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

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Abstract

Widespread adoption of smart phone applications have fundamentally changed how individuals navigate complex, information-rich environments. This paper examines how a key innovation in a ubiquitous smart phone app—Google Maps—influenced travel behavior. Using a new dataset on the availability of real-time transit tracking within Google Maps across 128 transit systems, we show that ridership per capita was 13.6% larger 3 years after the staggered rollout. Survey data on commutes confirms this pattern and shows commuters substituted away from car trips. We see suggestive evidence that air quality improved. Google's impact was largest in highly complex transit systems, and real-time tracking in alternative navigation applications had much smaller effects. Our findings highlight that cognitive costs are a crucial, but overlooked, determinant of urban travel.

Keywords : Public Transportation; Travel Behavior; Travel Time

JEL Classification Codes: R42, R41, H44

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1 Introduction

Advances in digital technology have fundamentally altered how individuals make everyday decisions. Central to this shift is the emergence of mobile phone applications (apps) that deliver real-time information at the moment decisions are made. Such information has been shown to reduce mortality in response to hourly air quality updates [Barwick et al., 2024], lower exposure to violence through crowd-sourced alerts [Aker and Mbiti, 2010], and decrease resource consumption via daily usage feedback [van den Berg et al., 2025].

In complex choice environments, app-based services affect decision making not only by providing timely information, but also by transforming, simplifying, and personalizing that information. For instance, urban transit systems—especially in the world's largest cities—are so complex that effective navigation can exceed individual cognitive capacity [Gallotti et al., 2016]. Navigation apps are designed to translate this high-dimensional spatial information into straightforward directions, which likely contributes to their widespread adoption.[1]

This paper studies a key innovation of one of the earliest and most widely adopted smartphone apps: Google Maps. We examine how the introduction of real-time public transit tracking information in Google Maps affected urban travel behavior in the United States (U.S.). Nearly three-quarters of U.S. smartphone users rely on Google Maps for real-time information on traffic conditions, transit schedules, routing options, and travel times [Lee, 2025]. Given the app's near-universal reach, an open question is whether it influences transit ridership. This question is of particular importance in the U.S., where transit use remains among the lowest in the developed world, where traffic congestion costs tens of billions annually, and where vehicles are among the largest contributors to greenhouse gas emissions and urban air pollution.[2]

Exploiting the staggered availability of real-time tracking across transit agencies, we find that Google increased transit usage and encouraged workers to choose public transit over private vehicles in their daily commutes. Our empirical analysis uses newly-assembled data on the roll-out of real-time transit tracking linked to monthly ridership logs across 128 transit systems, and individual-level data on commute mode choices across major U.S. cities. We find per capita monthly transit trips

[1] Google Maps ranks 25th globally in terms of app download frequency (https://www.blog.udonis.co/mobile-marketing/mobile-apps/most-downloaded-mobile-apps) and 7th among apps that Americans report they cannot live without (https://buildfire.com/app-statistics/).

[2] The transit fleet per urban resident is substantially lower in the U.S. compared to Singapore, Norway, the UK, or Germany [Centre for Science and Environment, 2019]. Couture et al. [2018] estimate that congestion alone costs more than $30 billion annually. Vehicles account for 17 percent of national CO_2 emissions [EPA, 2023c], up to 75 percent of carbon monoxide emissions, and 40 percent of nitrogen oxide emissions [EPA, 2023b].

increased by about 0.8, or 13.6% on average in the three years following Google's adoption of real-time updates. The effects increase over time to almost 1.5 additional trips per capita per month by the end of year three. Treatment effects are driven primarily by agencies with large operations and subway modes. Notably, the ridership effects of this digital intervention are similar in magnitude to those found in prior studies of large-scale transit infrastructure expansions (e.g., Baum-Snow and Kahn [2000], Severen [2021]).

Our results would overstate the effect of Google Maps if Google's rollout targeted cities that were already experiencing increases in transit ridership. Indeed, agencies that gained real-time tracking tend to have higher ridership, more transit modes, and more operating vehicles. Such differences in levels might indicate our estimates are biased if they signal differences in trends. We address this selection concern in several ways. First, we allow for differential trends based on baseline ridership and find no trend in pre-treatment coefficients in our event study specification. Sensitivity analyses on potential violations of the parallel trend assumption [Rambachan and Roth, 2023] suggest that that our results would remain significant even if we allow for large deviations from the estimated pre-trends. Second, we show that other measures of transit agency operations, like total service mileage and operating costs, cannot explain the observed changes in ridership after real-time tracking became available. Third, we match treated and control agencies based on several pre-treatment characteristics and find very similar results to our main findings. Lastly, we conduct a placebo test where we randomly assign the rollout date across agencies and find no effect on ridership. Together, these factors support our assumption that the implementation of Google Maps' real-time tracking across cities was conditionally uncorrelated with trends in transit ridership.

There are several channels through which Google Maps' real-time information may have influenced transit use. To shed light on which features of Google Maps drive our results, we combine a simple theoretical framework with newly compiled data on the rollout of static schedules and alternative transit apps—including proprietary applications developed by transit agencies and other third-party platforms—as well as measures of transit system complexity. We find that accurate, trip-specific travel information is substantially more valuable than basic schedule information. We also show that basic real-time information alone generates much smaller ridership responses than Google Maps' real-time information, suggesting an important role for Google's distinct methods of computing and presenting travel options. Finally, we find that ridership gains are greatest in more complex transit systems. Taken together, these findings indicate that Google's real-time tracking reduced the cognitive costs of urban travel decisions, rather than merely transmitting tracking information.

We quantify a lower bound of consumer benefits through a discrete choice model.[3] Following Berry [1994], we estimate that consumers are willing to pay about $0.70 per trip to access real-time tracking information. Given total ridership at baseline, and the approximate costs of adopting real-time tracking, our estimates suggest that the private benefits alone likely outweigh the costs to transit agencies of real-time tracking. For context, comparing our willingness-to-pay estimate with recent value of time estimates for in-transit travel [Goldszmidt et al., 2020, Buchholz et al., 2020, Wang, 2024] suggests that access to Google Maps real-time tracking is equivalent in value to saving up to 15 minutes of travel or wait time.

If greater ridership arose from substitution away from cars, Google Maps real-time tracking could also have generated substantial external benefits. Reductions in congestion and improvements in air quality would imply the treatment was not only privately beneficial, but also publicly important [Anderson, 2014, Chen and Whalley, 2012, Li et al., 2019, Gendron-Carrier et al., 2022]. Although commute trips comprise only a fraction of total urban travel,[4] we leverage survey data on commute mode choice to provide a transparent illustration of this substitution. Following the introduction of Google's real-time tracking, the share of individuals commuting by public transit rose by 1.16 percentage points (4.0%), while the share commuting by car *fell* by 1.3 percentage points (2.1%). The near mirror-image movement in these shares points to meaningful substitution from private vehicles to transit.

Because commuting behavior is typically the most habitual and least responsive to marginal nudges [Kristal and Whillans, 2020], these patterns likely understate the broader behavioral response. Consistent with this interpretation, we observe improvements in air quality that exceed what could plausibly be attributed to changes in work commutes alone, suggesting more diffuse substitution away from cars and possible congestion relief.

Beyond the aggregate effects of transit interventions, the extent to which transit interventions improve accessibility for low-socioeconomic groups remains a central policy question. A long-

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

[4] 15% of daily trips in the US are taken for commuting purposes. Source: https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-daily-travel-quick-facts.

standing literature emphasizes that public transit can disproportionately improve access to jobs and amenities for the urban poor (e.g., Kain [1968], Glaeser et al. [2008]). However, studies of transit infrastructure expansions often find larger benefits for higher-income riders, reflecting differences in location, travel patterns, and willingness to pay for time savings [Baum-Snow and Kahn, 2000, Mayer and Trevien, 2017, Majid et al., 2018, Wang, 2024]. In contexts where the treatment is information-based, predicting who is most impacted is further complicated by its interaction with individual prior beliefs about transit reliability and timeliness [Byrne et al., 2018]. We find that higher-income commuters account for the bulk of the response to the intervention: Google's use of real-time information induced above-median-income commuters to increase use of transit, and decrease use of cars, and these effects are even larger for above-90th-percentile income commuters. In contrast, real-time information had no impact on car usage for people with below-median income, and slightly reduced transit use for the same group. These results are consistent with our finding that ridership gains were largest among subway modes, which tend to serve higher-income riders [American Public Transportation Association, 2017]. This implies that real-time transit tracking alone is unlikely to improve transit access among the urban poor.

This paper contributes to a growing literature on how digital technologies reduce search frictions and shape economic behavior [Aker et al., 2017, Kroft and Pope, 2014]. Most closely related is work on the Uber economy, which shows that ride-hailing platforms reshape travel mode choice, consumption patterns, and the spatial distribution of economic activity by expanding the set of available travel options [Cohen et al., 2016, Hall et al., 2018, Norris and Xiong, 2023, Gorback, 2024]. In contrast, we study an information-based intervention that leaves the urban transportation landscape unchanged. This distinction allows us to isolate how improved information alone affects mobility, mode choice, and welfare. Relative to recent experimental studies using app-based technologies—often focused on intensive-margin decisions and restricted samples [Agarwal et al., 2025, Kreindler, 2024]—we examine an omnipresent navigation app at scale, covering the vast majority of transit trips among major U.S. cities across several transit modes over 18 years.

Our study also relates to a large, existing literature on transit infrastructure, transit subsidies, and economic development [Mayer and Trevien, 2017, Donaldson, 2018, Gonzalez-Navarro and Turner, 2018, Zárate, 2022]. We document novel findings that a navigation app can rival large-scale infrastructure policies in terms of its impacts on transit usage. Recent studies focused on infrastructure expansion efforts [Baum-Snow and Kahn, 2000, Tsivanidis, 2024, Majid et al., 2018, Severen, 2021] have found that 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 alternative policy levers to increase transit use.

Among studies examining real-time transit tracking and ridership [Ferris et al., 2010, Tang and Thakuriah, 2012, Chow et al., 2014, Brakewood et al., 2015], ours is the first to study Google Maps and to apply quasi-experimental methods at national scale. Using a multi-year, national panel of transit agencies, we find similarly modest effects for proprietary apps, but economically large and sustained ridership gains from Google's unique provision of real-time information generated.

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

Our paper is structured as follows. Section 2 provides background on Google Maps and the incorporation of real-time tracking. Section 3 outlines the data collected for the study. Section 4 describes the empirical strategy to identify the impacts of real-time tracking availability on ridership, and presents these results. Section 5 describes the analysis of the impacts of real-time on commute mode switching, and Section 6 on air quality. Section 7 presents the discrete choice model used to value its private benefits. Finally, Section 8 concludes.

2 Background

2.1 Google and Transit Tracking

"Real-time" tracking refers to the minute-by-minute tracking of transit vehicles.[5] When transit vehicles run on schedule, static transit schedules match real-time data. When vehicles are early, delayed, or disrupted, real-time tracking gives a more accurate prediction of arrival times and trip durations. Buses and other surface vehicles are tracked via GPS, while subways and other right-of-

[5] Transit professionals often refer to real-time tracking as "automatic vehicle location (AVL) systems".

way vehicles rely on signaling systems and onboard sensors to estimate vehicle locations. Transit agencies have historically used these data in operations management to track vehicles and adjust service long before it was presented to riders through trip-planning applications.

Dissemination of real-time transit tracking to the general public has been enabled by General Transit Feed Specifications or "GTFS" feeds. First developed by a Google employee in 2005, GTFS feeds are a standardized method for organizing transit information in a way that is easily analyzed by computer software.[6] Although the "G" originally stood for Google, GTFS soon became the *de facto* standard for sharing schedule and tracking information across transit agencies [Ferris et al., 2010]. GTFS feeds also enabled developers, including Google, to create mobile phone applications. Several major transit agencies like the BART in San Francisco, the MBTA in Boston, and the CTA in Chicago developed their own apps as early as 2011.[7] The availability of these proprietary agency apps and trip-planning tools meant that users could access real-time information through their mobile phones prior to Google Maps in some locations.

Google Maps' adoption of real-time tracking was particularly influential for several reasons. First, Google Maps was the earliest to map GTFS feed stop identifiers to a user's location [Ferris et al., 2010].[8] Second, the Google Maps app was broadly adopted by cell phone users during the time period of our study. One in two mobile phone users across the globe utilized the Google Maps app as early as 2013.[9] Third, Google Maps displayed transit information for *several* agencies, meaning users could look up transit information across multiple agencies within one app. Lastly, Google Maps incorporated real-time tracking into its unique prediction and optimization algorithms. While most agency apps provided onboard travel predictions, Google Maps provided users with travel time predictions inclusive of transfers, switching modes, and walking to and from transit stops.

Our study spans 2002–2019, a period during which the scope, accessibility, and accuracy of information provided by Google Maps expanded substantially. For example, this period saw broader smartphone access, improvements in travel-time and traffic predictions, and directions for biking and ride-hailing. As long as these changes do not correlate with the agency-mode-specific

[6] A GTFS feed is specifically a zip file containing multiple text files, each representing a different type of transit information (e.g. stops.txt, routes.txt, trips.txt, etc.) Each file has a specific schema which ensures that software can consistently parse and interpret the data, regardless of the transit agency.

[7] For 6 agencies in our sample, their earliest non-Google Maps trip planning app was either Transit or OneBusAway, which are multi-agency, third party apps. For the 114 other agencies in our sample for which we were able to find alternative apps, their earliest alternative apps were agency-specific.

[8] Throughout this paper, we refer to "Google Maps" synonymously with "Google Transit", however Google Transit is technically a feature within Google Maps focused on trip planning via public transit.

[9] Source: `https://www.businessinsider.com/google-smartphone-app-popularity-2013-9`)

rollout of real-time transit tracking, our empirical design remains valid. However, because these platform-wide improvements may generate time-varying treatment effects across adoption cohorts, we employ estimators that are robust to heterogeneous treatment effects in staggered adoption settings [Wooldridge, 2021, Borusyak et al., 2024] throughout our analysis.

2.2 Conceptual Framework

In this section, we illustrate how real-time transit tracking information can affect the decision to take public transit. For simplicity, consider an individual i choosing between two transport modes m, where $m = B$ is public transit, and $m = C$ is private transport. This individual prefers transport that is cheap, quick, certain, and simple. More formally, their utility is a function of the cost, or price of mode m (p_m), the time taken to complete the journey (Time_m), and other features of the journey (x_m) such as comfort. Travel time is stochastic with mean μ and variance σ. Risk-averse individuals make decisions based on their beliefs about the mean and variance of travel times $\Big(\mathbb{E}_i[\mathrm{Time}_m] = g(\mu), \mathbb{V}_i[\mathrm{Time}_m] = h(\sigma)\Big)$. They may also incur an additional decision-making, planning or attention cost, which is a function of route or network complexity (D_m). Let individual i's utility from taking m at time t be $u_{im} = f\Big(\mathrm{p}_m, \mathbb{E}_i[\mathrm{Time}_m], \mathbb{V}_i[\mathrm{Time}_m], x_m\Big)$. To account for the possibility that individuals are unaware of the utility from transit, we allow the salience of transit utility to vary with parameter $\lambda \in \{0, 1\}$, where $\lambda = 0$ means transit is not a salient option. Then the individual takes transit if $\lambda\,[u_{iB} - D_B] > u_{iC} - D_C$ and otherwise chooses private transport.[10]

Consider the introduction of transit schedules and real-time information in Google Maps. These technological improvements may affect the decision to take public transit through several channels. First, they might affect the salience of transit through λ, which increases the probability of taking transit. Second, real-time information may alter actual travel time because individuals re-optimize. This could occur if actual travel times μ and the variance of travel time σ falls, because for example, more accurate transit arrival times allow riders to reduce wait time or to select alternative routes that avoid delays.[11] All else equal, lowering the expected travel time and its variance unambiguously increases transit use. Third, real-time information may also correct beliefs about the distribution of transit times, holding constant μ and σ. For example, if an individual always expects the bus to be on time, then real-time information on delays will cause their beliefs about expected travel

[10] We assume that $u_{iC} - D_C > 0$ so the individual always chooses to travel

[11] It is also possible that actual travel times fell following real-time information because agencies may have improved on-time performance, although our analysis in Section 4.5 indicates that total service levels and operating costs did not change following Google's real-time rollout.

times to be more accurate. Thus, the effect of real-time information is ambiguous when considering its dependence on prior beliefs. Finally, real-time information within a navigation app may reduce the decision-making complexity of route planning (D_B). In particular, Google Maps simplifies the choice set by providing a succinct, user-friendly, and—crucially—real-time-dependent comparison of travel choices; and reduces the cost of taking more complex (i.e., multi-line or multi-mode) routes because users are no longer required to formulate their own expectations of whether connecting services are on time. These complexity-reducing effects should increase public transit use.

Although data limitations prevent us from isolating the precise channel through which real-time information affects transit use, the framework highlights that the expected effect of Google Maps' real-time rollout is theoretically ambiguous and likely varies between individuals and across agencies. To shed light on the underlying mechanisms, we first examine the ridership impact of integrating transit schedule information into Google Maps, assessing whether increased salience of transit (λ) can account for the observed effects. We then contrast the impact of real-time information in Google Maps with its availability in agency apps, which were less user-friendly and less effective at reducing system complexity. We also test whether the effect of Google integrating real time information is larger in more complex transit systems. Together, these analyses reveal whether reductions in decision-making costs (D_B), salience of transit (λ) or changes in beliefs ($g(\mu), h(\sigma)$) are responsible for changes in ridership. Finally, we explore heterogeneity by system size, mode, and income to characterize where treatment effects are most pronounced.

3 Data Description

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

3.1 Transit Agency Ridership and Operations

We measure transit ridership and transit agency operations using data from the National Transit Database (NTD). The NTD provides the most comprehensive data source of which we are aware on public transit systems in the U.S. The data source provides detailed information on over 600 transit agencies back to 2002. Our unit of observation is a transit agency-by-mode pair where a mode takes one of four categories: bus, subway, commuter rail, and light rail.[12] We collected

[12]The NTD data distinguishes between over 20 mode categories. We focused our roll-out date search for five categories: bus, subway, commuter rail, light rail, and streetcar. These five categories collectively make up over 75% of all

information on monthly ridership, and annual-level operating expenses, fare revenues, number of transit vehicles in service, and number of miles in service at the agency–by–mode level. We also construct a measure of the share of privatized operations based on the share of vehicle revenue miles operated by private contractors. One aspect of note is that our measure of ridership is based on a count of "unlinked passenger trips", meaning a unique vehicle boarding. A single journey with transfers, therefore, generates multiple observations in our data.

3.2 Google Maps & Agency-Specific App Real-time Data Rollout

We manually gathered information on the availability and rollout date of Google Maps' real-time tracking by transit agency and mode. We determined rollout dates using press releases, blog posts, tweets, and other media posts from Google, transit agencies, and local news sources.[13] Appendix Figure A.1 provides two examples. We used a similar strategy for collecting information on the availability of static transit schedules within Google Maps as well as the rollout of agency-specific transit tracking apps.

We focused our search on the 128 largest transit agencies by annual revenue and ridership to maximize the likelihood of identifying accurate rollout dates. Generally, Google implemented real-time tracking at the same time across modes within an agency, although there are exceptions. We found evidence of Google real-time tracking for at least one mode among 44 agencies, corresponding to 56 treated agency-by-mode pairs as of 2019. For the remaining modes within these agencies we found no evidence of real-time tracking for 18 agency-by-mode pairs—typically commuter rail. Among the other 84 agencies, we found no reports of real-time tracking adoption for any mode by 2019. These agencies contribute 126 untreated agency-by-mode pairs, which we use as controls.[14]

Figure 1 maps the rollout dates for the 44 treated agencies in our sample. Notably, early adopters were not always the largest cities; smaller metro areas such as Madison adopted in 2011 alongside major West Coast cities like Portland, San Diego, and San Francisco. Conversations with personnel from Madison's Metro Transit agency suggest that Google often prioritized transit agencies with more sophisticated data management practices when deciding where to implement GTFS-based real-time tracking. As a result, early adopters tended to have relatively high transit ridership, though not necessarily the largest populations.

vehicle revenue miles in the NTD ("vehicle revenue miles" is the NTD's measure of transit miles in service). For ease of exposition, we categorize streetcar modes in "light rail", resulting in 4 total modes.

[13] In 2022, the authors—with the help of Google's chief economist—requested roll-out date information from Google employees, directly. Google declined to share this information with the authors.

[14] Section 4.2 presents robustness checks on potential misclassification of treatment assignment.

3.3 Commuting, Demographics, Network Complexity, & City Characteristics

To investigate commuting patterns and demographic heterogeneity, we obtained individual-level data from the American Community Survey (ACS), accessed through IPUMS [Ruggles et al., 2024], for years 2005 through 2018 on the primary mode of commute as well as income and education levels for over 1.2 million individuals across 74 cities in our sample. ACS data only report the city of residence for individuals living in cities with populations over 250,000, thus some cities are dropped from analyses using these data. We collect city-level demographics from the 2000 and 2010 US Decennial Census, including racial composition, educational attainment, and poverty rate. As a robustness check, we control for the availability of Uber, which we source from Hall et al. [2018].

To measure transit system complexity, we collect agency-specific information on unique transit stop identifiers and stop sequences along unique routes using General Transit Feed Specification (GTFS) data. We searched for the earliest GTFS feeds—typically 2013 or 2014—of each agency in our sample in order to approximate the transit network in place at the advent of real-time tracking in Google Maps.[15] Our measure of complexity, "Area x Vertex Degree", is inspired by graph-theoretic measures of network complexity from Garrison and Marble [1962]. The average vertex degree captures the number of directly connecting stops accessible from a given stop, and reflects the transferability and size of local choice sets faced by riders.[16] We then interact the city's average vertex degree with it's total transit service area. Our resulting complexity measure captures how highly networked transit systems covering a larger geographic area tend be more difficult to navigate relative to those over a smaller geographic area.

3.4 Air Quality

Our air quality measures come from the EPA Daily Outdoor Air Quality Data. The EPA data provide monitor-level readings from 2008 through 2019 for 87 cities in our sample. We assign a monitor to a city if it is located within 25 miles of the city's centroid, and exclude air quality readings from exceptional events, like wildfires or dust storms. We use readings from a 1-hour sample duration for comparability, as NOx readings are only available with a 1-hour sample duration.[17]

[15] Although GTFS data are available by agency and mode, we aggregate our complexity measure to the city level due to data limitations. Among the 109 agencies for which we were able to find historic GTFS feeds, the vast majority reported data for only one mode. Further, for several multi-agency cities in our sample, we were only able to find one agency.

[16] To construct the measure, we use the stop identifiers and sequences from GTFS to identify direct connections between stops. We then average the number of connections per stop within a city's entire transit network to calculate the average vertex degree.

[17] CO results, available upon request, look very similar for readings from an 8-hour average sample duration.

We focus on carbon monoxide (CO) emissions and nitrogen oxides (NOx) for two reasons. First, both pollutants are highly indicative of motor vehicle exhaust: in the U.S. over 50% of CO emissions and 45% of NOx emissions are produced by on-road vehicles. These shares are higher in urban areas [EPA, 2023a, 2025]. Second, unlike particulates, NOx and CO are directly emitted from vehicle tailpipes and are locally concentrated in areas with heavy traffic, making them more informative about changes in urban vehicle use.

3.5 Descriptive Statistics

Table 1 reports mean agency characteristics for agencies that had real-time tracking as of 2019 and agencies that did not. The third column reports the p-value for the significance of the difference in means. Most characteristics are measured as of 2008—three years prior to the implementation of real-time tracking in any US city—except for population (measured in 2010), and 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 could reflect Google's profit incentive to prioritize locations that generate large volumes of passenger trip data. Real-time cities are also slightly more likely to be in Western states and less likely to be in the South.

Because differences in ridership levels may create differential ridership growth across agencies, our empirical design controls for time trends interacted with baseline agencies' ridership levels. We estimate treatment effects conditional on agency-by-mode fixed effects to net out fixed operational differences across agencies, as well as region-by-year fixed effects to account for regional growth differences across agencies. Notably, most city-level characteristics shown in Panel B are well-balanced, suggesting that local economic factors and demographics were not significant drivers of Google Maps' real-time rollout.

While our sample of 128 agencies captures just 20% of agencies in the NTD, this sample comprises the vast majority of transit usage: 92% of all passenger transit trips in the U.S. occur within the 128 agencies in our sample (see Appendix Figure A.2). Even within our sample, transit usage is distributed unevenly. Appendix Figure A.3 shows the composition of monthly ridership by mode (Panel A) and the composition of mode type (Panel B). The majority of all transit rides happen on subways. Although 68% of agency-modes are buses (124 agency-mode pairs), the vast majority of transit rides occur on just 7% of all agency-modes (one of 12 subway systems) in our sample.

4 Effects of Real-Time Tracking on Ridership & Operations

Our primary objective is to assess whether the introduction of real-time transit tracking through Google Maps affected transit ridership. This section presents our baseline estimates and a set of complementary analyses that evaluate whether alternative factors, such as the availability of pre-existing tracking apps or changes in agency operations, may explain the observed ridership effects.

We estimate changes in ridership, agency operations, and other outcomes using the following:

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

where r_{imt} is an outcome for agency i and mode m in month-of-sample t. 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. Equation 1 includes agency-by-mode fixed effects, η_{im}, to absorb time-invariant unobserved differences across agency–mode pairs. We also include region-by-year fixed effects, γ_{dy} (e.g., Northeast $\times$ 2015), and region-by-season fixed effects, τ_{ds} (e.g., Northeast $\times$ winter), to account for regional growth trends and geographically specific seasonality in transit use—such as the tendency for ridership in northern U.S. regions to peak in the fall and spring. Finally, $\boldsymbol{\rho}$ captures a set of agency–mode characteristics interacted with year fixed effects, including 2002 ridership per capita and an indicator for cases in which we observe only the date that Google Maps real-time tracking was actively in use rather than its initial availability. This latter category applies to 12 agency–mode pairs. Together, these controls allow for differential growth across agency–modes with different baseline ridership and for agencies that likely adopted earlier than our data allow us to observe.[18]

We weight observations in Equation (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. Vehicle revenue miles (miles covered by in-service transit vehicles) captures the combined size effects of population, service frequency, and geographic service density. Following Solon et al. [2015], we also directly model heterogeneity by agency-mode size in unweighted regressions. To account for arbitrary serial correlation in travel behavior within

[18] We exclude the 12 "in use" agencies as a robustness check in Section 4.2 and find very similar results.

a given metro area, standard errors ε_{it} are clustered by city.[19]

Empirical designs such as ours that are based on staggered treatment timing may produce biased estimates when treatment effects vary across units or over time [De Chaisemartin and d'Haultfoeuille, 2020, Sun and Abraham, 2021, Borusyak et al., 2024]. This bias arises because post-treatment outcomes for early adopters provide poor counterfactuals for later adopters in the presence of treatment effect heterogeneity in a standard two-way fixed effect (TWFE) approach. We adopt the imputation approach of Borusyak et al. [2024] (hereinafter "the BJS estimator" or "the BJS imputation method") to address this issue because it delivers efficiency gains relative to other robust estimators [Roth et al., 2023, Callaway and Sant'Anna, 2021] by exploiting all available untreated observations for imputation. In Section 4.2, we assess the sensitivity of our findings to alternative approaches, including conventional least squares TWFE, stacked TWFE, and the Wooldridge [2021] estimator.

One important point related to using the BJS estimator for event study designs is that the reference period includes all quarters in the sample that come before the pre-treatment window. We estimate coefficients for 12 pre-treatment quarters (three years before rollout), thus, the reference period to which δ_l in Equation 1 should be compared spans from the first quarter of 2002 up to the thirteenth pre-treatment quarter.

4.1 Ridership Results

We first examine how Google real-time tracking affected transit ridership. Outcome r in Equation 1 is measured as ridership per capita based on the agency's service area population size as of 2002.[20] Figure 2 shows our event study results. Immediately following Google Maps real-time rollout, we find transit trips increased by approximately 0.5 per month per capita. By quarter three the effect increased to nearly one additional trip, and increased again by the 11th quarter to nearly 1.5 trips. Conditional on our controls and fixed effects, we find no evidence that ridership was trending differentially between treatment and control agency-modes prior to Google Maps' use of real-time data.

In Table 2 we report the average treatment effect of Google Maps real-time tracking on ridership. Panel A shows results with a time window covering three years pre- and three years post-

[19] We define an agency's "city" using their "urbanized area" as defined by the NTD, which is the primary urbanized area served by the transit agency. Some cities in our sample are served by multiple transit agencies.

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

real-time adoption to match the event study time window. Ridership per capita increased by about 0.8 rides per month, or 13.6% based on the 2008 average. Panel B shows the results nearly double when considering effects over the entire panel, consistent with increasing treatment effects shown in Figure 2. Estimates are robust to controlling for the roll out of proprietary agency apps, static schedules, and Uber (among other controls) in column (4).[21]

4.2 Robustness Checks

We conduct a comprehensive set of robustness checks to assess the sensitivity of our results to alternative estimators, sampling and treatment definitions, outcome measures, and identifying assumptions. Across these exercises, the estimated increase in ridership following the introduction of Google Maps real-time tracking remains largely stable in magnitude, timing, and statistical significance, with no evidence of differential pre-trends.

Appendix Figure A.5 shows that event-study patterns remain qualitatively similar when using least squares, Wooldridge's saturated TWFE [Wooldridge, 2021], and stacked TWFE approaches. Although least-squares estimates are smaller—consistent with attenuation from comparisons between already-treated and newly-treated units—several confidence intervals overlap across estimators, and all specifications show no evidence of differential pre-trends alongside a gradual post-treatment increase in ridership.

We perform additional tests to address potential treatment misclassification and differences in observables across treated and control units. Further details and results of these analyses are shown in Appendix Figure A.6. These alternative estimates are comparable in magnitude and timing to our baseline results, which supports the validity of our treatment assignment and empirical design.

Our conclusions are likewise robust to alternative definitions of ridership, potential spatial spillovers, and a series of identification and sensitivity exercises. In Appendix Figure A.7, we employ alternative population denominators or log total ridership. Treatment effects under these alternative measurements of ridership are similar to or larger than our baseline. In Appendix Figure A.8, we employ a geographically restricted design comparing treated agencies to geographically-adjacent untreated or not-yet-treated agencies. These results are very similar to our main event study, implying little, if any, attenuation from spatial spillovers. Randomization inference shown

[21] We suggest caution in directly interpreting the coefficients on "Static Schedule" and "Agency App" in column (4) of Table 2 as the BJS imputation method eliminates bias from heterogeneity in the estimate for the main treatment, not for the coefficients on controls.

in Appendix Figure A.9 indicates that the observed treatment effect is unlikely to arise by chance, while the Rambachan and Roth [2023] sensitivity analysis in Appendix Figure A.10 confirms that results remain statistically significant even under substantial deviations from parallel pre-trends. Finally, a leave-one-out exercise shown in Appendix Figure A.11 reveals that ridership in New York City (NYC) contributes meaningfully to the aggregate magnitude: our average treatment effect falls by roughly two-thirds from 1.4 to 0.5 additional rides per capita per month (significant at 5%). This is, perhaps, unsurprising given that 40% of all transit rides tracked in the NTD occurred in NYC during our study period. The average treatment effect also falls slightly to about one additional ride when Washington D.C.—a pure control city—is dropped. We see almost no effect from dropping other cities from the sample. These findings show that while ridership effects in NYC contributed a large component to our overall point estimate, we still observe economically meaningful increases in ridership of nearly 9% when excluding NYC from the sample.

Collectively, these analyses support the conclusion that the introduction of real-time information in Google Maps produced sustained and meaningful increases in public transit ridership across U.S. transit systems.

4.3 Mechanisms Driving Ridership Effects

Our conceptual framework highlights that real-time tracking could affect travel behavior through multiple channels: increasing awareness and salience of transit options, reshaping expectations about reliability and duration, or simplifying the complexity of route planning. To distinguish among these mechanisms, we exploit earlier transit information shocks—many of which predate Google Maps' real-time tracking—to test whether improved salience or information accuracy alone can explain our findings. We then examine the complexity mechanism by testing for treatment effect heterogeneity across more highly connected, multi-route transit systems relative to simpler, more linear systems.

Static Transit Schedules: At least six years prior to their use of real-time tracking, Google Maps first incorporated static transit schedules into their app. Ridership may have responded to these local transit schedules in Google Maps as new information on transit availability became accessible to a wider audience. Consequently, comparing ridership responses to the roll-out of static schedules with those under real-time tracking informs whether the latter effect is driven by the salience of transit availability.

To test how ridership responded to the availability of static transit schedules in Google Maps, we searched news releases, social media, and blog posts for information on the initial availability of static schedules for each agency-mode pair in our sample.[22] We, then, estimated how ridership changed following static schedules using a version of Equation 1 where R indexes the initial quarter of static schedules in Google Maps for agency i and mode m. Results are shown in Figure 3. Static schedule effects, in diamonds, have no impact on ridership in all periods prior to and after the roll out of transit schedules into Google Maps. Average treatment effects shown in column (2) of Table 2 corroborate that static schedules had small and statistically insignificant effects on ridership. This suggests that improved salience on the availability of transit, alone, does not increase ridership.

Agency Apps: Our framework highlights two other channels through which real-time tracking in Google Maps may have affected ridership: improved travel time accuracy or reduced complexity and cognitive load. We explore this question by comparing our main results to the ridership effects from agency-specific transit tracking apps. For each agency, we searched for the availability and roll-out date of apps developed by transit agencies.[23] Like Google Maps, these apps improved travel time accuracy by enabling users to observe real-time tracking of public transit. However, agency apps—particularly those that pre-dated Google—often could not integrate a user's location or suggest customized routes. Instead, users typically searched for stations via drop-down menus or looked up specific transit lines. Moreover, agency apps rarely provided side-by-side comparisons of alternative modes.

Figure 3 suggests the effect of real-time tracking in agency-specific apps, shown as squares, had a smaller effect on ridership as compared to Google Maps. Column (3) of Table 2 shows roll out of agency apps increased trips per capita by 0.353 trips per month within 3 years of rollout (Panel A). This magnitude is about 40% of the Google real-time estimate of 0.838 trips per month, and is statistically different. These differences remain after considering effects over the entire study period in Panel B, particularly because Google's impacts grew substantially over time whereas the smaller Agency App effects plateaued. These results are suggestive that the majority of the ridership effect from Google Maps real-time tracking are from its ease of use and its ability to simplify complex information through, for instance, providing straightforward, real-time dependent comparisons of travel times across modes.

[22] Static transit schedules were more readily available relative to real-time tracking: out of 182 agency-mode pairs, 165 had transit schedules incorporated into Google Maps prior to 2019.

[23] For three agencies, we identify the rollout of real-time text alerts, and for six others, the rollout of real-time tracking in third-party (non-proprietary) apps.

Complexity Heterogeneity: To further explore the complexity channel, we test whether ridership effects differ across more versus less complex transit systems. We measure complexity using the area x vertex degree of a city's transit network. This measure is an interaction of the average number of directly connecting stops accessible from a given stop and the total transit service area. It reflects the transferability and size of local choice sets faced by riders.

Figure 4 presents estimates of Equation 1 separately for systems above and below the 75th percentile of area x vertex degree. We use this cutoff to distinguish the most complex systems from the rest of the distribution, which exhibits a pronounced left tail (see Panel A of Appendix Figure A.4). Following real-time tracking in Google Maps, the most complex transit systems experienced significant ridership gains. We report average treatment effects in Appendix Table A.1. The top quartile ridership gains (shown in column (1) of Panel A) are almost three times larger in magnitude compared to the bottom quartiles (shown in column (1) of Panel B). The average treatment effects across these subsamples are statistically distinct at the 10% level of confidence. These patterns support the interpretation that Google Maps increased ridership by simplifying an otherwise high-dimensional set of travel decisions.

Our findings have several important implications. First, the positive, significant effects of proprietary apps and Google Maps real-time tracking compared to the insignificant, zero effects of static schedules suggest that accurate information on arrivals, departures, and travel times is considerably more effective at improving transit use than information on the availability of transit. Second, tools that simplify and personalize high-dimensional information into straightforward directions have substantially larger effects on transit usage than tools that improve the accuracy of transit time information alone.

4.4 Ridership Heterogeneity by Size & Mode

Existing studies on transit access improvements find substantial heterogeneity in impacts based on pre-existing transit reliance and system characteristics [Tsivanidis, 2024, Severen, 2021, Gupta et al., 2022]. Related work further shows that responses differ markedly across transit modes: Hall et al. [2018] finds that Uber entry increased subway ridership but reduced bus ridership, while Bull et al. [2021] shows that fare-free transit increased subway use with little effect on buses. These findings suggest that interventions affecting transit use may be stronger in larger, more complex systems and in subway-oriented networks. Motivated by this prior work, we next examine whether our estimated effects vary systematically across large and small transit systems and across transit modes.

Figure 5 reports estimates of Equation 1 across subsamples defined by operating size and mode.[24] To explore whether treatment heterogeneity is correlated with the weighting variable in our main specification, we present unweighted estimates following Solon et al. [2015]. Panel B shows that ridership gains concentrate among agencies in the top decile of vehicle revenue miles, while smaller systems show no detectable response.[25] Panel C shows a similar pattern across modes: the overall effect is driven almost entirely by increases in subway ridership, with little to no change in buses, light rail, or commuter rail. Subway ridership rises steadily following adoption, reaching roughly two additional monthly trips per capita by quarter eight and three by quarter eleven.

The size and mode patterns support our interpretation that Google Maps is most valuable in more intricate transit systems. Larger systems and subway networks tend to involve more routes, transfers, and travel alternatives, increasing the scope for real-time navigation tools to matter.

In summary, we find that the introduction of real-time tracking in Google Maps increased transit ridership, with effects concentrated in large, complex, and subway-oriented systems. Evidence from earlier information shocks shows that salience alone has no effect and that improvements in timing accuracy, while beneficial, cannot fully account for the magnitude of the response. Instead, the results point to reductions in informational and cognitive complexity as the primary mechanism through which digital transit information influences behavior. The magnitude of these effects is economically meaningful: after three years, real-time tracking produces ridership gains comparable to those observed in some fare-free transit programs [Bull et al., 2021, Cats et al., 2017], yet at substantially lower cost. Together, these findings suggest that providing integrated, real-time travel information can be a highly cost-effective way to increase transit use.

4.5 Transit Operations

A key concern in interpreting the estimated ridership effects is whether the rollout of Google Maps' real-time tracking coincided with contemporaneous changes in transit agency operations. If agencies expanded service, adjusted fares, or altered operating intensity around the time real-time information became available, such changes could independently affect ridership and confound

[24] Appendix Table A.7 lists agencies in our heterogeneity subsamples: those with subway modes, those in the top decile of operations, and those in cities in the top decile of transit complexity. Appendix Table A.1 reports corresponding average treatment effects.

[25] We use the 90th percentile cutoff because the distribution of vehicle revenue miles has a long right tail for values above the 90th percentile. See Panel B of Appendix Figure A.4.

attribution to Google Maps. In this section, we therefore examine whether the introduction of real-time tracking was accompanied by systematic changes in transit operations, including service levels, fleet size, operating costs, and fares.

We implement our tests by inserting each of these variables as the outcome in a version of Equation 1 where t indexes years (rather than months), and plotting changes in these outcomes five years prior and five years following real-time tracking.

Results in Figure 6 suggest that changes in transit operations or service cannot explain the change in ridership following real-time tracking. Panel A plots vehicle revenue miles per capita and Panel B plots vehicles in operation (i.e., fleet). There is neither evidence of differential growth prior to real-time adoption, nor evidence that miles traveled or fleet size were affected by real-time implementation in the post period. Panels C and D test for changes in total costs per capita and fares, respectively. We find no evidence that costs or fares trended differently before the implementation of real-time tracking. However, we do see some evidence that fares increased after Google Maps real-time tracking. Agencies may have responded strategically to increased willingness to take transit by increasing the fares charged to riders. Assessing whether these fare changes improved agency finances is left for future work. Notably, observed fare changes run counter to the hypothesis that lower prices could have influenced the observed increase in ridership.

These findings strengthen our interpretation that the observed positive ridership gains reflect the informational content of Google Maps rather than concurrent shifts in transit supply.

5 Real-Time Tracking & Mode Choice

Our results indicate that the introduction of real-time tracking generated economically and statistically significant increases in public transit ridership. An important question is whether these increases reflect the creation of new trips or substitution from private vehicles for existing trips. Distinguishing between these channels is central for assessing the welfare implications of information-based interventions. If real-time tracking induces travelers to substitute from cars to public transit, the resulting reduction in congestion and vehicle emissions would generate positive externalities. In contrast, if the ridership response primarily reflects an expansion in transit use without offsetting reductions in private vehicle travel, the associated benefits are largely private.

We leverage microdata from the ACS to better understand how Google Maps influenced the mode-specific composition of commuting trips. While commuting represents less than one fifth of all trips made in privately owned vehicles in the U.S. [Small et al., 2007], it is also the most habitual and, consequently, the least responsive to influence. We, then, use data on household income in the ACS to explore whether higher-income commuters responded differently to the treatment than lower-income commuters.

To explore how the adoption of real-time tracking in Google Maps impacted commute mode choices, we leverage a question from the ACS annual survey that asks respondents what mode they most often use to commute to work. Respondents may commute by means other than transit or car (for example, walking, biking, or working from home), thus the likelihood of commuting via car or transit are not mechanically inverse. Because commute mode choices are often interrelated within household, we conduct our analysis at the household level. We estimate an event study specification following that of Equation 1 where the unit of observation is a household by city by year. We include a vector of city fixed effects, region-by-year fixed effects, and an interaction of year fixed effects with 2002 city-level ridership per capita to control for differential trends in commuting across cities. Our specification also includes a vector of household-specific controls related to the highest education level in the household, the household income, and indicators for the household income decile. We cluster standard errors by urbanized area and weight the regression by the household survey weight. For computational tractability with household-level data and controls, we employ a traditional least squares TWFE for our estimation.[26]

Figure 7 shows the effect of real-time information in Google Maps on the mode choice in each of five years before and after rollout. Panel A shows an increase in commuting via transit. The effect increases with time from about 1.2 percentage points to nearly 4 percentage points by year 5. The average effect size over the entire panel—shown in Table 3—is approximately 1.16 percentage points, or about 4% of the baseline mean. Panel B of Figure 7 shows a decline of a similar magnitude in propensity for urban residents to commute by car. The likelihood of commuting by car falls by 1.3 to 1.5 percentage points, as shown in Panel B of Table 3. These results from the ACS sample corroborate our main findings from the NTD —real-time tracking increased usage of public transit. The ACS sample further shows that real-time tracking in Google Maps increased public transit commuting trips at the same time that it decreased commutes in private vehicles. This suggests that at least some of the increase in transit ridership was the result of substitution away from cars.

[26] We show that results are qualitatively similar under the BJS estimator after aggregating the ACS data to the city-year-level, and measuring commute mode choice using city-level shares. The event study point estimates, shown in Appendix Figure A.12, are not statistically significant after the city-level aggregation, but show a very similar pattern to Figure 7.

This finding is noteworthy as it indicates that real-time information likely generated broader public benefits.

Next, we explore whether there is heterogeneity in responses to real-time transit based on household income. Such heterogeneity could help explain the large estimated effects for subway ridership, as subway riders on average have higher income [American Public Transportation Association, 2017] and a higher opportunity cost of wait time [Small, 2012, Goldszmidt et al., 2020]. To test for differential treatment effects, we use data on household income from the ACS. We explore heterogeneity under traditional least squares in order to interact the Google Maps treatment indicator with indicators for the distribution of household income. We distinguish three categories of household income: below the 50th percentile, between the 50th and 90th percentile, and above the 90th percentile. Results of the income heterogeneity analysis are shown in Figure 8. Diamonds correspond to estimates where the outcome is whether any household member commutes by public transit, while circles correspond to commuting by car.

Figure 8 provides two findings. First, above-median income households were substantially more likely to commute via transit following Google Maps real-time tracking and less likely to commute via car, and these effects are even more pronounced at higher levels of income. Second, the likelihood of below-median income households commuting via var was statistically unchanged by real-time information. Majid et al. [2018] also find that new high-speed transit lines in Lahore disproportionately attracted ridership among highly educated riders. Because high-income individuals are most likely to use the subway, this pattern is consistent with larger effects on ridership of subway modes. By contrast, for commuters with access to less reliable services such as buses, real-time information may reduce transit ridership by making wait times and delays more salient in comparison to alternative modes, such as private car travel.[27] If lower-income commuters are less likely to have access to reliable subways, they may therefore be more likely to reduce ridership once this reliability is made more salient.

6 Real-Time Tracking & Air Quality

We next test whether changes in travel behavior induced by the introduction of real-time transit tracking in Google Maps had a detectable impact on air quality. We estimate a version of Equation 1 where the outcome is the average air quality for a transit agency's headquarter city in a given month.

[27]In New York city, for example, buses are 15 percentage points less likely than subways to arrive within 5 minutes of their scheduled time, see https://www.mta.info/document/168286.

We measure air quality using carbon monoxide (CO) and nitrogen oxides (NOx). To account for the large differences in population across cities with a monitor, we weight our regressions by city population as of 2010.[28]

Figure 9 shows our event study results, while Table 4 reports average treatment effects. We find that air quality improved following Google Maps real-time tracking. In particular, CO concentrations fell by 0.025 parts per million for the average city resident, or by 6%, following real-time adoption. This effect is stable across specifications with additional controls accounting for the arrival of Uber and the existence of proprietary agency apps (column 2). Estimates become larger after controlling for temperature and county-level attainment status (column 3). To put the magnitude of the CO treatment effect in context, we compare this 6% decline in CO to our main ridership result as measured over the same (entire) study period, 2002-2019. Real-time tracking led to an average increase in public transit ridership of 22.5% (Panel B of Table 2). Motor vehicles are the dominant source of CO in most cities, comprising up to 75% of emissions in congested cities [EPA, 2023b]. As a back-of-the-envelope comparison, if the entire increase in ridership came from reductions in car trips, then an upper bound on the decrease in carbon monoxide would be approximately 16.9% (0.75×22.5), well above our estimate of 6%. Notably, air quality may be particularly responsive to increased transit ridership if real-time tracking reduced congestion in addition to car trips. Under peak traffic, stop-and-go conditions, small reductions in congestion can yield nonlinear improvements in air quality [Currie and Walker, 2011, Schlenker and Walker, 2016].

Panel B of Figure 9 and Table 4 also show evidence of reductions in NOx. The estimates indicate that NOx fell by 3.9 parts per billion (or about 12%) for the average city resident. However, we interpret this result as suggestive, as Panel B of Figure 9 shows that NOx concentrations may have been falling in advance of real-time tracking becoming available. Because traffic emissions are a lower overall share of NOx compared to CO [EPA, 2023b], they vary more substantially across cities with comparable traffic emissions due to differences in industrial pollution, which may have been trending differently across cities.

[28]Weighting by population means that our results should be interpreted as the treatment effect on the average urban resident, as opposed to the average air quality monitor. We show unweighted results in Appendix Table A.5. Patterns are similar, however unweighted estimates are smaller and less precisely estimated compared to our weighted estimates.

7 Rider Welfare

As a final exercise, we 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. We assume travelers are agnostic about transit agencies, but care about their mode of travel. Let $m = 1$ represent public transit modes including light rail (LR), heavy rail (HR), commuter rail (CR) and metro bus (MB), and $m = 0$ represent the outside option of private transportation such as driving or walking. The conditional indirect utility of traveler i taking mode m in city c and region r at time t for a given trip is:

$$u_{icmt} = \beta X_{cmt} + \delta R_{cmt} + \alpha p_{cmt} + \lambda_c + \Phi_{rq} + \nu_{cmt} + \epsilon_{icmt} \tag{2}$$

where R_{cmt} represents whether Google Maps had real-time tracking information in city c at period t, p_{cmt} represents the one-time cost of that mode[29], X_{cmt} represents the characteristics of city c including log(service area population) and average household income. In the regression λ_c are city fixed effects, Φ_{rq} are region-quarter-year fixed effects, ν_{cmt} are unobserved city-time-mode shocks, and ϵ_{icmt} is a mean-zero stochastic term, which is assumed to follow the type I extreme-value distribution. The parameter δ indicates the marginal utility of Google Maps with real-time tracking, and α indicates the marginal utility of price. We assume preference parameters do not vary by individual i and interpret the introduction of real-time transit tracking in Google Maps as a marginal change in the technology.

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

$$s_{cmt} = \frac{exp(\beta X_{cmt} + \delta R_{cmt} + \alpha p_{cmt} + \lambda_c + \Phi_{rq} + \nu_{cmt})}{\sum_{k=0}^{1} exp(\beta X_{ckt} + \delta R_{ckt} + \alpha p_{ckt} + \lambda_c + \Phi_{rq} + \nu_{ckt})} \tag{3}$$

Normalizing the utility of the outside option ($m = 0$, private transportation) to 0, Equation 3 implies that $ln(s_{c0t}) = -ln(\sum_{k=0}^{1} exp(\beta X_{ckt} + \delta R_{ckt} + \alpha p_{ckt} + \lambda_c + \gamma_t + \Phi_{rq} + \nu_{cmt})$. The difference

[29] In Appendix Table A.6, we use monthly cost as a robustness check.

between the log market share for taking transit ($ln(s_{c1t})$) and the log market share for the outside option ($ln(s_{c0t})$) is then:

$$ln(s_{c1t}) - ln(s_{c0t}) = \beta X_{c1t} + \delta R_{c1t} + \alpha p_{c1t} + \lambda_c + \Phi_{rq} + \nu_{c1t}, \tag{4}$$

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

Empirically, we construct the market shares for public transportation s_{c1t} as follows. Let P_{ct} be the population of city c in year t. We assume that the number of individuals in city c represents potential travelers and that each individual takes T_c city-average trips daily.[30] We then convert the number of daily trips to monthly trips by multiplying by 20 (we assume people travel 20 days out of the month, on average). To convert the number of rides reported in the NTD to the number of potential trips, we assume 1 ride is equivalent to 1 trip. In sum, the share of public transit usage is $s_{c1t} = Ridership_{ct}/(20P_{ct}T_c)$.

To identify δ, we leverage variation in the use of real-time information in Google Maps across cities as in our earlier analysis. To identify α, we leverage changes in fares across agencies. The main empirical concern in the literature is that market-level prices are simultaneously determined by supply and demand, rendering them endogenous and necessitating the use of instruments [Berry, 1994, Nevo, 2001]. In our context, however, public transit fares are not the outcome of a market equilibrium and change slowly —oftentimes through political and bureaucratic processes.[31] Furthermore, transit agencies are highly subsidized, largely operate on "soft" budgets, and prioritize lower-income and minority populations in their decisions [Huang and Kahn, 2023, Wang, 2024]. For example, when considering price changes, public transit agency boards cite equity and affordability as key criteria.[32] Thus, transit fares are not the outcome of a competitive market and are plausibly uncorrelated with month-to-month variation in ridership.

Results from estimating Equation 4 are shown in Table 5. The estimation sample is smaller than our main sample because adult fare data from APTA were unavailable for some agencies, and

[30] 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 A.6 shows that our results are not sensitive to the choice of rides per trip.

[31] 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`.

[32] 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 Federal Transit Administration provides service and fare equity guidance to transit agencies through Circular 4702.1B for agencies in large urbanized areas (over 200,000 in population).

because fares data were unavailable prior to 2008. The first column shows results with city and region-by-quarter-by-year fixed effects, the second column adds average household income for cities in the ACS as a control, the last column adds the log of population as a control. Columns (2) and (3) have a smaller sample relative to column (1) because they include only cities that report income data in the ACS (sample includes 82 cities). The willingness-to-pay estimate increases with additional controls and in the smaller sample.

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

8 Conclusion

This paper demonstrates that a technological improvement to one of the most widely used smartphone applications—Google Maps—generated meaningful and sustained increases in public transit use across major U.S. cities. By exploiting the staggered introduction of real-time tracking information within the app, we show that access to accurate, trip-specific transit information increased monthly ridership by over 13 percent in the first three years of implementation, with effects growing over time. These gains are comparable in magnitude to those produced by costly physical infrastructure expansions or fare elimination policies, underscoring the outsized potential of low-cost, information-based interventions in shaping urban mobility.

Our findings also shed light on plausible mechanisms. The larger impacts in more complex transit systems are consistent with real-time information reducing the effective complexity of travel decisions by lowering uncertainty about arrivals and simplifying path selection. Moreover, the fact that Google's real-time integration yields substantially larger effects than static schedules or agency-specific apps suggests that it is not merely salience of transit options or improved accuracy of travel times, but how Google computes and presents options that plausibly drives the stronger behavioral responses. Overall, our findings suggest there may be substantial informational frictions in complex urban transit networks that can deter transit take-up in absence of digital tools that integrate accuracy with salient, personalized navigation.

The distributional consequences of the intervention reveal an important limitation. The increases in transit use are concentrated among higher-income commuters. These patterns likely reflect the strength of the treatment on subway ridership, but may also indicate an important role of prior beliefs and transit expectations in shaping the value of information-based mobility improvements.

Our results give rise to several policy implications. First, investments in digital information systems may offer unusually high returns relative to their modest costs, especially in large and complex transit networks. Policymakers considering options to increase ridership or reduce vehicle use may find that upgrading their data systems or integrating with widely used platforms like Google Maps provides a cost-effective alternative to more capital-intensive interventions. An important avenue for future research is whether navigation apps complement infrastructure investments and magnify their public benefits. Second, the unequal distribution of benefits suggests that information improvements alone are insufficient to address longstanding inequities in urban mobility [Fu et al., 2024]. To ensure that all riders benefit, information upgrades may need to be paired with targeted service improvements, reduced fares, or reliability enhancements in lower-income neighborhoods.

Our results show that digital information tools can reshape mobility patterns at scale, even without altering the underlying infrastructure. As cities continue to grapple with congestion and pollution, understanding the potential of technology to influence travel choices will be increasingly central to designing effective transportation policy.

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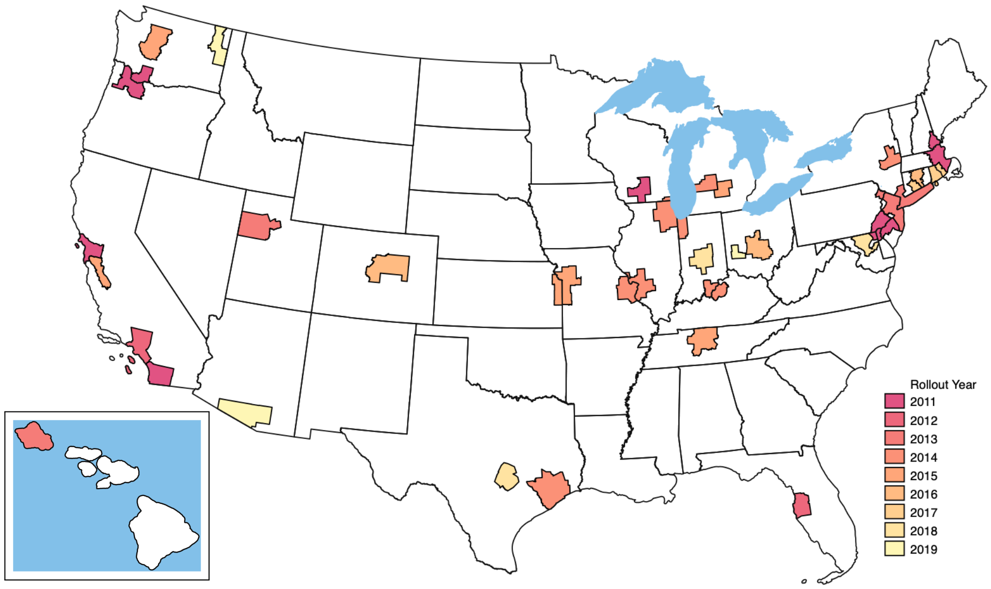


Figure 1: Year that Google Maps implemented real-time tracking by metro area

Note: Map displays the year in which Google Maps introduced real-time transit tracking for each treated agency in our sample, displayed by the metropolitan area in which the agency is headquartered. For metro areas with multiple agencies, the earliest adoption date is shown.

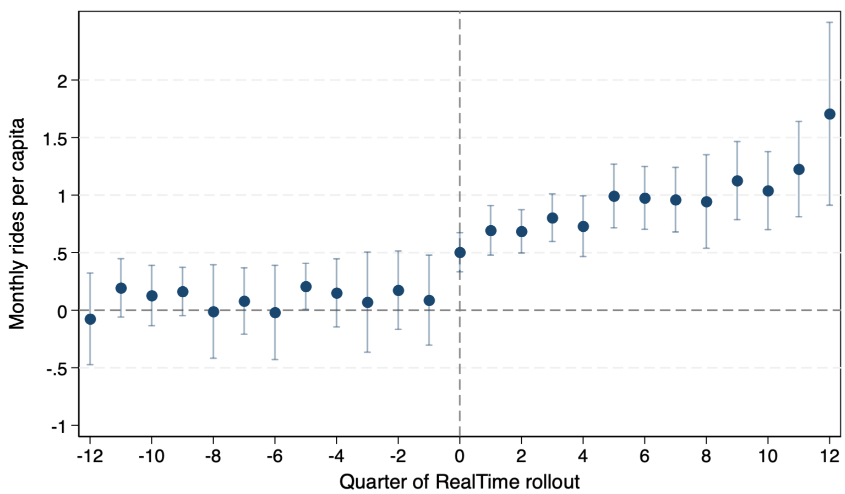


Figure 2: Effect of Real-time Information on Public Transit Ridership

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

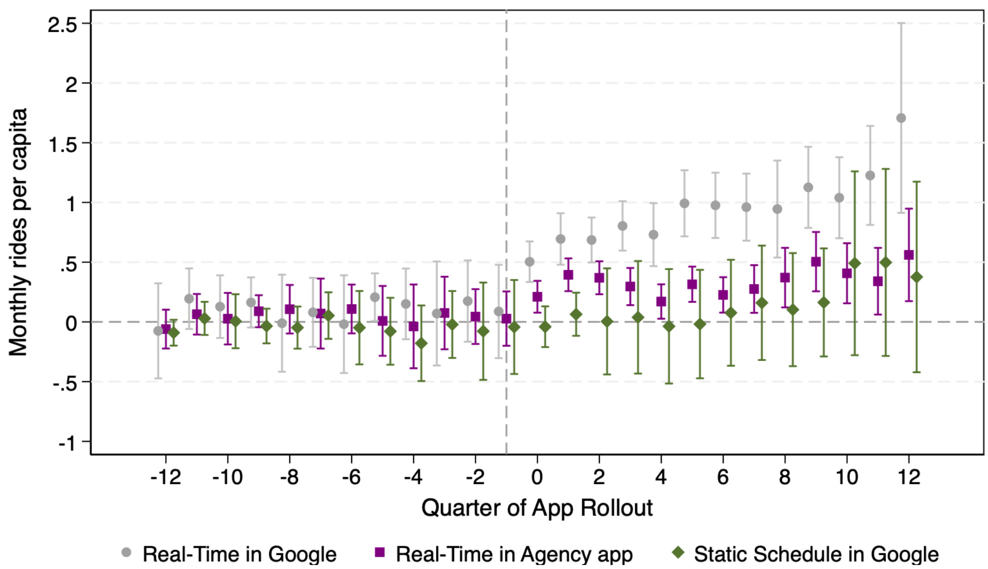


Figure 3: Effect of Agency Tracking Apps & Static Schedules on Public Transit Ridership

Note: Figure plots the estimates and 95% confidence intervals of δ_l using a version of Eq. 1. The gray circles replicate the specification shown in Figure 2. For the purple squares, R_i is the quarter when an agency's proprietary app was introduced. For the green diamonds, R_i is the quarter when an agency-mode's static transit schedules became available in Google Maps. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, and 2002 ridership-by-year fixed effects. Standard errors clustered by urbanized area. Observations weighted by 2002 vehicle revenue miles. Parameters estimated using the BJS imputation method.

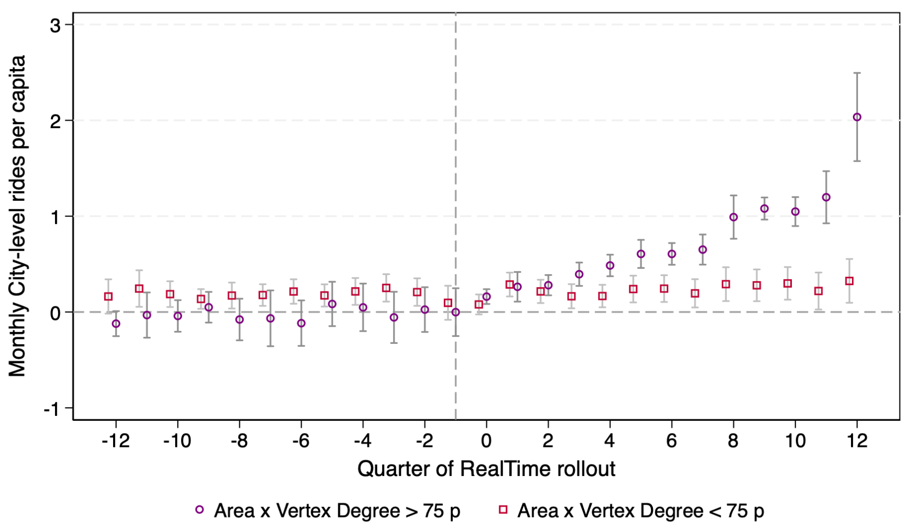
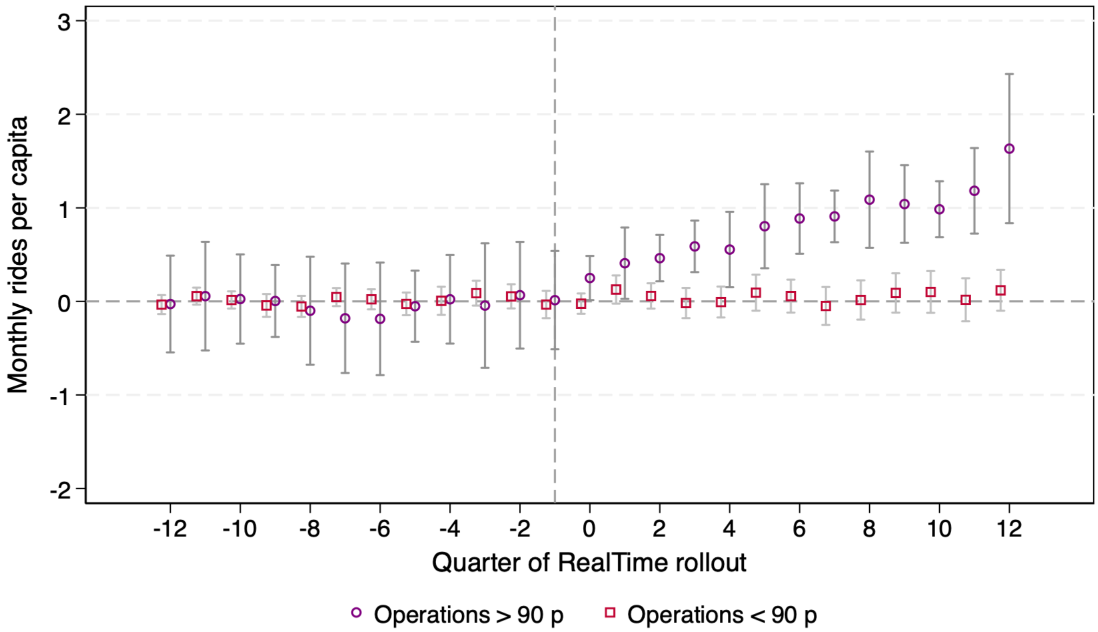
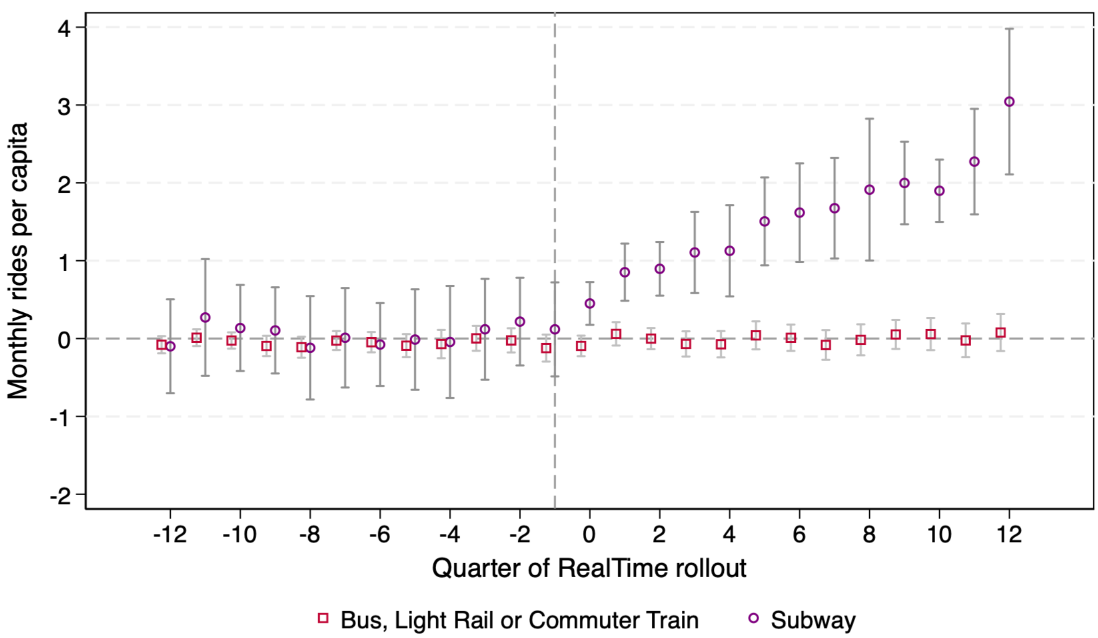


Figure 4: Effect of Real-time Information in High vs Low Complexity Transit Systems

Note: Figure shows estimates and 95% confidence intervals of δ_l using a version of Eq. 1 where monthly ridership per capita r_{ct} is aggregated to the city level c, and real-time roll out quarter R_c is the earliest roll out date for any agency in city c. Controls include city fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether Google Maps real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. The red squares and purple circles indicate estimates from distinct samples: cities with total service area x average vertex degree below versus above the 75th percentile, respectively. Observations are weighted by 2002 vehicle revenue miles. Standard errors are clustered by urbanized area. Parameters estimated using the BJS imputation method.



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



(b) Real-time Effect by Mode

Figure 5: Heterogeneity of Real-time Information Effect on Ridership by Size and Mode

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

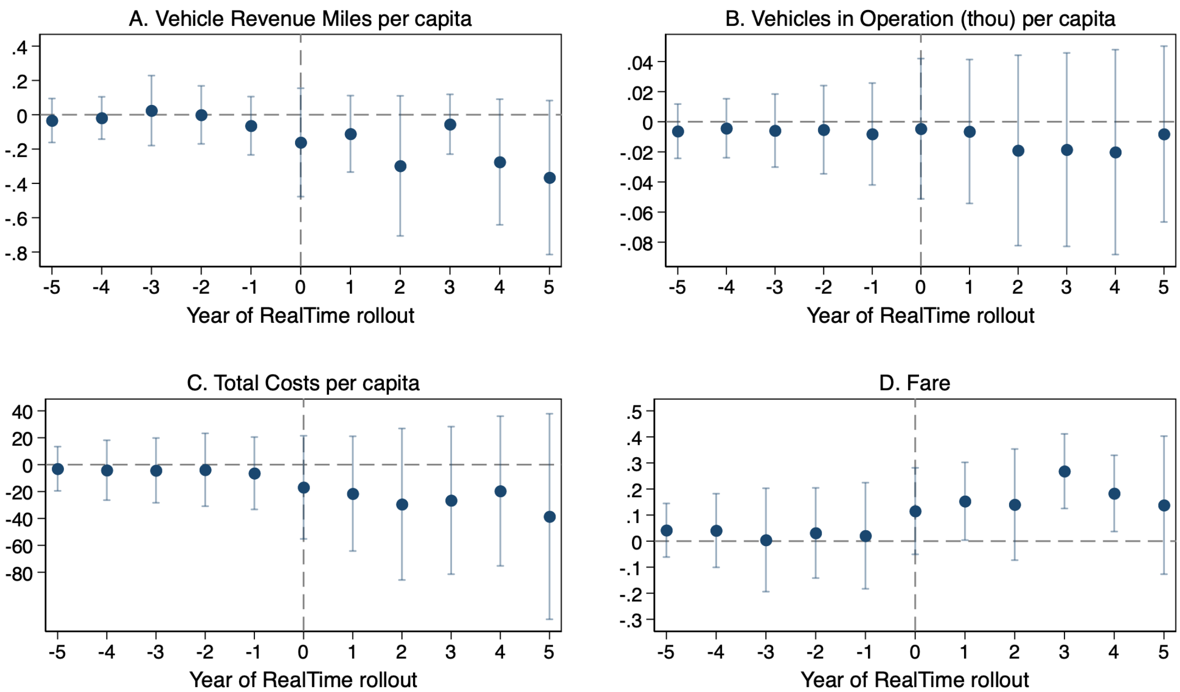


Figure 6: Transit Agency Operations and Google Real-time Rollout

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

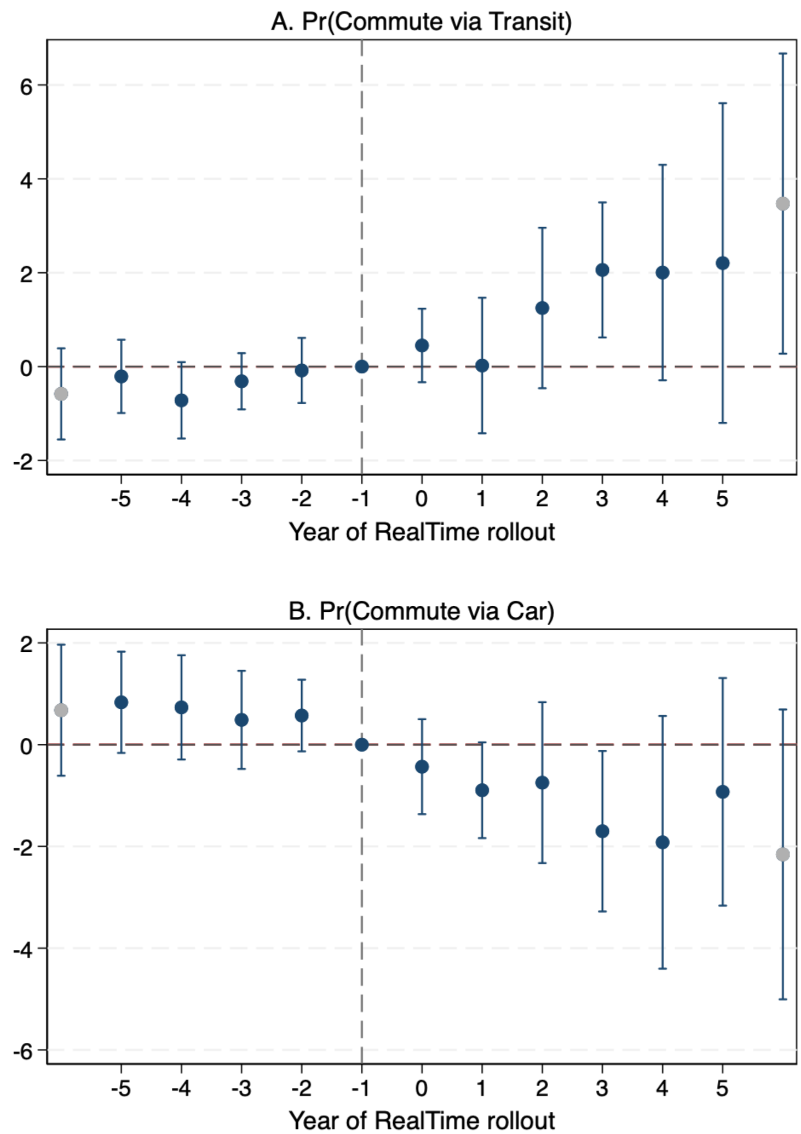


Figure 7: Effect of Real-time Information on Commute Mode Choice

Note: Figure plots the estimates and 95% confidence intervals of κ_l from the following specification: $\Pr(c_{njt}) = \sum_{l=-5(\ni-1)}^{5} \kappa_l \mathbf{1}\left[y - R_j = l\right] + \alpha_j + \mathbf{X_{jt}}\theta + \mathbf{Z_n}\zeta_t + \varepsilon_{jt}$ where $\Pr(c_{njt})$ is an indicator for whether any individual in household n in city j in year t reports commuting by mode choice c where c is either car (Panel A) or public transit (Panel B). R_j is the earliest adoption year of real-time tracking for all agencies in city j. Estimates based on traditional least squares. Controls include city fixed effects α_j, and a vector of time-invariant attributes interacted with year fixed effects $\mathbf{Z_j}\zeta_t$ including: region, 2002 ridership per capita, 2002 vehicle revenue miles, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date for any agency in city j. $\mathbf{X_{nt}}$ additionally includes the log of household income, indicators for whether household income is below the 50th percentile, between the 50th and 90th, and above the 90th percentile, and indicators for the household's highest level of education. Observations are weighted by the ACS household sampling weight. Standard errors clustered by urbanized area.

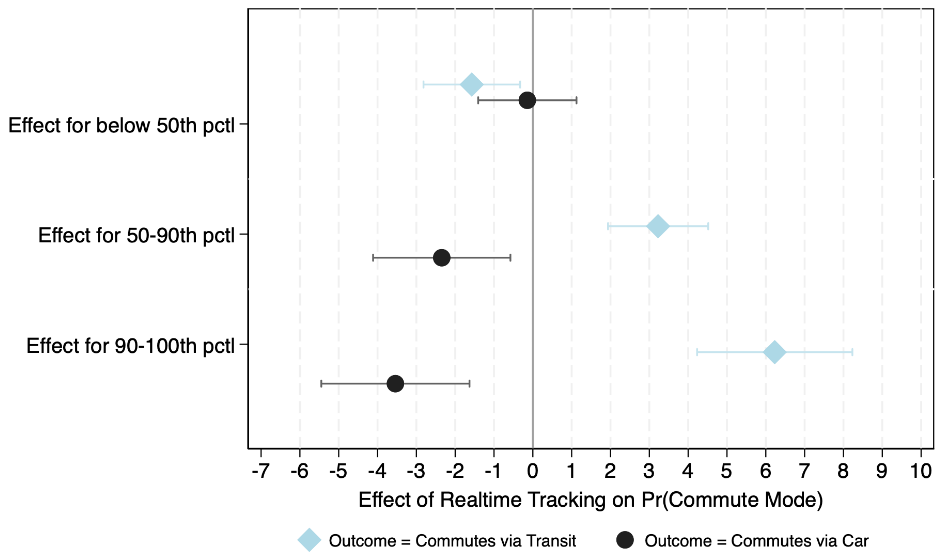


Figure 8: Real-time Information, Commute Mode Choice, and Household Income

Note: Figure shows the effect of real-time tracking on commute mode choice, and the heterogeneous effect by household income bin from the following specification: $\Pr(c_{njt}) = \beta_1 R_{jt} + \beta_2(R_{jt} \times I_{50-90,nj}) + \beta_3(R_{jt} \times I_{90-100,nj}) + \eta I_{nj} + \alpha_j + \mathbf{X_{it}}\theta + \mathbf{Z_i}\zeta_t + \varepsilon_{it}$ where $\Pr(c_{njt})$ is an indicator for whether any individual in household n in city j in year t reports commuting by mode choice c where c is either car (estimates shown in black circles) or public transit (estimates shown in blue diamonds). $R_{jt} = 1$ if real-time tracking is available for any agency in city j in year t, $I_{50-90,nj}$ and $I_{90-100,nj}$ are indicators for whether household n has income in the 50-90th percentile and top decile, respectively. Income is measured in 2018 USD. All other variables follow the definitions described in the notes of Figure 7. The top row of the figure shows the estimate for β_1, the effect for households with income below the 50th percentile. The middle row shows the total effect $(\beta_1 + \beta_2)$ for households with income between the 50th and 90th percentiles; and the bottom row shows the total effect $(\beta_1 + \beta_3)$ for households with income above the 90th percentile. Both regressions estimated using traditional least squares. Observations are weighted by the ACS household sampling weight. Standard errors clustered by urbanized area.

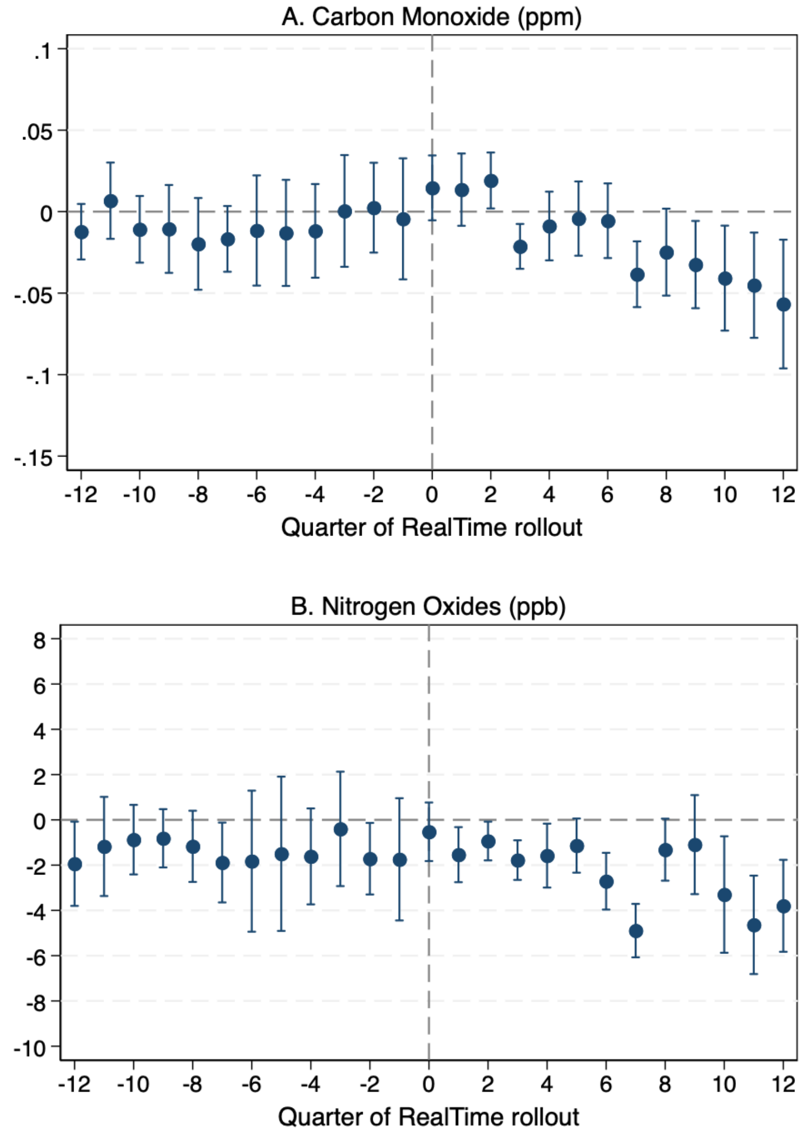


Figure 9: Effect of Real-time Information on Air Quality

Note: Figure plots the estimates and 95% confidence intervals of a version of Eq. 1 where the outcome varies by city i and month-of-sample t and R_i is the earliest month that real-time tracking in Google Maps becomes available for any agency in city i. The outcome r_{it} in Panel A is carbon monoxide (ppm). The outcome in Panel B is nitrogen oxides (ppb). Controls include city fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether real-time tracking was "in use" for any agency in city i as of it's assigned treatment date interacted with a year fixed effect. Standard errors clustered by urbanized area. Estimates are weighted by the 2010 city population. Parameters estimated using the BJS imputation method.

Table 1: Summary Statistics

	RealTime (μ_r)	Non-RealTime ($\mu_n r$)	$p(H_0 : \mu_r - \mu_{nr} = 0)$
Panel A: 2008 Agency Characteristics			
Ridership per capita	8.958	4.690	0.000
Service Area population (thou)	10,779.054	10,259.116	0.815
Service Area sq. mi.	2,297.016	2,313.512	0.977
Fare Revenues ($ mn)	1,322.227	279.071	0.000
Base Adult Fare ($)	1.798	1.750	0.693
Vehicle Revenue Miles (thou)	15,479.553	4,336.465	0.000
Operating Vehicles	3,821.285	949.826	0.000
Total Cost ($ mn)	2,609.221	651.223	0.000
Share of operations privatized	0.053	0.167	0.005
Number of modes	2.220	1.832	0.013
Pr(Subway)	0.656	0.208	0.000
Pr(Proprietary App by 2019)	0.952	0.831	0.023
Panel B: 2008 City Characteristics			
Population (2010)	3,637,716	3,575,101	0.946
Area (sq.mi.)	914.364	850.488	0.707
Pr(Northeast)	0.205	0.202	0.977
Pr(South)	0.159	0.357	0.019
Pr(West)	0.409	0.262	0.089
Share black (2010)	0.192	0.230	0.275
Share of commutes by car	0.357	0.350	0.716
Share of commutes by public transit	0.069	0.059	0.507
Average commute time (min)	24.736	24.809	0.951
Average vertex degree (2013 or 2014)	1.279	1.237	0.734
Share below poverty line	0.195	0.212	0.226
Share with bachelor's degree	0.240	0.199	0.051
Share of households with internet (2013)	0.778	0.748	0.128
Share of households with cellular data (2013)	0.358	0.317	0.118
Share of households with highspeed internet (2013)	0.658	0.627	0.175
Average Daily NOx (ppb)	36.533	33.195	0.417
Average Daily CO (ppm)	0.545	0.507	0.325
Number of Agencies	44	84	

Note: Panel A means weighted by agency vehicle revenue miles as of 2002. Panel B means measured in available year closest to 2008 where noted in parentheses. The last column shows the p-value for t-tests of mean equivalence across Realtime and Non-Realtime agencies.

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

A. Dep. Var: Trips per capita per month - 3 Years Pre/Post	(1)	(2)	(3)	(4)
Realtime(=1)	0.838***			0.786***
	(0.147)			(0.154)
Static Schedule(=1)		0.141		-0.118
		(0.242)		(0.097)
Agency App(=1)			0.353***	0.101**
			(0.083)	(0.048)
Controls				Y
Dep. Var. Mean	5.880	5.880	5.880	5.880
Weights	BaseVRM	BaseVRM	BaseVRM	BaseVRM
Observations	35184	24536	31508	34709
$p(H_0 : \beta^1 = \beta^i)$		0.004	0.000	

B. Dep. Var: Trips per capita per month - Full Panel	(1)	(2)	(3)	(4)
Realtime (=1)	1.328***			1.434***
	(0.301)			(0.268)
Static Schedule (=1)		0.145		-0.072
		(0.244)		(0.098)
Agency App (=1)			0.486***	0.106**
			(0.169)	(0.047)
Controls				Y
Dep. Var. Mean	5.880	5.880	5.880	5.880
Weights	BaseVRM	BaseVRM	BaseVRM	BaseVRM
Observations	36657	35780	35786	36149
$p(H_0 : \beta^1 = \beta^i)$		0.001	0.001	

Note: Table reports estimates of the average treatment effect from Equation 1. All specifications include the following fixed effects: agency-mode, season-by-region, year-by-region, 2002 ridership per capita-by-year, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. "Controls" include an indicator for whether Uber is available, the 2010 share of city population that is black interacted with a year fixed effect; and the agency-mode share of operations that are privatized. All parameters estimated using the BJS imputation method. Standard errors clustered by urbanized area. Sample sizes vary across specifications because the BJS estimator only uses untreated and not-yet-treated observations to estimate time and unit fixed effects: across columns, sample sizes vary with the designated "treatment"; and across panels, samples vary with the designated number of estimated post-treatment coefficients (i.e., we estimate 12 post-treatment coefficients for panel A (shown as an average) and 1 post-treatment coefficient for Panel B). In Panel A, we estimate the 3-year average treatment effect by calculating a weighted average of 12 quarters of post-treatment coefficients as follows: $ATE_{0-12} = \sum_{h=0}^{12}[(c_h * \tau_h)]$, where τ_h is the estimated treatment effect at event time h; and $c_h = W_h/\sum_h(W_h)$ is the normalized BJS aggregation weight. W_h denotes the total (un-normalized) aggregation weight assigned to horizon h. Dependent variable mean measured as of 2008 for treated agency-modes and is weighted by 2002 VRM. $p(H_0 : \beta^1 = \beta^i)$ is the p-value for a cluster-robust Wald test of equality of treatment effects across model (i) relative to model (1). The covariance between estimates is computed using the BJS estimator's aggregation weights and residuals. The coefficients on "Static Schedule" and "Agency App" in column (4) should be interpreted as the change in the outcome *during pre-treatment periods* given a unit change in each of these variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

A. Dep. Var: Pr(Commute on Transit)	(1)	(2)	(3)
Realtime(=1)	1.182**	1.206**	1.195**
	(0.555)	(0.559)	(0.562)
Income Controls	Y	Y	Y
App Controls		Y	Y
Education Controls			Y
Dep. Var. Mean	29.167	29.167	29.167
Weights	ACS Survey Weight	ACS Survey Weight	ACS Survey Weight
Adjusted R^2	0.250	0.250	0.251
Observations	1262691	1262691	1262691

B. Dep. Var: Pr(Commute in Car)	(1)	(2)	(3)
Realtime(=1)	-1.407**	-1.333**	-1.304**
	(0.646)	(0.656)	(0.647)
Income Controls	Y	Y	Y
App Controls		Y	Y
Education Controls			Y
Dep. Var. Mean	62.980	62.980	62.980
Weights	ACS Survey Weight	ACS Survey Weight	ACS Survey Weight
Adjusted R^2	0.244	0.244	0.247
Observations	1262691	1262691	1262691

Note: Table reports results from the following specification: $\Pr(c_{njt}) = \beta R_{jt} + \eta I_{nj} + \alpha_j + \mathbf{X_{it}}\theta + \mathbf{Z_i}\zeta_t + \varepsilon_{it}$ where $\Pr(c_{njt})$ is an indicator for whether any individual in household n in city j in year t reports commuting by mode choice c where c is either public transit (Panel A) or car (Panel B). $R_{jt} = 1$ if real-time tracking is available for any agency in city j in year t. All variables follow the definitions described in the notes of Figure 7. All specifications include city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, 2002 vehicle revenue miles-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date for any agency in city i interacted with a year fixed effect. "Income Controls" include indicators for whether the household has income in the 50-90th and top deciles as well as ln(household income). "App Controls" include controls for the roll out of Uber, static time tables in Google Maps, and proprietary tracking apps. "Education Controls" include an indicator for the households highest level of education. Parameters estimated using standard two-way fixed effects. Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities and is weighted by the household survey weight. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

A. Dep. Var: CO (ppm)	(1)	(2)	(3)
Realtime (=1)	-0.025*	-0.026*	-0.033**
	(0.013)	(0.014)	(0.014)
App Controls		Y	Y
Temp & Attainment Controls			Y
Dep. Var. Mean	0.426	0.426	0.426
Weights	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)
Observations	13139	13139	10174
B. Dep. Var: NOx (ppb)	(1)	(2)	(3)
Realtime (=1)	-3.215***	-3.325***	-3.956***
	(0.845)	(0.847)	(1.011)
App Controls		Y	Y
Temp & Attainment Controls			Y
Dep. Var. Mean	32.827	32.827	32.827
Weights	City Pop. (2010)	City Pop. (2010)	City Pop. (2010)
Observations	11823	11823	9623

Note: Table reports estimates of the average treatment effect from a version of Eq. 1 where the outcome varies by city i and month-of-sample t and $R_i = 1$ after the earliest year that real-time tracking in Google Maps became available for any agency in city i. All specifications include city fixed effects, year-by-region fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date for any agency in city i interacted with a year fixed effect. "App Controls" include controls for the roll out of Uber, the roll out of static timetables in Google Maps, and the roll out of proprietary tracking apps. "Temp & Attainment Controls" include controls for city-average monthly temperature and the county's non-attainment status, where non-attainment=1 if the county is in non-attainment for any criteria pollutant in a given year. All parameters estimated using the BJS imputation method. Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities and is weighted by 2010 city population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

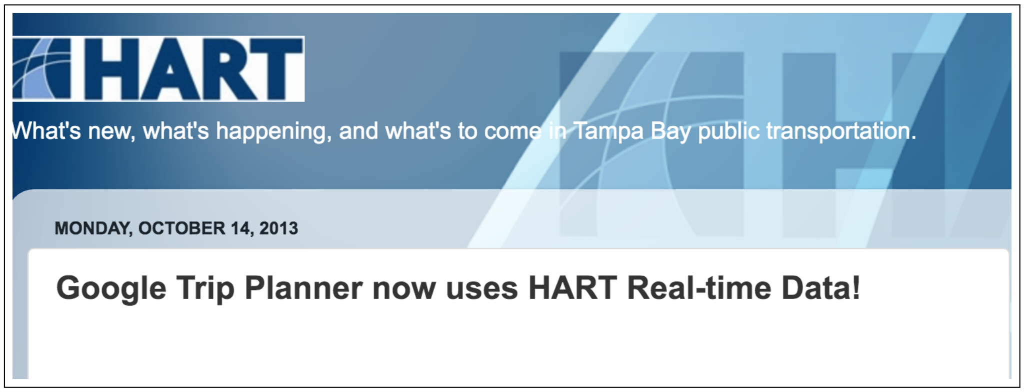
Table 5: Welfare Analysis of Google Maps Real-time Transit Tracking

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

Note: Table reports results from estimating Eq. 4. All regressions include region-quarter-year fixed effects and city fixed effects. Standard errors are clustered by urbanized area. Regressions weighted by vehicle revenue miles as of 2002. Parameters estimated using the BJS imputation method. In column (1), 38 (82) cities are included in the treatment (control) group. In columns (2) and (3), 28 (54) cities are included in the treatment (control) group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Additional Figures

A. Hillsborough Transit Authority (HART), Tampa Bay, FL



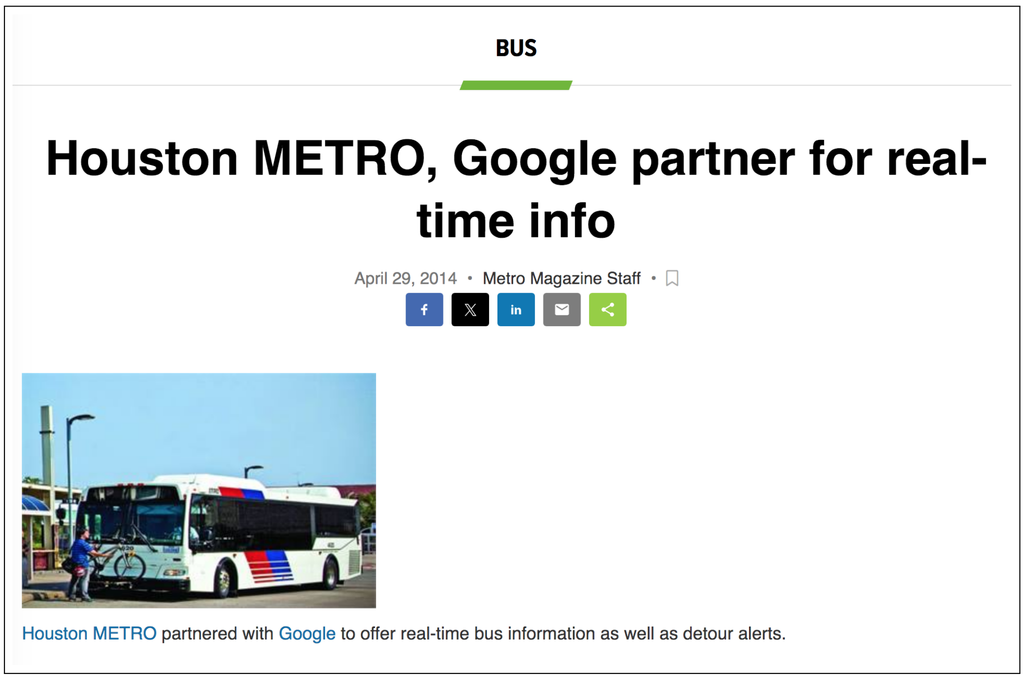
HART

What's new, what's happening, and what's to come in Tampa Bay public transportation.

MONDAY, OCTOBER 14, 2013

Google Trip Planner now uses HART Real-time Data!

B. Houston METRO, Houston, TX



BUS

Houston METRO, Google partner for real-time info

April 29, 2014 • Metro Magazine Staff •

Houston METRO partnered with Google to offer real-time bus information as well as detour alerts.

Figure A.1: Example of Roll-out Date News Releases

Note: Figure shows two examples of news releases used to establish the month of roll-out of Google Maps real-time transit tracking. Panel A source: https://gohart.blogspot.com/2013/10/. Panel B source: https://www.metro-magazine.com/news/houston-metro-google-partner-for-real-time-info.

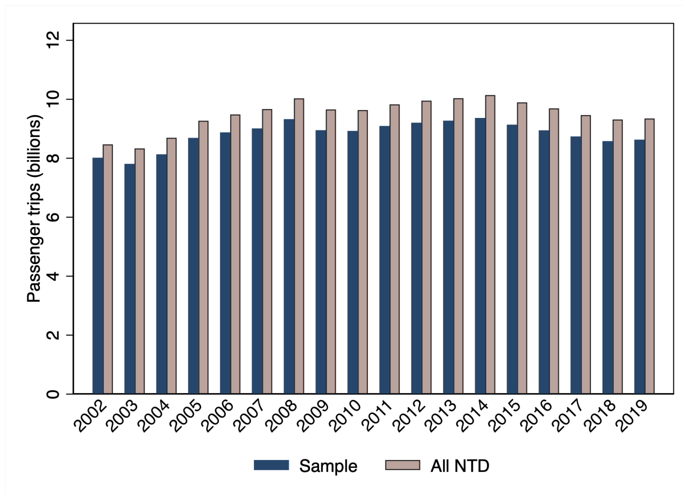


Figure A.2: Annual Passenger Trips for Sample vs Population of Transit Agencies

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 the NTD database in pink.

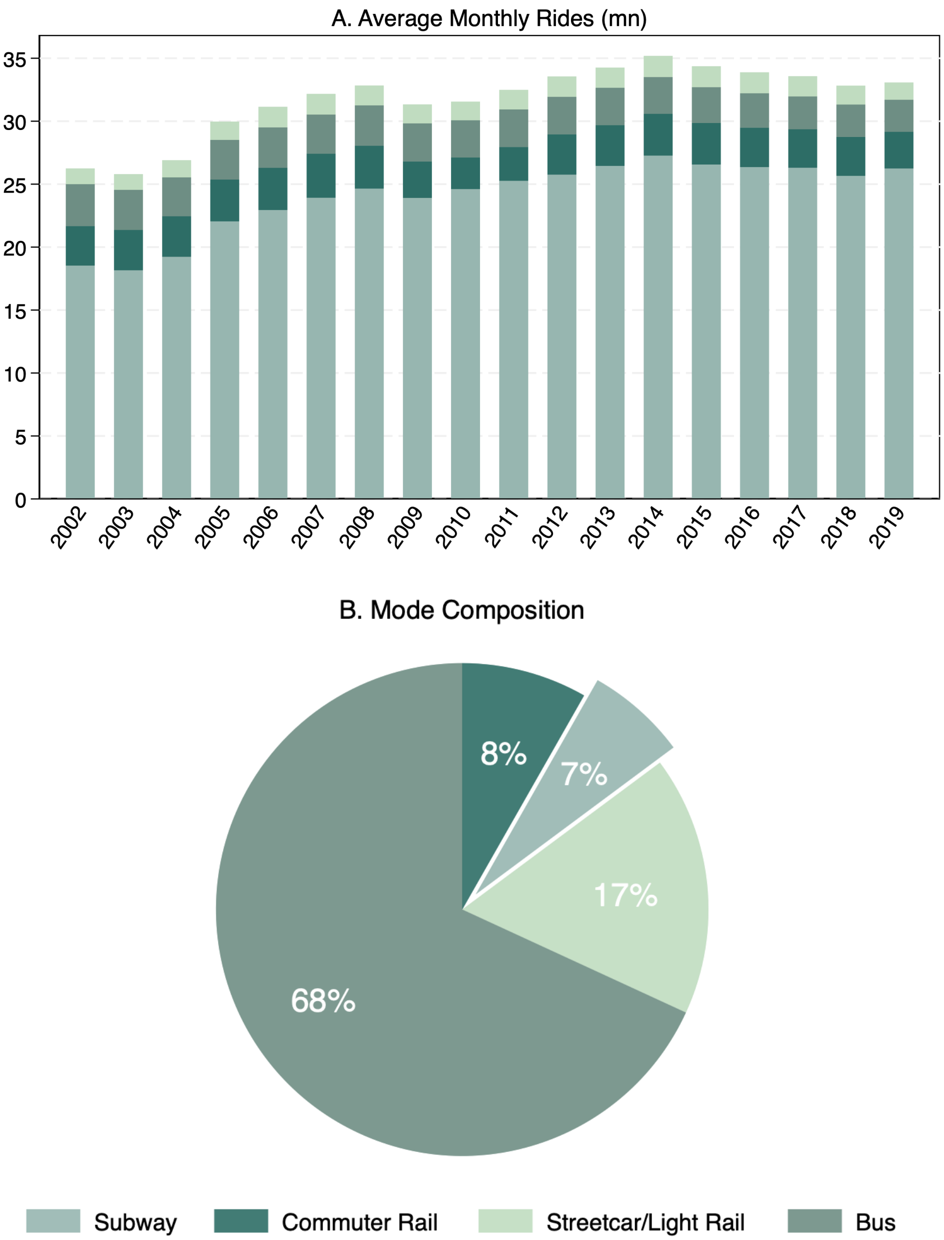


Figure A.3: Composition of Transit Operations by Mode

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 ridership (in millions). Panel B shows the composition of mode types.

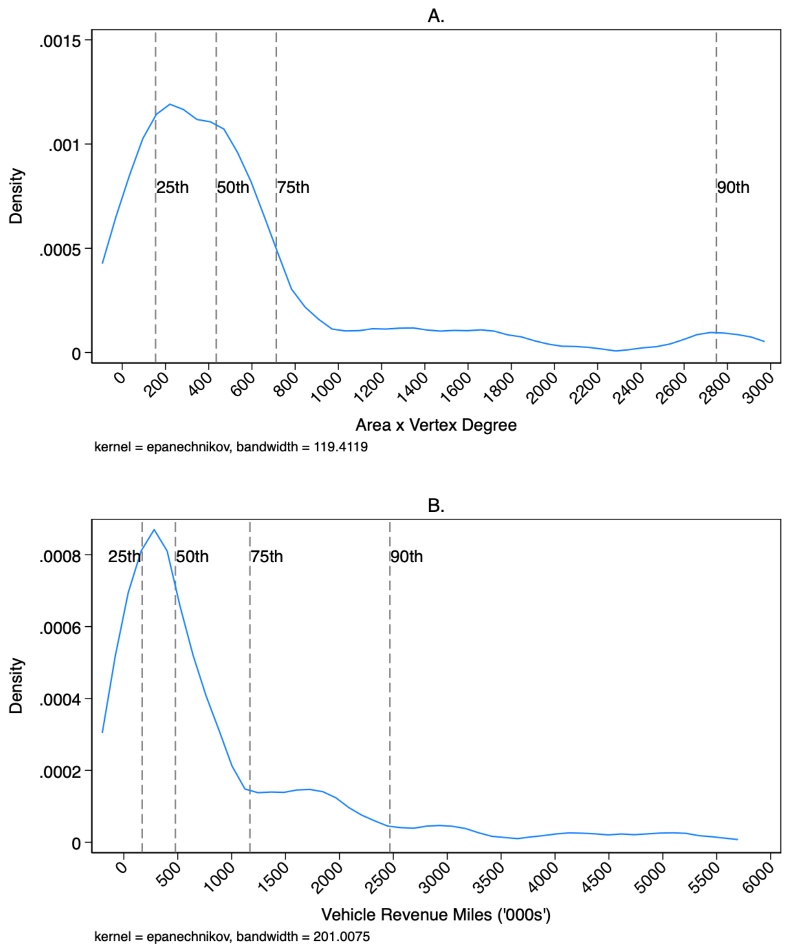


Figure A.4: Kernel Density Plots of Heterogeneity Characteristics

Note: Panel A plots the kernel density of transit system complexity, measured as the product of service area and average vertex degree. Values larger than 3,000 are cut off for exposition purposes. Sample includes 101 cities. Panel B plots the kernel density of vehicle revenue miles measured as of 2002. Values larger than 6,000,000 are cut off for exposition purposes. Sample includes 182 agency-mode pairs.

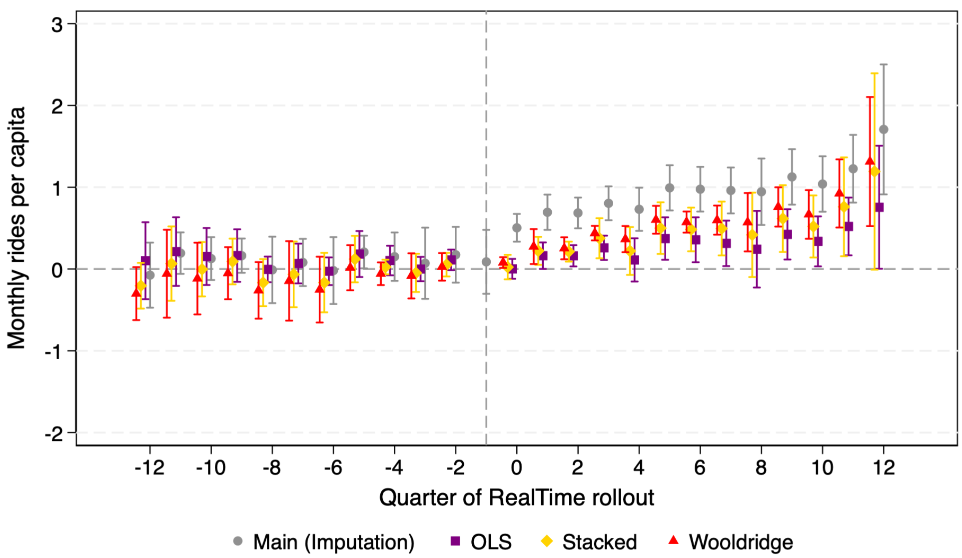


Figure A.5: Sensitivity to Estimation Method

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1. Each symbol indicates a different estimation methods as follows: circles are the BJS imputation method; squares are traditional least squares; diamonds are a "stacked" TWFE approach, and triangles are Wooldridge [2021]. Each estimate shows the change in monthly trips per capita in quarter q relative to the omitted quarter (under the imputation method, the omitted quarter is all quarters prior to $q = -12$. In all other estimation methods, the omitted $q = -1$.) All specifications include season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, agency-by-mode fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. The "stacked" approach also includes cohort-by-agency-by-mode fixed effects. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area. The Wooldridge [2021] method provides an alternative way of overcoming the problem of negative weights associated with TWFE regressions by adopting a regression-based solution that relies on a set of saturated interaction effects. The model includes treatment cohort dummies, time period dummies, and a set of cohort-by-time treatment indicators. The "stacked" TWFE approach provides explicit design-based identification, whereby each treated agency is compared to only "pure control" agencies over contemporaneous time periods, and includes cohort-by-year fixed effects, so that identification comes from within-cohort comparisons across event time.

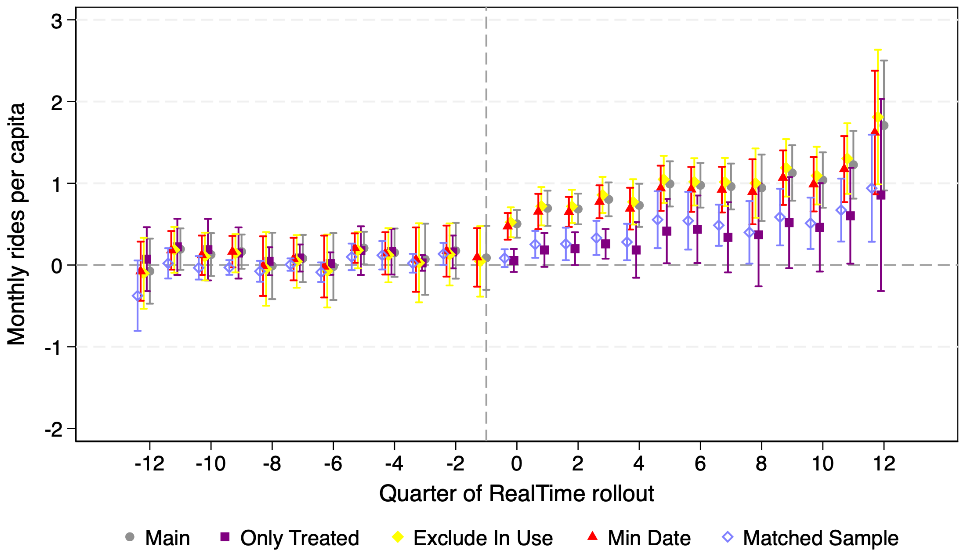


Figure A.6: Sensitivity to Sample & Treatment Assignment

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1. Each estimate shows the change in monthly trips per capita in quarter q relative to the omitted quarter. Each symbol indicates a different sample or specification of treatment assignment as follows: circles employ our main approach. Squares use only treated units in the sample, comparing outcomes before versus after rollout. Estimation is via traditional least squares because the BJS method requires sufficient data on untreated units (i.e., "pure controls" or never-treated units) to estimate unit and time fixed effects. Solid diamonds exclude the "in-use" agency-mode pairs thereby excluding instances where true real-time adoption date likely predates our assigned adoption date. Triangles assign the rollout date to be the earliest date among all modes within an agency, as it is plausible that we erroneously assigned untreated modes in treated agencies as "pure controls". Finally, hallow diamonds use a matched sample, wherein each treated agency-mode is matched to two controls using Mahalanobis nearest-neighbor matching. Observations are matched based on agency-mode vehicle revenue miles as of 2002, agency-mode ridership as of 2002, the mode type, whether the agency has a subway, the share of city residents that are black as of 2010, and the square mileage of the city, leaving a sample of 82 agency-mode pairs (52 treated and 30 control). All specifications include season-by-region fixed effects, city fixed effects, and year-by-region fixed effects. All specifications other than the "Exclude In Use" specification include an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. All specifications other than the matched sample approach include agency-mode fixed effects, and 2002 ridership per capita-by-year fixed effects. The matched sample estimation approach includes matched-group fixed effects. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area. The "Only Treated Sample" and "Matched Sample" results are estimated via traditional least squares, and the omitted quarter is $q = -1$. All others are estimated via the BJS imputation method, and the omitted quarter include all quarters up through $q = -12$.

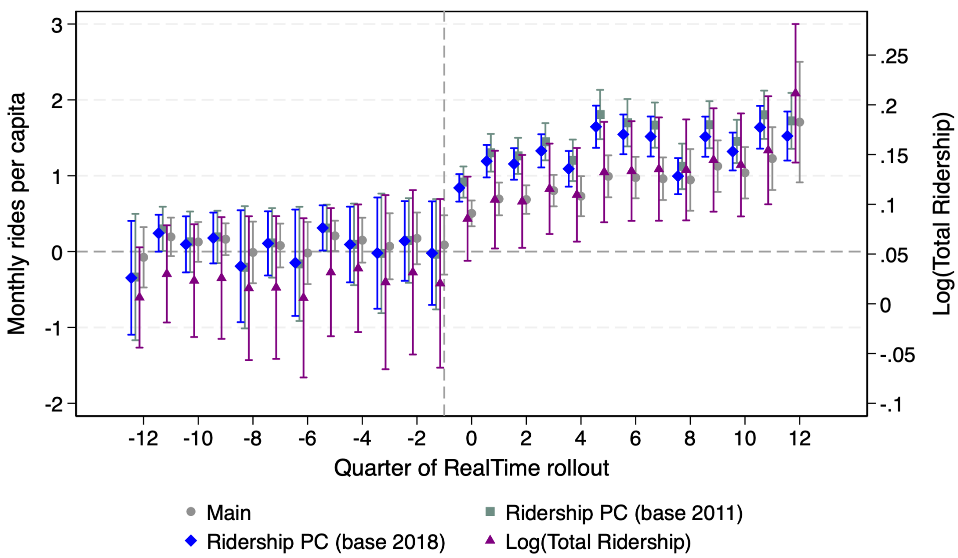


Figure A.7: Sensitivity to Outcome Definition

Note: Figure plots the estimates and 95% confidence intervals using Eq. 1 where y is one of four alternative definitions of ridership. The gray dots show our main specification where ridership per capita, with 2002 population as the base. We use this base year's population as the denominator rather than a contemporaneous year's population because population could respond to the treatment itself, and because the NTD does not have consistent updates of service area population across agencies across years. However, if Google Maps targeted agencies with growing populations, this definition may overstate the true effect. To address this concern, we employ three alternative measures of the outcome: ridership per capita with 2011 population as the base, which is the first year Google real-time tracking was available among any agency (shown in squares); ridership per capita with 2019 population as the base, which is the last year in our sample (shown in diamonds), and log(total ridership) (shown in triangles). Each dot shows the change in monthly trips per capita in quarter q relative to the omitted quarter (all quarters prior to $q = -12$). All specifications include agency-by-mode fixed effects, season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and "In Use"-by-year fixed effects (where "In Use"=1 if the treatment date for an agency-mode represents the earliest in-use date of Google Maps real-time tracking, as opposed to the actual roll-out date). All parameters estimated using the BJS imputation method. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area.

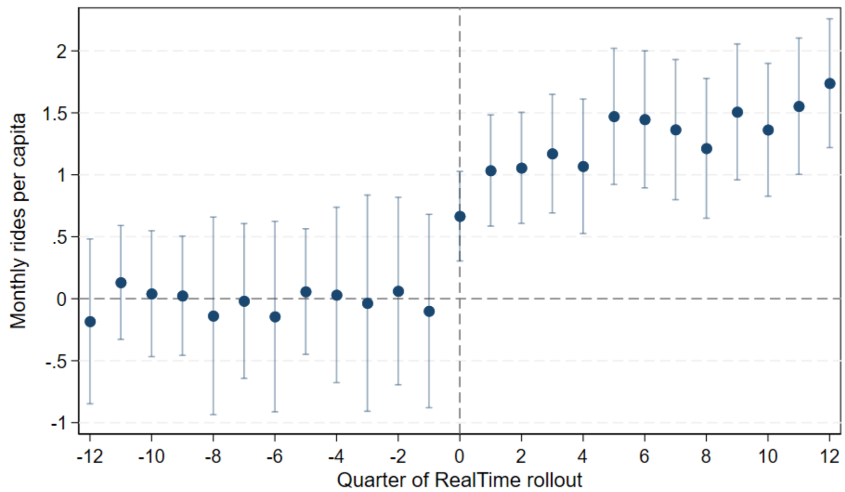


Figure A.8: Effects of Real-time Transit Tracking - Neighboring Group Analysis

Note: Figure plots the estimates and 95% confidence intervals of δ_l using Eq. 1. Controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, an indicator for whether Google Maps real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect; and a vector of geographically-adjacent group fixed effects interacted with the fixed effects in the baseline model. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by geographically-adjacent group. Parameters estimated using the BJS imputation method. Clusters are urban areas whose centroids are within one-hour driving distance of one another. In total, there are 46 cities in the control group, 17 cities in the treatment group and 17 clusters, totaling 22,248 agency-month observations. Appendix Table A.4 lists the treated cities and neighboring cities in detail. Because the event study pattern and point estimates using this restricted neighboring-pairs approach is very similar in magnitude to our main results, any spatial spillover from one agency's adoption to another agency's ridership is likely minimal.

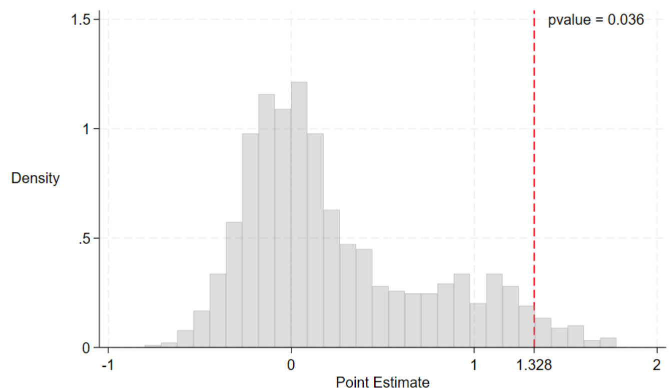


Figure A.9: Randomization Inference

Note: Figure plots the distribution of point estimates utilizing a randomization inference procedure (Horowitz [2019]). The procedure operates in two steps. First, we randomly assign exactly 43 agencies (the true number of treated agencies) to the treatment group. Second, we randomly assign a rollout date to each of these 43 agencies and estimate the average treatment effect from Equation 1. We repeat this exercise 5000 times. The gray histogram shows the distribution of treatment effect estimates from these 5000 iterations, and the red dotted line denotes our main estimate of 1.32. Randomization inference yields exact small-sample-valid p-values; in our exercise, $p = 0.036$. The true effect lies above the 95th percentile—which suggests that our results are not an artifact of random chance. For all estimates, controls include agency-mode fixed effects, region-by-year fixed effects, season-by-region fixed effects, and base ridership-by-year fixed effects. Observations are weighted by their 2002 vehicle revenue miles. Standard errors clustered by urbanized area. Parameters estimated using the BJS imputation method.

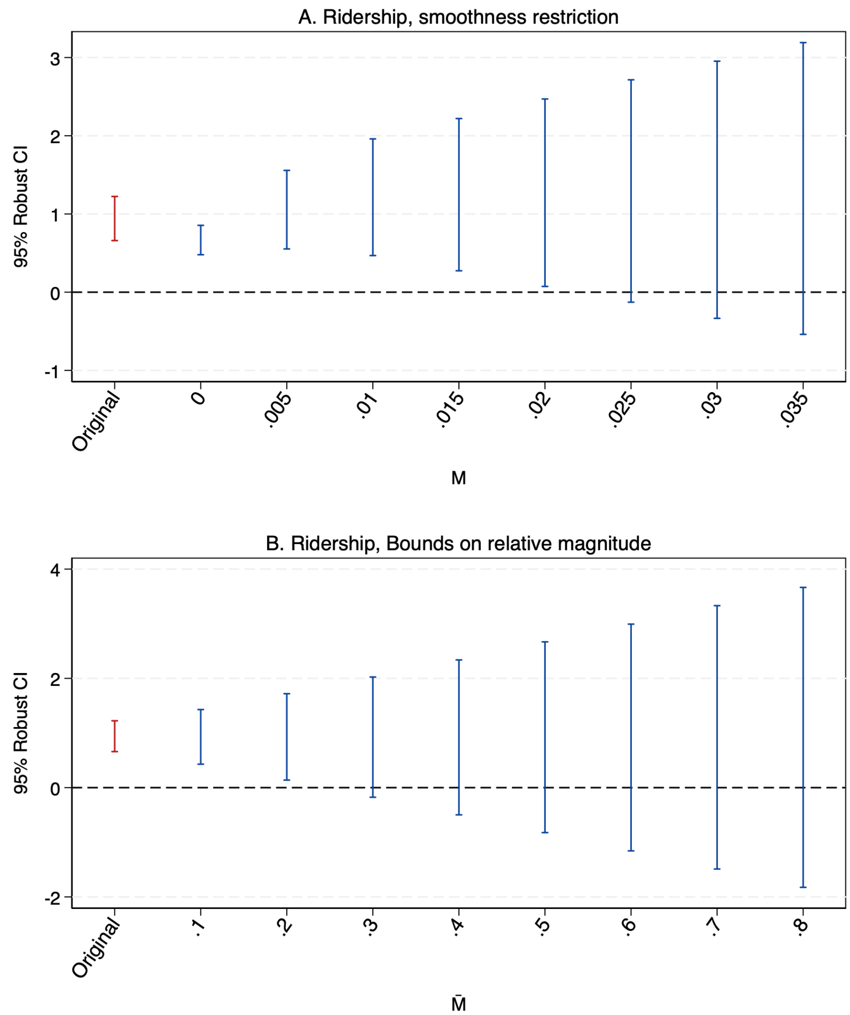


Figure A.10: Parallel Trends Sensitivity Analysis for Ridership Effect

Note: The figure shows the sensitivity of our results to violations of the parallel trends assumption using the "honest" approach from Rambachan & Roth (2023). We show sensitivity to their two proposed approaches—the smoothness restriction in Panel A; and the bounds on relative magnitudes in Panel B—both of which show the magnitude of post-treatment violations of parallel trends that would render our main ridership results statistically insignificant. Panel A compares post-treatment trends to deviations (indexed by M) from a linear extrapolation of pre-treatment differences in trends. At $M = 0$, the post-treatment trends are assumed to match estimated pre-treatment trends. In red, we show the 95% confidence interval of the treatment effect (averaging all post-treatment periods), while in blue we show the 95% confidence interval when allowing for violations of the pre-period parallel trends up to parameter M. Our treatment effect estimate would remain significant up to $M = 0.025$, meaning the results remain significant if the deviation from the linear extrapolation of the estimated pre-trend is up to 70% of the average change in slope observed in the pre-period ($\approx$ -0.036). Panel B shows that the treatment effect would remain significant up to $M = 0.3$, suggesting that our results would no longer be significant if we allow the deviation from parallel trends to be over 30% of the maximum violation observed in the pre-period.

Table A.1: Effects of Real-time Transit Tracking on Ridership by Agency Size, Transit Mode, and System Complexity

	Size	Mode	Complexity
Panel A. Sample:	VRM > 90p	Subway	Area x Vertex Degree > 75p
β^1: Realtime (=1)	1.217***	2.381***	0.803***
	(0.243)	(0.259)	(0.350)
Observations	3,912	2,496	9,468
Panel B. Sample:	VRM $\leq$ 90p	Subway	Area x Vertex Degree $\leq$ 75p
β^2: Realtime (=1)	0.089	0.031	0.008
	(0.084)	(0.088)	(0.100)
Observations	32,553	34,065	16,200
Weights	None	None	Base VRM
$p(H_0 : \beta^1 = \beta^2)$	0.000	0.000	0.031

Note: "VRM > 90p" and "VRM < 90p" denote agency-by-mode pairs with 2002 vehicle revenue miles in the top 10th and bottom 90th percentiles, respectively. "Subway" sample includes only subway modes and "Bus,LR,CR" includes bus, light rail, and commuter rail modes. "Area x Vertex Degree >75 p" and "Area x Vertex Degree $\leq$ 75p" includes only cities with system complexity in the top quartile and bottom 75th percentiles, respectively where complexity is measured as the total service area x the average vertex degree. All specifications include season-by-region fixed effects, city fixed effects, year-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date interacted with a year fixed effect. Specifications (1)-(2) also include agency-by-mode fixed effects. $p(H_0 : \beta^1 = \beta^2)$ is the p-value for a cluster-robust Wald test of equality of treatment effects across sub-samples for a given heterogeneity characteristic. In other words, for each column, $p(H_0)$ is the p-value for equivalence of the treatment effect in Panel A (β^1) relative to Panel B (β^2). All parameters estimated using the BJS imputation method. Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated units. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

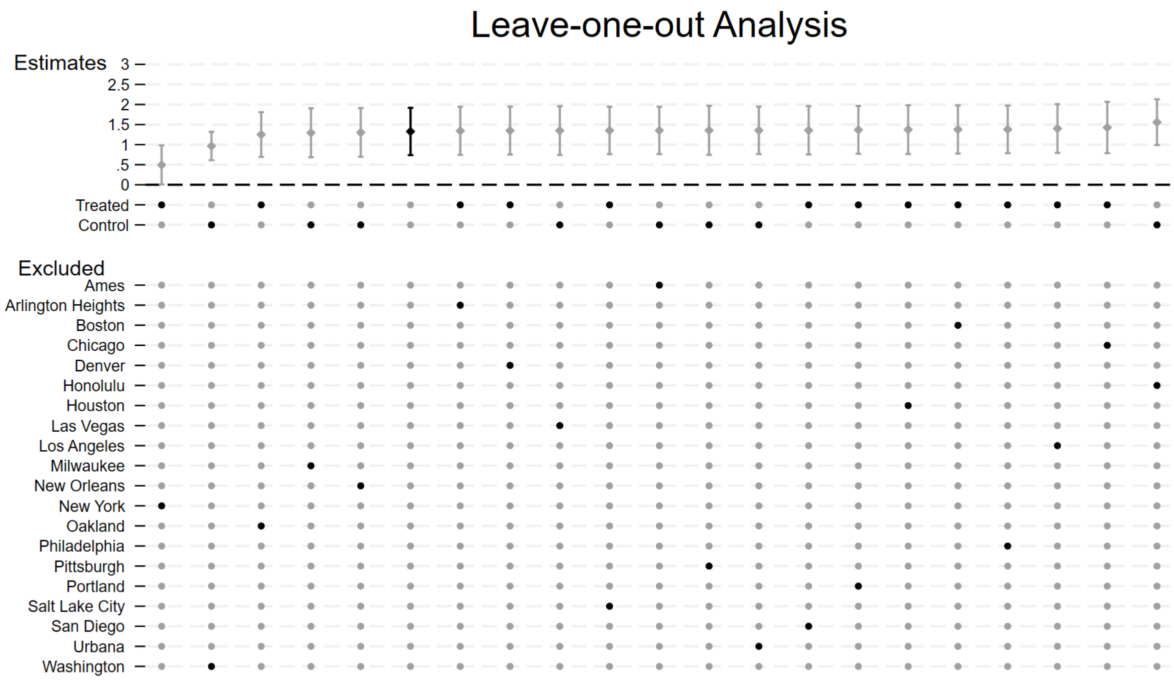


Figure A.11: Leave-one-out Analysis

Note: This figure shows the 20 largest absolute difference from the baseline estimate of 1.4 obtained by sequentially excluding individual cities. The corresponding city that was dropped to generate that estimate is denoted in the bottom panel. Average treatment effects associated with dropping each city are shown in Appendix Table A.3. We see the biggest difference after excluding New York City (NYC)—a treated city: the average treatment effect reduces by roughly two-thirds from 1.4 to 0.5 additional rides per capita per month, although it remains statistically significant. The average treatment effect also falls slightly to about 1 additional ride when Washington D.C.—a pure control city—is dropped. We see almost no effect from dropping other cities from the sample. All parameters estimated using the BJS imputation method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

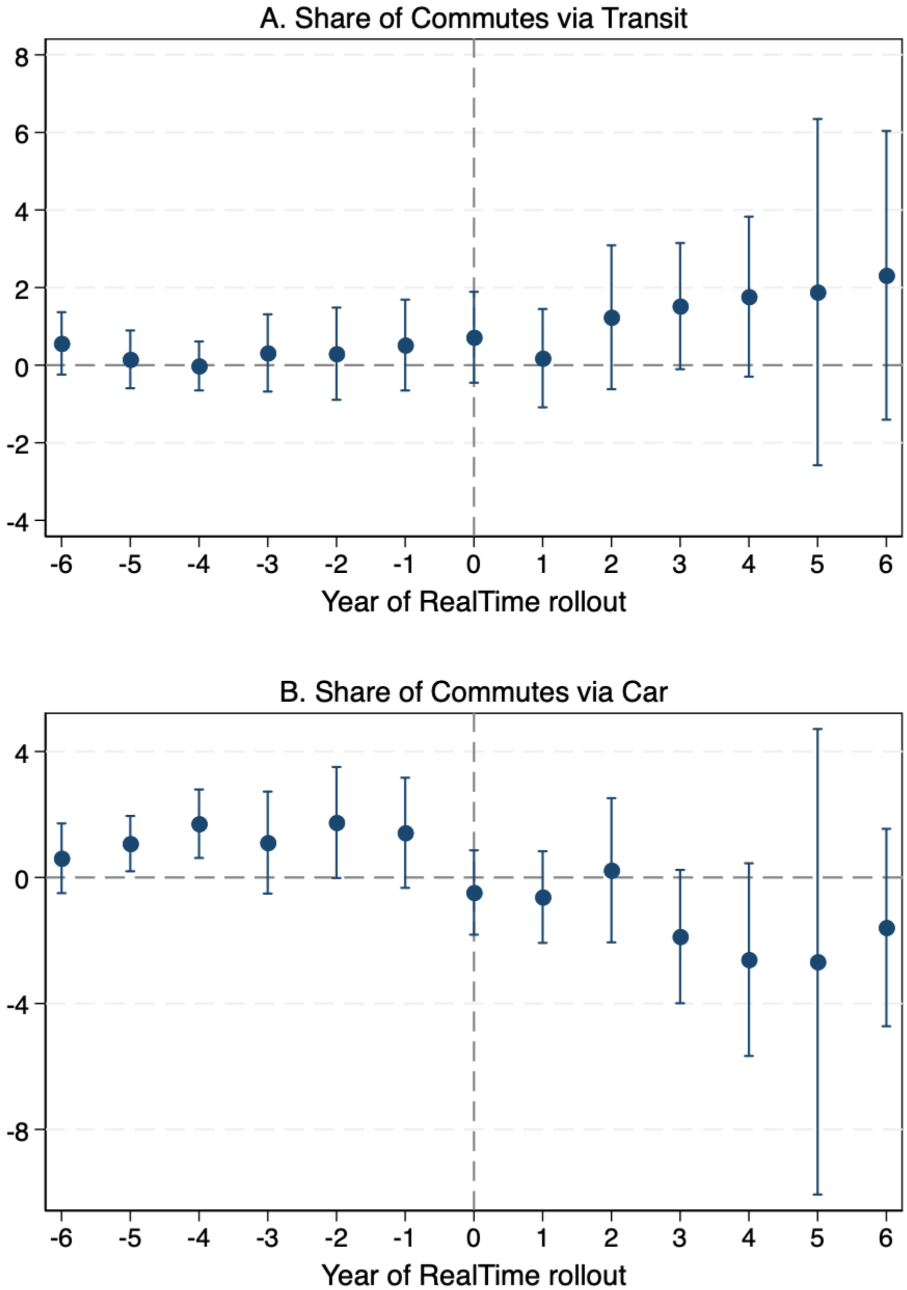


Figure A.12: Real-time Information and Commute Mode Choice at City Level

Note: Figure shows the effect of real-time tracking on average city-level commute mode choice based on the following specification: $\Pr(c_{jt}) = \sum_{l=-5(\ni-1)}^{5} \kappa_l \mathbf{1}\left[y - R_j = l\right] + \alpha_j + \mathbf{Z_j}\zeta_t + \varepsilon_{jt}$ where $\Pr(c_{jt})$ is the city-level share of individuals in city j in year t that primarily commute via mode c where c is either public transit (Panel A) or car (Panel B). $R_j = 1$ is the year when real-time tracking became available for any agency in city j. Controls include city fixed effects α_j, and a vector of the following controls interacted with year fixed effects $\mathbf{Z_j}\zeta_t$: region, 2002 ridership, 2002 vehicle revenue miles, and an indicator for whether real-time tracking was "in use" for any agency as of the assigned treatment date. Standard errors clustered by urbanized area. Parameters estimated using the BJS imputation method.

Table A.2: Average Effects of Real-time Transit Tracking on City-Level Commute Modes

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

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

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

Table A.3: Leave-one-out Analysis (Full Sample)

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

Continuation of Table A.3			
Detroit	1.328	[.738 , 1.917]	-.042
Dover	1.328	[.738 , 1.918]	.017
Durham	1.328	[.738 , 1.918]	.001
El Paso	1.328	[.739 , 1.918]	.021
Eugene	1.324	[.732 , 1.917]	-.281
Everett	1.329	[.742 , 1.916]	.073
Fairfax	1.328	[.738 , 1.918]	-.033
Flint	1.328	[.739 , 1.918]	.023
Fort Lauderd	1.329	[.739 , 1.919]	.078
Fort Myers	1.328	[.738 , 1.918]	-.03
Fort Worth	1.328	[.737 , 1.918]	-.042
Fresno	1.328	[.738 , 1.917]	-.032
Gainesville	1.337	[.746 , 1.928]	.659
Garden City	1.329	[.737 , 1.921]	.076
Grand Rapids	1.33	[.738 , 1.922]	.142
Greensboro	1.328	[.738 , 1.918]	-.012
Hampton	1.328	[.737 , 1.918]	-.044
Hartford	1.332	[.741 , 1.923]	.291
Houston	1.374	[.767 , 1.98]	3.429
Indianapolis	1.33	[.738 , 1.921]	.109
Iowa City	1.329	[.739 , 1.919]	.072
Ithaca	1.338	[.748 , 1.928]	.746
Jacksonville	1.327	[.737 , 1.917]	-.065
Kansas City	1.334	[.742 , 1.927]	.462
Lafayette	1.329	[.74 , 1.919]	.098
Lansing	1.33	[.739 , 1.92]	.122
Las Vegas	1.351	[.746 , 1.956]	1.711
Lexington	1.328	[.738 , 1.918]	.002
Long Beach	1.338	[.743 , 1.933]	.731
Los Angeles	1.401	[.795 , 2.007]	5.507
Louisville	1.336	[.743 , 1.929]	.569

Continuation of Table A.3			
Madison	1.329	[.737 , 1.922]	.096
Memphis	1.328	[.739 , 1.918]	.004
Miami	1.326	[.736 , 1.917]	-.123
Milwaukee	1.296	[.687 , 1.906]	-2.403
Minneapolis	1.336	[.742 , 1.93]	.59
Montebello	1.328	[.741 , 1.915]	.01
Nashville	1.33	[.739 , 1.921]	.135
New Haven	1.33	[.74 , 1.92]	.147
New Orleans	1.304	[.697 , 1.911]	-1.849
New York	.496	[.009 , .982]	-62.683
Newark	1.33	[.748 , 1.911]	.105
North Charle	1.328	[.738 , 1.918]	-.017
Oakland	1.252	[.694 , 1.81]	-5.733
Oceanside	1.337	[.744 , 1.929]	.64
Olympia	1.328	[.738 , 1.919]	.018
Orange	1.325	[.75 , 1.9]	-.244
Orlando	1.329	[.739 , 1.919]	.064
Philadelphia	1.381	[.789 , 1.973]	3.969
Phoenix	1.328	[.738 , 1.918]	-.001
Portland	1.368	[.773 , 1.964]	3.023
Providence	1.332	[.741 , 1.923]	.276
Raleigh	1.328	[.738 , 1.918]	-.034
Reno	1.328	[.738 , 1.919]	.013
Richmond	1.328	[.738 , 1.918]	-.002
Riverside	1.328	[.738 , 1.917]	-.025
Rochester	1.33	[.74 , 1.919]	.129
Sacramento	1.326	[.739 , 1.914]	-.134
Saint Louis	1.343	[.744 , 1.942]	1.11
Saint Peters	1.335	[.739 , 1.93]	.496
Salt Lake Ci	1.354	[.763 , 1.944]	1.92
San Antonio	1.333	[.742 , 1.924]	.354

Continuation of Table A.3

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

Note: All parameters estimated using the BJS imputation method. Each row shows the point estimate in column 1, 95% confidence interval in column 2, and the percentage difference compared to the beseline estimate. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.4: Effects of Real-time Transit Tracking - Spatial Spillovers

Neighboring City	Treated City	Cluster Group
Fairfax	Baltimore	1
Providence	Boston	2
Arlington Heights	Chicago	3
Milwaukee	Chicago	3
Dayton	Columbus	4
Cleveland	Columbus	4
Akron	Columbus	4
Lansing	Grand Rapids	5
Detroit	Grand Rapids	5
Ann Arbor	Grand Rapids	5
Flint	Grand Rapids	5
New Haven	Hartford	6
Springfield	Hartford	6
Bridgeport	Hartford	6
San Antonio	Houston	7
Austin	Houston	7
Lafayette	Indianapolis	8
Anaheim	Long Beach	9
Riverside	Long Beach	9
Orange	Long Beach	9
West Covina	Long Beach	9
Los Angeles	Long Beach	9
Santa Monica	Long Beach	9
Montebello	Long Beach	9
Culver City	Long Beach	9
San Bernardino	Long Beach	9
Lexington	Louisville	10
Milwaukee	Madison	11
Garden City	New York	12

Continuation of Table A.4		
Newark	New York	12
Yaphank	New York	12
Allentown	New York	12
White Plains	New York	12
San Francisco	Oakland	13
San Carlos	Oakland	13
San Jose	Oakland	13
Sacramento	Oakland	13
Santa Cruz	Oakland	13
Allentown	Philadelphia	14
Boston	Philadelphia	14
Vancouver	Portland	15
Tampa	Saint Petersburg	16
Everett	Tacoma	17
Seattle	Tacoma	17
Olympia	Tacoma	17
Bellingham	Tacoma	17

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

A. Dep. Var: CO (ppm)	(1)	(2)	(3)
Realtime (=1)	-0.017	-0.018	-0.031
	(0.016)	(0.016)	(0.019)
App Controls		Y	Y
Temp & Attainment Controls			Y
Dep. Var. Mean	0.426	0.426	0.426
Observations	13139	13139	10174

B. Dep. Var: NOx (ppb)	(1)	(2)	(3)
Realtime (=1)	-1.669	-1.738	-2.947*
	(1.109)	(1.094)	(1.543)
App Controls		Y	Y
Temp & Attainment Controls			Y
Dep. Var. Mean	25.291	25.291	25.291
Observations	11823	11823	9623

Note: Table reports estimates of the average treatment effect from a version of Eq. 1 where the outcome varies by city i and month-of-sample t and $R_i = 1$ after the earliest year that real-time tracking in Google Maps became available for any agency in city i. All specifications include city fixed effects, year-by-region fixed effects, season-by-region fixed effects, 2002 ridership per capita-by-year fixed effects, and an indicator for whether real-time tracking was "in use" as of the assigned treatment date for any agency in city i interacted with a year fixed effect. "App Controls" include controls for the roll out of Uber and the roll out of proprietary tracking apps. "Temp & Attainment Controls" include controls for city-average monthly temperature and the county's non-attainment status, where non-attainment=1 if the county is in non-attainment for any criteria pollutant in a given year. All parameters estimated using the BJS imputation method. Standard errors clustered by urbanized area. Dependent variable mean measured as of 2008 for treated cities. Regressions are unweighted. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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

Note: Observations in the table are aggregated at the agency-city-month-year level. Sample spans three years prior and three years after real-time rollout. All regressions include region fixed effects interacted with quarter interacted with year fixed effects and city fixed effects. Standard errors are clustered by urbanized area. Regressions weighted by agency-mode vehicle revenue miles as of 2002. Column (1) - (3) assume various number of trips per ride. Column (4) uses monthly fare and assumes that each rider takes 20 trips per month. Column (5) - (6) report the estimation by varying the number of trips per day for each individual. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: List of Sample Transit Agencies with Subways and Top Decile Operations

	City	State	Agency	GoogleMaps Realtime Rollout	Top Decile VRM Agency-Mode (2002)	Top Decile Complexity City	Subway Agency
1	Arlington Heights	IL	Pace - Suburban Bus Division	2015m1		X	
2	Atlanta	GA	Metropolitan Atlanta Rapid Transit Authority				X
3	Baltimore	MD	Maryland Transit Administration	2018m6			X
4	Boston	MA	Massachusetts Bay Transportation Authority	2011m6			X
5	Chicago	IL	Chicago Transit Authority	2014m3	Bus, Subway		X
6	Chicago	IL	Northeast Illinois Regional Commuter Railroad Corporation		Commuter Rail		
7	Cleveland	OH	The Greater Cleveland Regional Transit Authority				X
8	Dallas	TX	Dallas Area Rapid Transit		Bus	X	
9	Denver	CO	Denver Regional Transportation District	2016m1	Bus	X	
10	Houston	TX	Metropolitan Transit Authority of Harris County, Texas	2014m4	Bus	X	
11	Los Angeles	CA	Los Angeles County Metropolitan Transportation Authority	2015m12	Bus	X	X
12	Los Angeles	CA	City of Los Angeles			X	
13	Miami	FL	County of Miami-Dade				X
14	New York	NY	MTA New York City Transit	2013m3	Bus, Subway	X	X
15	New York	NY	Port Authority Trans-Hudson Corporation			X	X
16	New York	NY	MTA Long Island Rail Road		Commuter Rail	X	
17	Newark	NJ	New Jersey Transit Corporation		Bus, Commuter Rail	X	
18	Oakland	CA	San Francisco Bay Area Rapid Transit District	2011m6	Subway		X
19	Philadelphia	PA	Southeastern Pennsylvania Transportation Authority	2011m6	Bus	X	X
20	Pittsburgh	PA	Port Authority of Allegheny County		Bus	X	
21	Seattle	WA	King County Department of Metro Transit	2015m6	Bus	X	
22	Washington	DC	Washington Metropolitan Area Transit Authority		Bus, Subway	X	X

Note: This table lists all transit agencies in our sample that either have a subway, have at least one mode (displayed) with annual vehicle revenue miles as of 2002 in the top decile of the sample, or operate in a city with system complexity in the top decile of the sample as measured by total transit stops.