases and the likelihood of commuting via car decreases following the rollout of Google Maps real-time tracking. Second, higher income households are more likely to commute via transit following Google Maps real-time tracking relative to lower income households. These results support our hypothesis that higher income households are the most responsive to the treatment due to a high opportunity cost of waiting time. Majid & Vyborny (2018) similarly 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.

5.1 Air Quality

We next test whether these commute mode adjustments have any 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 real-time information l quarters after rollout. We include a vector of city fixed effects α_i, region-by-year fixed effects γ_{dy}, τ_{ds} season-by-region fixed effects, and a control for 2002 ridership per capita interacted

with year fixed effects, ρ_{iy}. We weight observations by the city population as of 2010 to account for the higher degree of transit activity in larger cities.

Figure 7 shows results of Equation 4. This figure provides suggestive evidence that air quality improved following Google Maps real-time tracking. In Panel A, carbon monoxide concentration fell by about 0.013 parts per million on average, or about 3.5%, in the first three years following real-time adoption. Results for nitrogen oxides are also suggestive of air quality improvements. Panel B shows that NOx fell by 2.2 parts per billion (or about 8.5%) on average. However, these results are noisily estimated and are somewhat more sensitive to the choice of control group, thus we interpret these results as suggestive. We show average treatment effects in Panels D and E of Table 2. Again, estimates for NOx are slightly more precise than that of CO, but are marginally insignificant at the 10% level.

6 Private Welfare Calculation

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:

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

where $Google_{cmt}$ 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[9], λ_c are city fixed effects, Φ_{rt} 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

[9]In Table **??**, we use monthly cost as a robustness check.

parameters do not vary by individual i.

Traveller 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:

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

Then normalizing the utility of the outside option ($m = 0$, private transportation) to 0, equation 6 implies that $ln(s_{c0t}) = -ln(\sum_{k=0}^{1} exp(\beta X_{ckt} + \delta Google_{ckt} + \alpha p_{ckt} + \lambda_c + \gamma_t + \Phi_{rq} + \nu_{cmt})$. 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:

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

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 travellers and that each individual takes T_c city-average trips daily[10]. 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 the variation in the use of real-time information in Google Maps across cities. 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.[11] 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).

[10] 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 **??** shows that our results are not sensitive to the choice of rides per trip.

[11] 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.

When considering price changes, public transit agency boards cite equity and affordability as key criteria.[12] Combined this evidence suggests fares are not the outcome of a competitive market and are uncorrelated with shocks to ridership.

The estimated coefficients are shown in Table 3. The estimation sample is smaller than that our our main sample because adult fares data from APTA for specific agencies and modes were only available for a subset of our sample. The results indicate that the willingness-to-pay for Google real-time tracking per trip is between \$0.73 and \$1.3. 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, the last column adds the log of population. Columns (2) and (3) have a smaller sample because household income is sourced from the ACS, which is a subsample of cities. The willingness-to-pay estimate increases with additional controls and with the smaller sample.

7 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 13%, 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

[12] For example 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).

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

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URL: *https://en.wikipedia.org/wiki/General˙Transit˙Feed˙Specification*

Wood, W. & Neal, D. T. (2009), 'The habitual consumer', *Journal of Consumer Psychology* **19**(4), 579–592.

Wood, W., Quinn, J. M. & Kashy, D. A. (2002), 'Habits in everyday life: thought, emotion, and action.', *Journal of personality and social psychology* **83**(6), 1281.

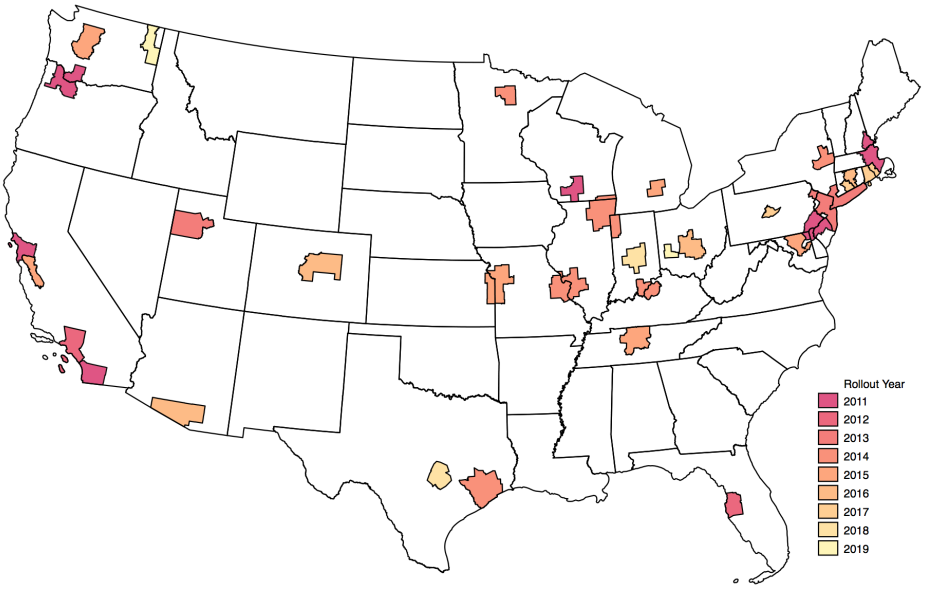


Figure 1: Year that Google Maps implemented Real-time Tracking by Sample Metro Area

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

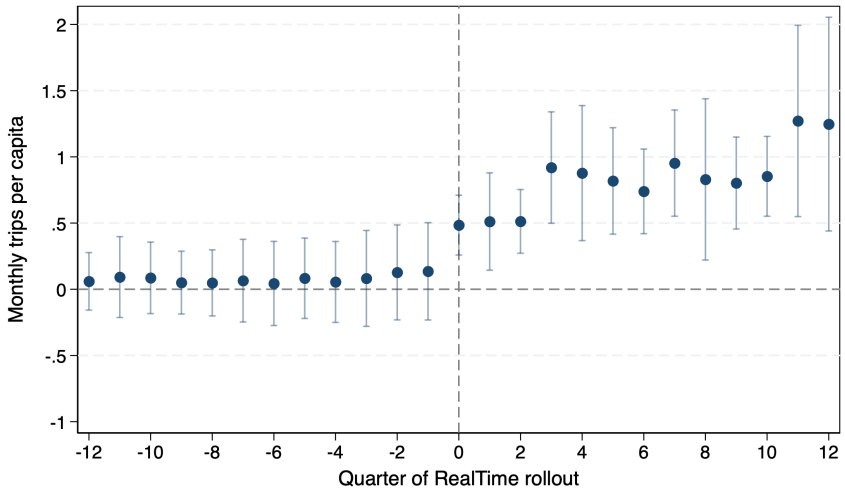
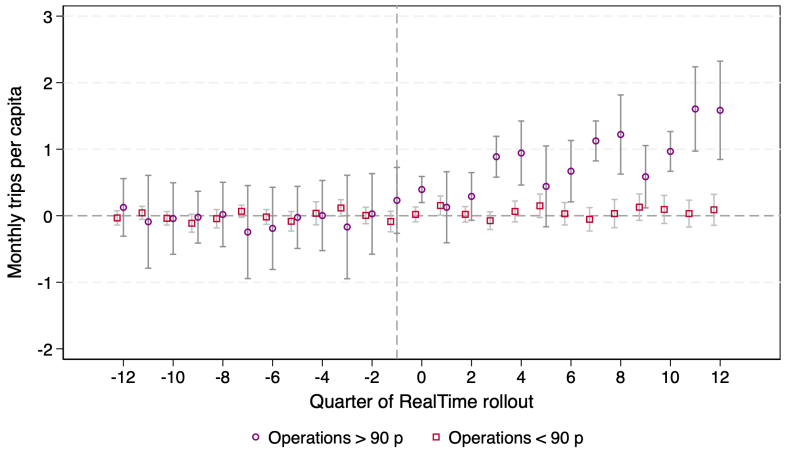


Figure 2: Effect of Real-time Information on Public Transit Ridership

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, and base ridership-by-year fixed effects. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by city. 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

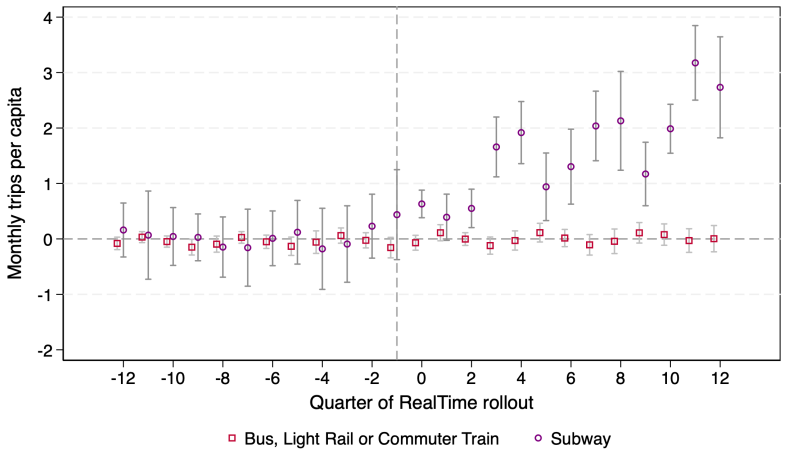


Figure 3: Real-time Effect Heterogeneity

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, and base ridership-by-year fixed effects. Standard errors clustered by city. 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.)

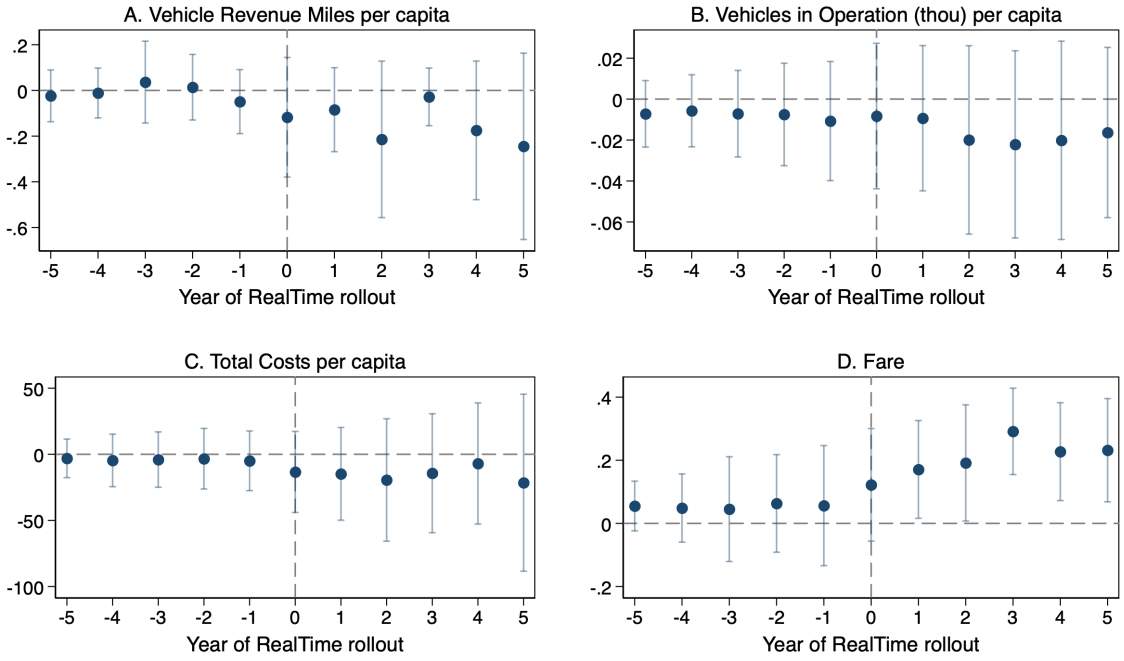


Figure 4: Trends in Transit Agency Operations Relative to Google Real-time Rollout

Note: Figure plots the estimates and 95% confidence intervals of Google Real-time Effect on one of four transit agency operation outcomes using Eq. 1. Each dot shows the change in an outcome in year t relative to year $y = 0$, the year of Google Maps real-time implementation. All estimates based on the imputation method (Borusyak et al. 2024). Panel A is annual vehicle revenue miles per capita. Panel B is vehicles in operation per capita. Panel C is total annual costs per capita. Panel D is the average single-ride adult fare sourced from the APTA. 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 at by city.

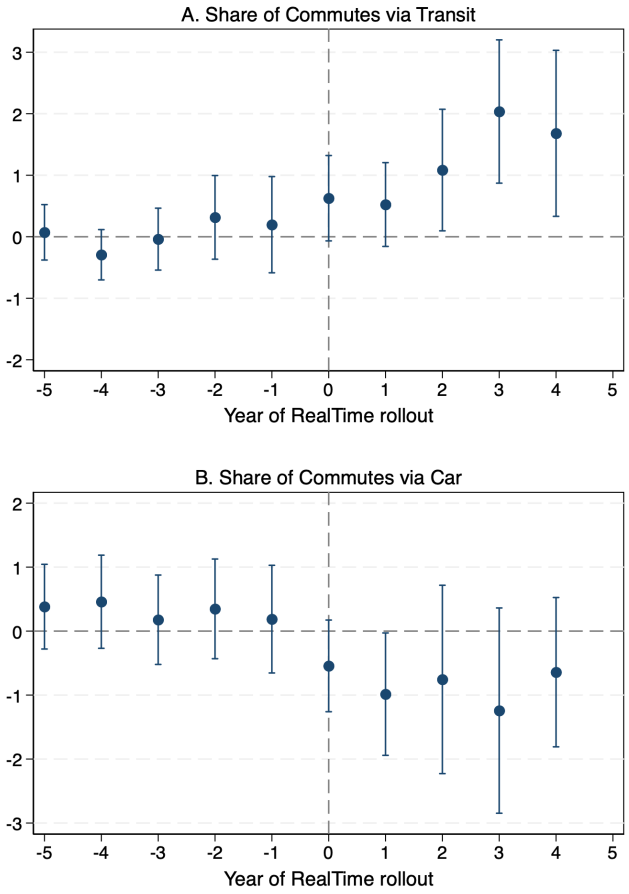


Figure 5: Effect of Real-time Information on City-Wide Composition of Commutes

Note: Figure plots the estimates and 95% confidence intervals of κ_l using Eq. 2. The outcome is the share of a city's population who commute via public transit in Panel A; and the share of a city's population who commute via car in Panel B. All estimates based on the imputation method (Borusyak et al. 2024). Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, and base ridership-by-year fixed effects. Standard errors clustered by city. City-level commute shares sourced from ACS.

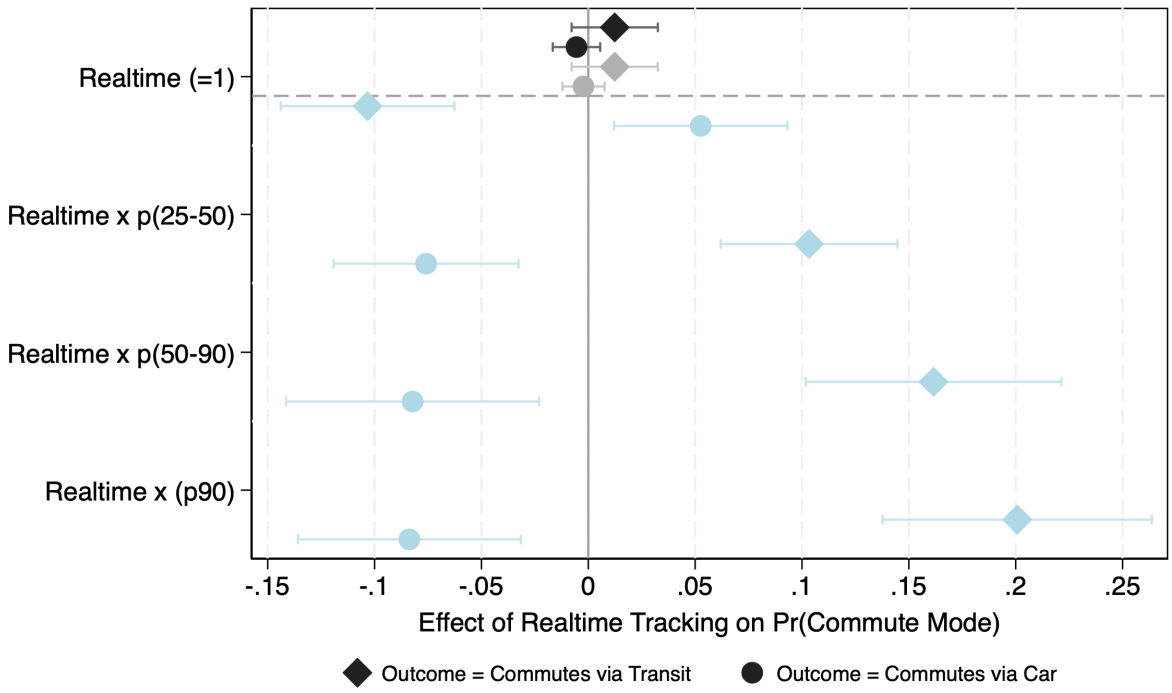


Figure 6: Real-time Information, Commute Mode Choice, and Household Income

Note: Figure shows estimates from Eq. 3, the effect of real-time tracking on commute mode choice, and the heterogeneous effect by household income. Point estimates above the dotted line show the average treatment effect β_1 from Equation 3 estimated without the interaction terms (β_2, β_3, and β_4). The diamonds and circles show, respectively β_1 when the outcome is whether the respondent uses public transit to commute or a car to commute. The black color shows results using the imputed fixed effect estimator while the gray color shows results using traditional least squares. Point estimates in blue show estimates of β_1 through β_4 from Equation 3 estimated using traditional least squares. Standard errors clustered by city. Data on commute modes and household income sourced from the ACS. Estimates based on a sample of 2,020,656 observations.

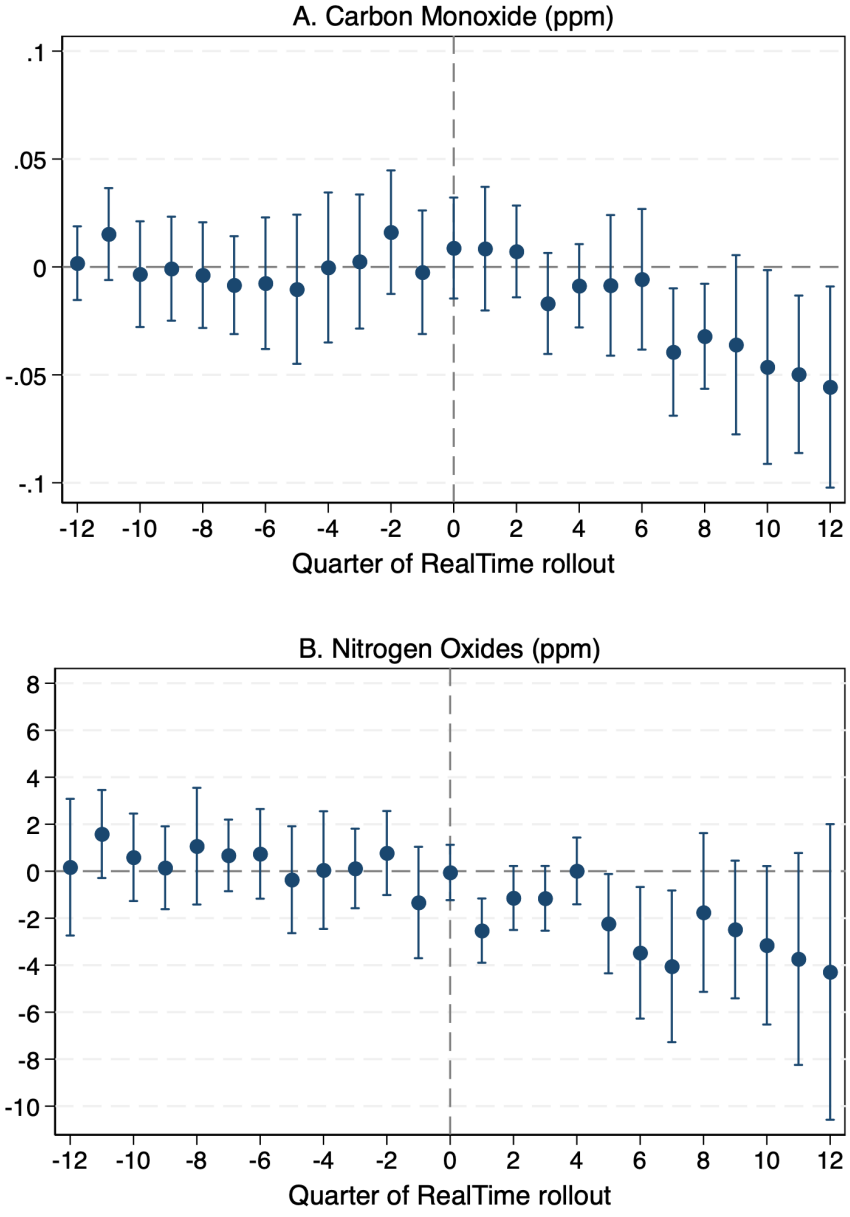


Figure 7: Effect of Real-time Information on Air Quality

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 agency-mode fixed effects, region-by-year fixed effects, and season-by-region fixed effects. Standard errors clustered by city. Air quality data sourced from the EPA. Estimates are weighted by the 2010 city population.

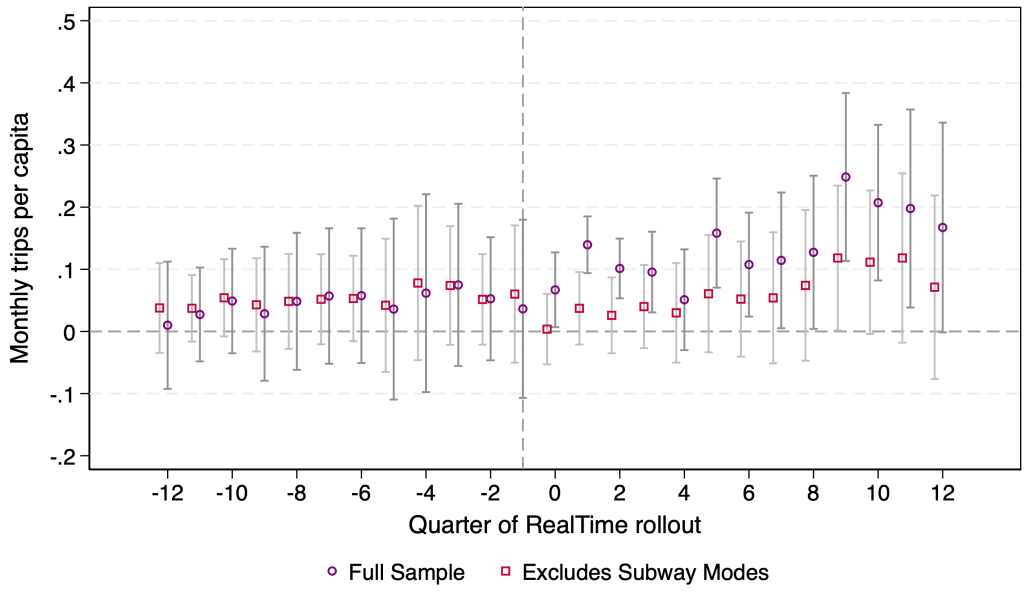


Figure 8: Effect of Proprietary Tracking Apps on Public Transit Ridership

Note: Figure plots the estimates and 95% confidence intervals of δ_l using a version of Eq. 1 where R_i is the quarter when an agency's proprietary app was introduced. The red squares and purple circles indicate distinct samples. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, base ridership-by-year fixed effects, and an indicator for Google real-time rollout. Standard errors clustered by city. Observations weighted by 2002 vehicle revenue miles. Parameters estimated using the imputation method (Borusyak et al. 2024).

Table 1: Summary Statistics

	RealTime	Non-RealTime	P-val
Panel A: 2002 Agency Characteristics			
Ridership per capita	3.414	2.005	0.020
Service Area population (thou)	4,609.814	2,036.312	0.044
Service Area sq. mi.	1,802.558	3,723.965	0.654
Fare Revenues ($ mn)	145.321	44.977	0.064
Base Adult Fare ($)	1.722	1.392	0.030
Vehicle Revenue Miles (thou)	2,709.509	900.826	0.009
Operating Vehicles	762.329	263.389	0.010
Total Cost ($ mn)	360.233	124.375	0.018
Share of operations privatized	0.043	0.158	0.024
Number of modes	1.721	1.271	0.001
Pr(Subway)	0.186	0.047	0.011
Pr(Proprietary App by 2019)	0.884	0.800	0.239
Panel B: City Characteristics			
Population (2010)	3,789,053.500	3,499,278.750	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 (2000)	0.211	0.220	0.801
Share of commutes by car (2005)	0.359	0.351	0.696
Share of commutes by public transit (2005)	0.083	0.071	0.478
Average commute time (min, 2005)	24.134	24.779	0.601
Share below poverty line (2005)	0.208	0.213	0.704
Share with bachelor's degree (2005)	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 high-speed internet (2013)	0.658	0.627	0.175
Average Daily NOx (ppb, 2008)	40.234	37.141	0.477
Average Daily CO (ppm, 2008)	0.587	0.572	0.699
Number of Agencies	43	85	

Note: Panels A data sourced from National Transit Database (NTD). 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; outcomes measured in 2005 cover 79 agencies, and outcomes measured in 2013 cover 55 agencies.

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

A. Dep. Var: Trips per capita per month	(1)	(2)	(3)	(4)	(5)
Realtime (=1)	1.328***	1.322***	1.322***	1.217***	2.383***
	(0.301)	(0.303)	(0.306)	(0.244)	(0.257)
OwnApp (=1)		0.080	0.082		
		(0.056)	(0.055)		
Uber (=1)			0.076		
			(0.064)		
Observations	36657	36657	36657	3912	2496
Sample	Full	Full	Full	Above 90p	Subway Mode
Weighted	BaseVRM	BaseVRM	BaseVRM	None	None

B. Dep. Var: Share of Commutes on Transit (%)	(1)	(2)	(3)
Realtime (=1)	1.269***	1.247**	1.244**
	(0.472)	(0.484)	(0.489)
OwnApp (=1)		0.113	0.113
		(0.196)	(0.200)
Uber (=1)			0.030
			(0.311)
Observations	812	812	812
Sample	Full	Full	Full
Weighted	None	None	None

C. Dep. Var: Share of Commutes in Car (%)	(1)	(2)	(3)
Realtime (=1)	-0.961**	-1.050**	-1.040**
	(0.456)	(0.463)	(0.458)
OwnApp (=1)		0.451	0.447
		(0.330)	(0.331)
Uber (=1)			-0.121
			(0.347)
Observations	812	812	812
Sample	Full	Full	Full
Weighted	None	None	None

D. Dep. Var: CO (ppm)	(1)	(2)	(3)
Realtime (=1)	-0.013	-0.013	-0.013
	(0.013)	(0.013)	(0.013)
OwnApp (=1)		-0.001	-0.001
		(0.008)	(0.008)
Uber (=1)			-0.007
			(0.025)
Observations	12328	12328	12328
Sample	Full	Full	Full
Weighted	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)

E. Dep. Var: NOx (ppb)	(1)	(2)	(3)
Realtime (=1)	-3.347	-3.358	-3.586
	(2.271)	(2.278)	(2.728)
OwnApp (=1)		0.148	0.165
		(0.397)	(0.398)
Uber (=1)			-0.568
			(1.515)
Observations	10821	10821	10821
Sample	Full	Full	Full
Weighted	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)

Note: Dependent variable is transit trips per month per capita. Standard errors clustered at the UZA (city) level. Sample spans three years prior and three years after real-time rollout. Controls include agency-mode fixed effects, year-by-region fixed effects, quarter-by-region fixed effects, and base ridership per capita-by-year fixed effects. "BaseVRM" stands for vehicle revenue miles as of 2002. Parameters estimated using the imputation method (Borusyak et al. 2024). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Standard Logit: Reduced-Form Estimation Results

	(1)	(2)	(3)
Realtime (δ)	0.610***	0.944***	1.037***
	(0.155)	(0.222)	(0.211)
Fare (α)	-0.832***	-0.904***	-0.797***
	(0.134)	(0.126)	(0.149)
Ln(Service Area Population)			-0.996**
			(0.407)
Ave Household Income(x 10^4)		0.006	0.202*
		(0.115)	(0.122)
Observations	11,911	5,557	5,557
Region-by-quarter-by-Year FE	Y	Y	Y
City FE	Y	Y	Y
$WTP = -\frac{\delta}{\alpha}$ per trip	0.733	1.044	1.300

Note: Observations in the table are aggregated at the agency-city-month-year level. All regressions include region fixed effects interacted with quarter interacted with year fixed effects and city fixed effects. Standard errors are clustered at city level. Parameters estimated using Borusyak et al. 2024. Regressions weighted by agency-mode vehicle revenue miles as of 2002. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

A Additional Figures

Figure A.1: 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.

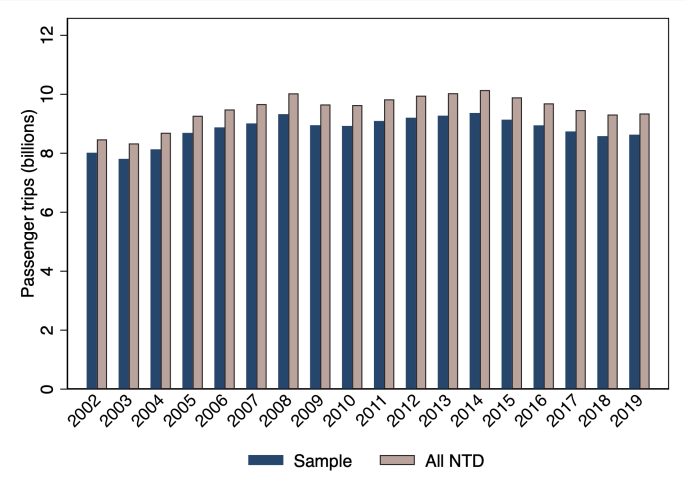


Figure A.2: Annual Passenger Trips for Sample vs Population of Transit Agencies

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.

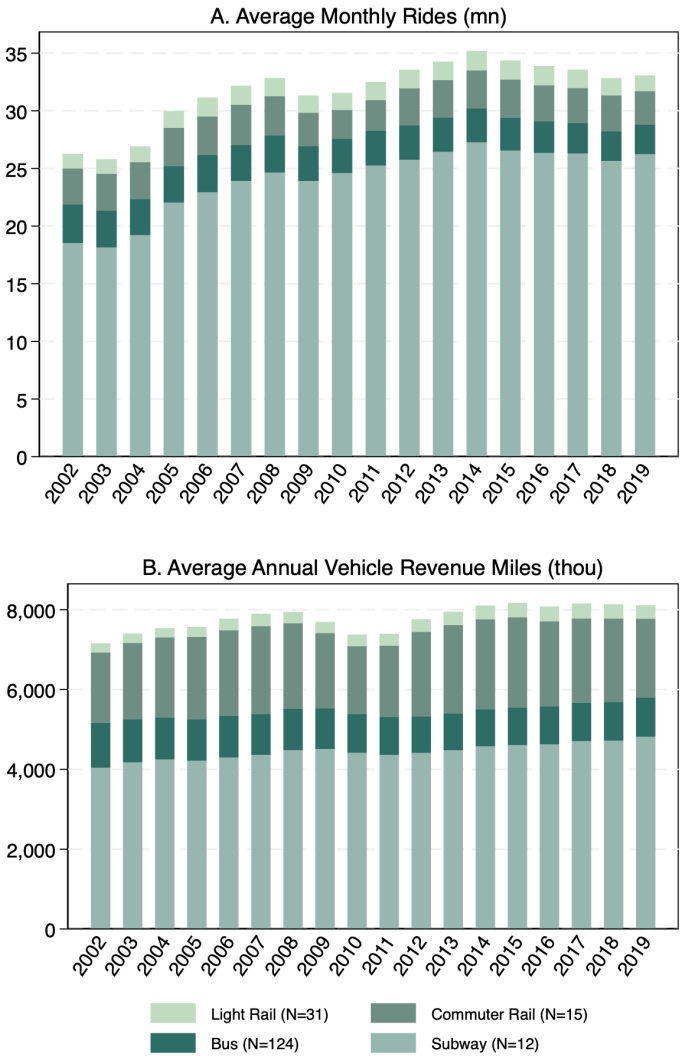


Figure A.3: Composition of Public Transit Operations

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.

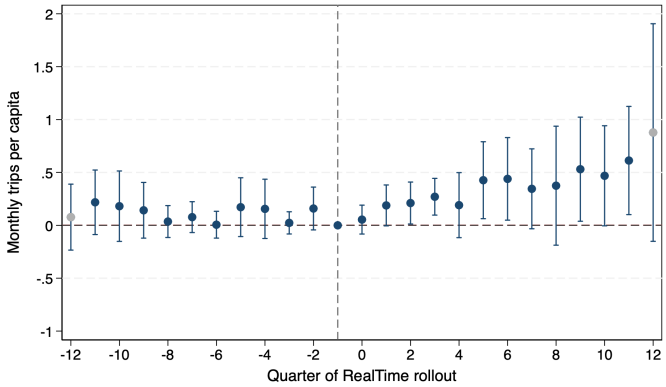
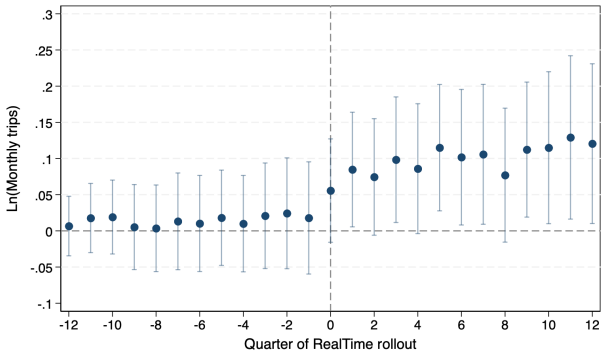


Figure A.4: Difference-in-Differences Method: Effect of Real-time Information on Ridership

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 quarter $q = -1$, the quarter prior to Google Maps real-time implementation. 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 at the agency and year level. Parameters estimated using traditional least-squares.

A. Imputation Method



B. Difference-in-Differences Method

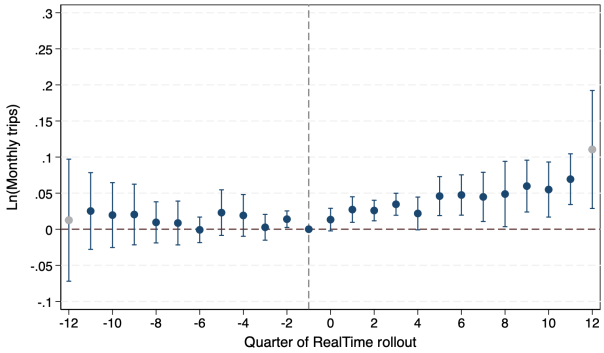


Figure A.5: Specification Sensitivity: Log(Monthly Trips)

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1 where y is log(monthly trips). Each dot shows the change in log(monthly trips) in quarter q relative to quarter $q = -1$, the quarter prior to Google Maps real-time implementation. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, and base ridership-by-year fixed effects. Standard errors clustered at the UZA level. Panel A is estimated using the imputation method (Borusyak et al. 2024). Panel B is estimated using traditional least squares.

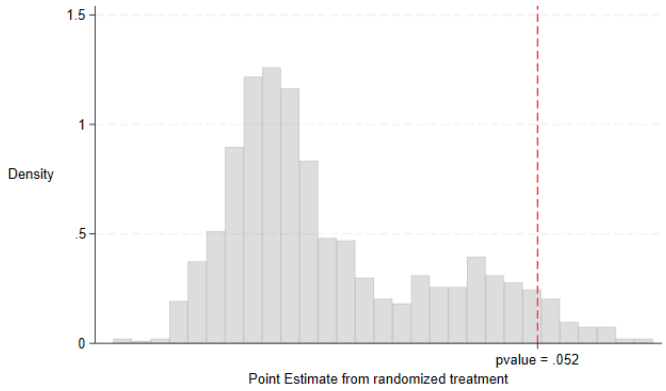


Figure A.6: Placebo test: Effect of Real-time Information on Never-treated Agencies

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1 by randomly assign the treatment time of agencies in the treatment group including never-treated. 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. 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 city. Parameters estimated using the imputation method (Borusyak et al. 2024).

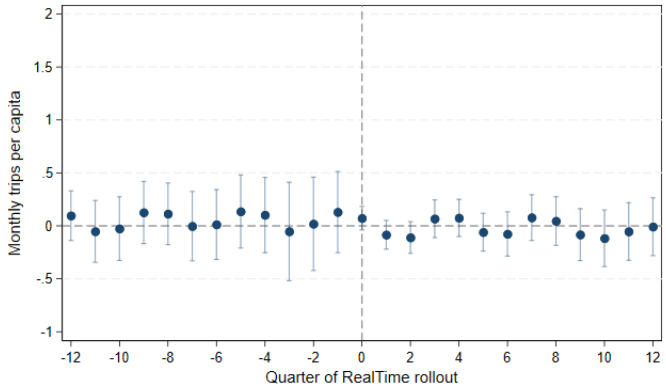


Figure A.7: Placebo test: Effect of Real-time Information on Never-treated Agencies

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1 by randomly assign the treatment time of never-treated agencies. 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. 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 city. Parameters estimated using the imputation method (Borusyak et al. 2024).

Table A.1: Least Squares Estimates of Effects of Real-time Transit Tracking on Ridership

A. Full Panel (2002-2019)

	Imputed	Diff-in-Diff				
Dep. Var: Trips per capita per month	(1)	(2)	(3)	(4)	(5)	(6)
Realtime (=1)	1.328***	0.352	0.012	0.074	0.354	0.355
	(0.448)	(0.301)	(0.085)	(0.068)	(0.283)	(0.306)
Realtime x Subway Mode			1.226***			
			(0.427)			
RealTime x over p90				0.335		
				(0.298)		
OwnApp (=1)					0.018	-0.055
					(0.128)	(0.105)
Uber (=1)					-0.104	-0.084
					(0.195)	(0.144)
Privatized Share						-0.048
						(0.166)
Ln(Service Area Population)						-0.219*
						(0.129)
Share population with bachelor's degree or more						-4.866
						(6.524)
Share of population below poverty line						-1.052
						(2.670)
Avg Travel time to work (min)						0.127**
						(0.048)
APTA adult fare						0.340*
						(0.175)
Observations	36657	36657	36657	36657	36657	8952
Adjusted R^2		0.975	0.905	0.904	0.975	0.984
Sample						
Weighted	BaseVRM	BaseVRM	None	None	BaseVRM	BaseVRM

B. Panel Includes 3 Years Before & After Rollout

	Imputed	Diff-in-Diff				
Dep. Var: Trips per capita per month	(1)	(2)	(3)	(4)	(5)	(6)
Realtime (=1)	0.592**	0.267*	0.053	0.058	0.255*	0.407*
	(0.251)	(0.147)	(0.060)	(0.061)	(0.140)	(0.235)
Realtime x Subway Mode			0.445**			
			(0.193)			
RealTime x over p90				0.195		
				(0.158)		
OwnApp (=1)					0.089	0.180
					(0.071)	(0.138)
Uber (=1)					0.041	0.017
					(0.094)	(0.131)
Privatized Share						0.021
						(0.148)
Ln(Service Area Population)						-0.125*
						(0.074)
Share population with bachelor's degree or more						-3.539
						(2.779)
Share of population below poverty line						-0.660
						(1.728)
Avg Travel time to work (min)						0.030
						(0.018)
APTA adult fare						0.217
						(0.130)
Observations	29187	29187	29187	29187	29187	7353
Adjusted R^2		0.981	0.894	0.894	0.981	0.987
Weighted	BaseVRM	BaseVRM	None	None	BaseVRM	BaseVRM

Note: Dependent variable is transit trips per month per capita. Standard errors clustered at the UZA (city) level. Sample spans three years prior and three years after real-time rollout. Controls include agency-mode fixed effects, year-by-region fixed effects, quarter-by-region fixed effects, and base ridership per capita-by-year fixed effects. "BaseVRM" stands for vehicle revenue miles as of 2002. Parameters estimated using standard least-squares. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

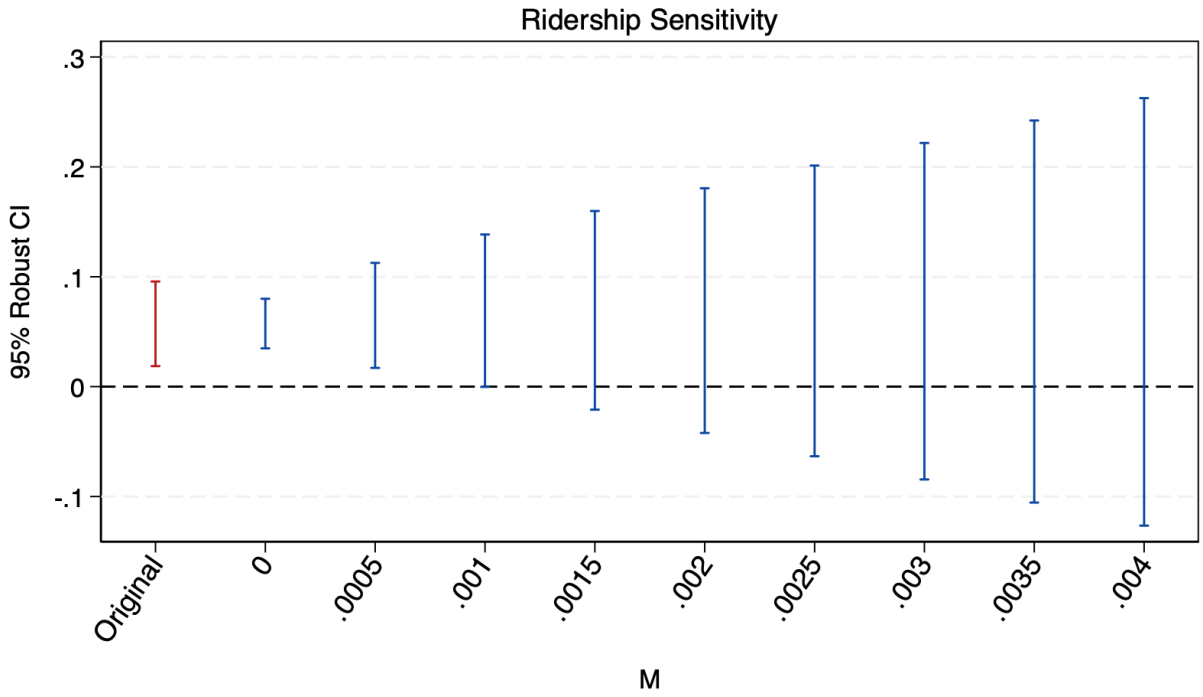


Figure A.8: Parallel Trends Sensitivity Analysis for Ridership Effect

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

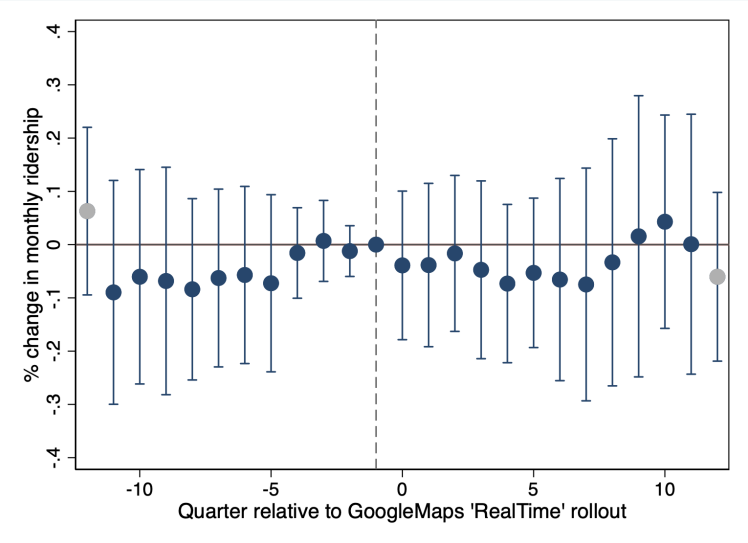


Figure A.9: Placebo Test: Effect of Randomized Rollout Date on Public Transit Ridership

Note: Figure plots point estimates and 95% confidence intervals for the effect of randomly-assigned rollout dates on log ridership. S
and control agencies. Coefficients are estimated at the quarterly level using monthly data. Standard errors clustered at agency and

Table A.2: 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



Figure A.10: Rollout of Proprietary App relative to Google Maps Real-time Tracking

Figure A.11: 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-s
- 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/