Do ride-hailing services worsen freeway congestion and air quality? Evidence from Uber in California*

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Abstract

We investigate the effects of Uber on freeway traffic and pollution in California. We use a panel difference-in-differences design and exploit variation in Uber's entry into different counties using hourly freeway traffic data and daily pollution data between 2009 and 2015. We find reductions in weekday freeway congestion and PM2.5 concentrations in the average county entered. However, this reduction occurs at off-peak times and in less populated counties, with congestion and pollution worsening during the evening rush hour and in the most populated counties. We also provide evidence that access to public transit mediates the effect of Uber on congestion.

JEL Codes: R4, L91, C21, C23

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1 Introduction

Ride-hailing (RH) services such as Uber and Lyft have greatly expanded worldwide by offering an affordable, flexible and convenient mode of travel in urban areas. These services rely on smartphone-based applications to match drivers with private vehicles with users desirous of rides. There has been massive growth in their usage since they entered major metropolitan areas a decade ago: between 2017 and 2019, the number of monthly active Uber users more than doubled, from 49 to 111 million.[1]

RH services remain an important component of urban transportation, in particular, several studies highlight the influence of RH services on two critical traffic-related externalities, specifically congestion and air pollution (e.g., Tarduno 2021, Li, Hong, and Zhang 2017, Erhardt et al. 2019, Nelson and Sadowsky 2018, Agarwal, Mani, and Telang 2021, Ward, Michalek, and Samaras 2021). Yet, in previous explorations of the broader welfare implications of RH services, externalities related to traffic congestion and pollution were unaccounted for largely due to data constraints.[2] To address this, many of these previous studies utilized surveys, mobile application data, or computer simulations, but very few addressed this relationship using high-resolution traffic data which could provide a more detailed and objective basis for assessing traffic flow patterns. Furthermore, studies examining the effect of RH services on various measures of congestion (e.g., vehicle speeds, travel time) typically focus on cities that were initially targeted, mainly major metropolitan areas (e.g. Tarduno 2021, Erhardt et al. 2019, Agarwal, Mani, and Telang 2021), with little known regarding the effects at smaller urban agglomerations

In this paper, we investigate the effects of RH services on two key automobile externalities in California: congestion and air quality. The negative effects of traffic congestion, such as wasted productivity, are well noted (e.g. Parry, Walls, and Harrington 2007), and so are the health risks from excess exposure to air pollution, including cardiovascular or respiratory disease and worsened infant health outcomes (e.g. Currie et al. 2014, Neidell 2004). We focus on freeways (as opposed to city streets) due to the availability of real-time traffic data, noting that freeways

1. Source: https://www.statista.com/statistics/833743/us-users-ride-sharing-services/

2. To illustrate, a study by Cohen et al. (2016) finds increased consumer surplus resulting from the availability of on-demand transport services provided by Uber, but doesn't account for either congestion-related or pollution-related externalities.

in California are among the most congested in the U.S., with traffic congestion imposing costs of $28 billion annually due to wasted time and fuel.[3] This problem is expected to worsen as California's population is predicted to increase by 50 million. As a result, an assessment of how RH services contribute to freeway congestion could help policymakers calibrate RH service-related regulations.

We leverage the spatial and temporal variation of Uber's entry[4] into different counties in California using a panel-based difference-in-difference (DiD) framework. It is unlikely that factors affecting freeway congestion or air quality are correlated to when (and if, as we later suggest) Uber enters a given county, since both the entry decision and the precise entry date are based upon idiosyncratic factors independent of the specific levels of congestion and pollution concentrations in a county.[5] Our data include different traffic measures at the county and hourly time-scale along freeways in California and are derived from the Caltrans Freeway Performance Management System (PeMS). Our outcomes of interest include the following county-level aggregates: a measure of average speed (called "travel efficiency"), a vehicle delay measure, and vehicle miles traveled (VMT), where the first two are alternative (and complementary) measures of congestion while the last one measures traffic volume. In regards to pollution outcomes, we focus on four criteria air pollutants as designated by the U.S. Environmental Protection Agency (EPA): fine particulate matter (PM2.5), nitrogen dioxide (NO_2), ground level ozone ozone (O_3), and carbon monoxide (CO). These pollutants are known primary or secondary pollutants associated with vehicle emissions that are regulated by the U.S. EPA due to their health-related risks.

We make two important contributions to the literature. First, our measures of traffic outcomes utilize high-resolution hourly sensor data along freeways throughout California, enabling us to explore heterogeneous effects along two key dimensions: hour of day and county characteristics. We thus provide the first high-resolution empirical estimates of the effects of Uber's entry on traffic patterns over a large geographic scale, complementing existing work that has focused on

3. Source: rebuildingca.ca.gov/congested-corridor.html

4. Following previous literature, we focus only on Uber, since the share of Lyft (which also operated in CA during 2009-2015), is very low (at 6% for all of the U.S. Anderson and Davis (2021)).

5. This line of reasoning is consistent with several other studies in economics examining the effects of Uber on a variety of outcomes (e.g., Hall, Palsson, and Price 2018, Barreto, Silveira Neto, and Carazza 2021, Barrios, Hochberg, and Yi 2020, Nelson and Sadowsky (2018)).

a single city or a handful of large cities (e.g.,Tarduno 2021, Agarwal, Mani, and Telang 2021, Erhardt et al. 2019). The focus in the existing literature on large or densely populated cities may obscure the degree to which the effect of RH services differ across urban areas of varying sizes, especially as RH services continue to expand into smaller or medium-sized areas. We explore whether there is any significant heterogeneity in the effect of Uber's entry on traffic and pollution outcomes across different county characteristics in California, as observed for other travel modes such as public transit, following Uber's entry (Hall, Palsson, and Price 2018). Furthermore, the effects of RH services on traffic outcomes are likely sensitive to time-of-day, since congestion-related externalities are often greatest during peak travel times. Yet, very few studies (e.g., Tarduno 2021, Agarwal, Mani, and Telang 2021) use traffic data detailed enough to observe intra-day variation, making it difficult to assess if RH services alleviate traffic during these peak travel times. Using these hourly-traffic data, we examine the effect of RH service's entry during different hours of a day to more precisely characterize the effect of Uber upon congestion.

Second, we evaluate the effects of RH services on air pollution throughout California. Though air pollution is clearly linked to traffic outcomes, this relationship is often complex and varies across space and time. To our knowledge, very few studies (e.g., Ward, Michalek, and Samaras 2021) explicitly examine the relationship between RH services and air pollution empirically. Yet, a greater understanding of the environmental effects of RH services is needed for policymakers to fully assess the externalities and costs associated with the introduction of RH services in a given county or city.

Our main results are that, for the average county entered and the average hour on a weekday, Uber's entry is associated with reduced freeway vehicle delay, our preferred measure of congestion, of 0.19 seconds per capita. This implies freeway traffic congestion fell by approximately 13% of average hourly vehicle delay in treated counties, a sizeable reduction in congestion. This fall in congestion is consistent with the increase in travel efficiency, an alternative congestion measure, by 2.5%. We also find that traffic volume, measured by VMT, increased by 8%. As for pollution, we find that for the average county entered, daily weekday PM2.5 concentrations decreased by up to 10% after Uber's entry, though we find no significant effect on any of the other pollutants.

However, we also show the effects of Uber's entry on freeway traffic and pollution outcomes are sensitive to hour-of-day and county characteristics, specifically population. For the five most populated counties in California and for counties in Southern California, we find worsened congestion of 0.2 seconds per capita, which is comparable in size to our main result, while in less populated counties and outside southern California, congestion improved. In the most populated counties, we also find increases in O_3 of 0.91 ppb (3% of average O_3) and NO_2 of 1.25 ppb (8% of average NO_2), while in other counties we find large reductions in PM2.5 concentrations. Additionally, we show that congestion worsened during evening rush hour by four times the main result, while there was major congestion relief during non-peak travel times, specifically the afternoon and nighttime.

While our reduced form approach makes identifying causal mechanisms challenging, we nonetheless provide suggestive evidence that our findings, of reduced congestion on average with significant heterogeneity across counties, are likely driven by changes in county-level transit ridership and vehicle ownership. The literature on the effect of RH services on mode split, especially public transit, is mixed and yields nuanced findings, depending on city size, trip characteristics, and type of transit (e.g., Hall, Palsson, and Price 2018, Nelson and Sadowsky 2018). Similarly, the link between RH services and vehicle ownership is also ambiguous due to the absence of high resolution vehicle ownership data (e.g., Ward, Michalek, and Samaras (2021)). Using monthly transit ridership, we find that in counties where per capita transit ridership is high, especially in counties where rail-based transit is available, vehicle delay decreases following Uber's entry. This suggests a complementary relationship, at least for these county groupings, between public transit and Uber. This is further reinforced by our findings using annual vehicle registration data. In counties where vehicle ownership is relatively low (which includes many counties with high transit ridership), we also find Uber's entry is associated with reduced vehicle delay. The latter finding suggests following Uber's entry, people may shift to alternative transportation modes, such as public transit.

The remainder of this paper is structured as follows: sec:Data-Summary-Stats discusses the data sources and presents summaries while section 3 presents the empirical analysis for traffic outcomes. Section 4 presents suggestive evidence that public transit usage and automobile ownership may represent two prominent channels through which Uber's entry affects congestion. Section 5 presents our main empirical results regarding the effects of Uber on pollutant concentrations. Section 6 briefly discusses valuing the impacts of Uber's entry on congestion and pollution and section 7 concludes. A supplementary online appendix presents further details related to the sample, summary statistics along various dimensions and robustness checks.

2 Data and Summary Statistics

2.1 Data

We assemble a dataset consisting of three distinct components: data on Uber's entry into California's counties, data on freeway congestion, and data on pollution concentrations. Dates of Uber's entry into different counties are derived from a compilation of entry dates by Forbes (up to December 2014) from Uber's now defunct blog (blog.uber.com), local news articles on Uber's global launch cities and dates,[6] and a dataset from the study by Hall, Palsson, and Price 2018 (up to the year 2015). Table 1 shows the exact date of Uber's entry into different counties in California between 2009 and 2015, our study period. Following the previous literature, we focus on the entry of the more affordable, widely used (and default on the Uber app) service, UberX, instead of the elite service UberBlack.

For freeway traffic outcomes, we use data from the PeMS (California Performance Measurement System, http://pems.dot.ca.gov/), which is maintained by the California Department of Transportation and collects real-time data every 30 seconds from detectors placed along freeways statewide as well as data from partner agencies. County-level aggregate data from PeMS are obtained at the hourly time-step for our analysis. A key reason for our choice of a county as the unit of analysis (instead of the city) is data availability, which is significantly better at the county-level than at lower levels of aggregation for our main outcomes of interest: traffic and pollutant concentration.[7] Furthermore, while Uber primarily enters at the city- as opposed

6. See https://github.com/voxmedia/data-projects/tree/master/verge-uber-launch-dates

7. We note that both pollution and freeway congestion are relatively larger-scale phenomenon, since they cross typical small-scale aggregates such as neighbourhood or census-tract-level. To illustrate, Anderson and Davis (2021) find that the average Uber trip was five miles in length, with the 90th percentile being as long as ten miles (p.4). In consequence, the use of a market-entry indicator is a good proxy for changes in traffic and pollution

to the county-level (with the exception of Orange county), it usually enters the largest city in that county (with Riverside, Santa Barbara, and Monterey County being exceptions). Finally, RH services such as Uber are regulated at the state level: the California Public Utilities Commissions (CPUC) is responsible for creating statewide policies governing RH services.[8] Cities can supplement these with special restrictions and regulations, such as where RH services can operate. As long as RH services adhere to these rules, they can operate anywhere in California, meaning there is no significant impediment to considering the county as our unit of analysis, especially since traffic patterns (and therefore pollutant emissions) in areas outside the main city entered are also likely affected.[9]

PeMS provides a data-rich setting to observe the effects of Uber's entry on various measures of freeway traffic (see appendix A.4 for details). We collect information on the three key traffic outcomes. First, vehicle delay, which represents the total number of extra seconds a vehicle spends on freeways in a given county relative to the time it would have spent at a standard free-flow speed of travel of 60 mph. Vehicle delay is a reliable measure of congestion, since it reflects changes in time actually spent on a freeway relative to that of an idealised vehicle speed absent congestion. This measure is complemented with an alternative, imperfect measure of congestion, travel efficiency, which is an aggregate travel speed measure calculated by dividing VMT by vehicle hours traveled (VHT). Third, we use data on VMT, which is the sum of miles driven in a given county, as a measure of traffic volume that is commonly used in the literature.[10]

Our other outcome of interest is pollutant concentration, and we obtain information on the average daily concentrations of CO, PM2.5, NO_2, and O_3 at the county-level from the U.S. EPA. We focus on these four pollutants because they are "criteria pollutants" regulated by the U.S. EPA due to their health risks and are known primary or secondary pollutants of vehicle emissions. In California, data from the 2014 U.S. EPA National Emissions Inventory report showed that mobile sources directly contributed to 28% of CO, 72% of NOx, 5% of PM2.5,

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patterns following Uber's entry into a county or city.

8. See https://tinyurl.com/mrcfjdyr for details.

9. We note that infrastructure planning is coordinated either by the largest city in the county or by the county itself, meaning that traffic patterns are affected around the entity approving entry of the RH service. Consequently, congestion and traffic outcomes at the county-level better captures the effects of the entry of RH services.

10. We note that for both traffic and pollutant concentration, data is missing for many sparsely populated counties, with data for about 37 (out of 58) counties largely available for analysis. See appendix A.5 for details.

and 6% of VOC emissions, the latter of which contributes to ground-level ozone. However, this does not account for the much larger amount of PM2.5 formed as a secondary pollutant from gaseous mobile sources, so the effect of transportation on PM2.5 is actually much greater (US EPA 2015).

We also control for annual socioeconomic (SES) characteristics at the county-level including information from the 1-year American Community Survey (ACS) between 2009 and 2015 on median age and income, population density, the number of people unemployed, and the number of people who have high school degrees or higher education at the county-level.[11] Finally, since weather patterns are known to affect both traffic outcomes and pollutant concentration, we obtain daily maximum temperature and precipitation from the National Centers for Environmental Information and include them as controls in all our specifications. We use average daily measures across all weather stations at the county-level.

2.2 Summary Statistics

Table 2 presents the means of annual socioeconomic characteristics (panel A), weekday hourly traffic congestion (panel B) and weekday daily air pollution (panel C) in counties where Uber never entered ("Never treated counties") and counties where Uber entered at some point between 2009 and 2015 ("Treated counties"). Column 1 shows means throughout our study period across all counties, while columns 2 and 5 show means during the entire study period for never treated and treated counties (resp.). In never treated counties between 2009 (column 3) and 2015 (column 4), there is a reduction in population density, median income, travel efficiency, and among all pollutants except O_3,[12] over the sample period. However, vehicle delay and VMT per capita increases. We find a similar pattern for treated counties (columns 6 and 7), suggesting that both groups of counties experience trends in the same direction (upward or downward).

Results of the t-test in the last column show statistically significant differences along all socioeconomic characteristics. Median income, age, number of high school graduates per capita

11. Some counties, specifically Amador, Calaveras, Colusa, Del Norte, Glenn, Inyo, Mariposa, Plumas, San Benito, Siskiyou, Tehama, Trinity and Tuolumne, did not have information available in the 1-year ACS, in which case, we used data from the 5-year ACS, where data from the 2009-2013 5-year ACS represented the years 2009 to 2012 and data from the 2013 to 2015 5-year ACS represented 2013 to 2017.

12. To put these figures in perspective, we take the case of PM2.5, and note that the U.S. EPA's 24-hr PM2.5 standard is 35 μg/m^3 (https://tinyurl.com/epa-pm25). The 24-hr standard is met if the 98th percentile of 24-hr PM2.5 concentrations in a given year (averaged across the preceding 3 years) is ≤ 35 μg/m^3.

are greater in never treated counties, while population density and the number of unemployed per capita are higher in treated counties. Among our outcome variables, travel efficiency and vehicle delay are greater in treated counties, while VMT is higher in never treated counties. Finally, concentrations of PM2.5, CO, and O_3 are higher in never treated counties while NO_2 is greater in treated counties.[13] In consequence, we include several control variables to account for many of the key determinants of Uber's entry suggested in our data and identified in previous studies.

3 Traffic Congestion

3.1 Empirical Specification

We investigate the effects that Uber's entry exerted on freeway traffic congestion and volume in California. We use Uber's entry into a county as our source of identifying variation. While details of our identification strategy are discussed further below, we note that two important features related to Uber's entry aid our identification strategy. First, congestion (and traffic volume) was unlikely to be the main motivator of the precise timing of Uber's entry into a county, meaning that the timing of entry into a given county can be considered to be essentially random, conditional on observables.[14] In addition, there were no documented large-scale changes in transit or road usage patterns related to Uber's entry. We anticipate that any differences in congestion identified between counties entered by Uber and those not entered were largely driven by Uber itself (conditional on relevant covariates). We therefore use a panel-based difference-in-difference (DiD) framework to estimate the effect of Uber's entry on weekday freeway traffic congestion and volume. We use the following specification,

$$\text{traffic}_{cht} = \alpha_1 uber_{ct} + \mathbf{time}_{ht} + \text{date}_t + \text{county}_c + \text{county}\times\text{year}_{ct} + \mathbf{SES}_{ct} + \mathbf{weather}_{ct} + \epsilon_{ct} \quad (1)$$

13. The latter likely reflects major improvements in air quality in large cities. For example, of the 14 counties currently in non-attainment (i.e., an area that does not meet the air quality standard as outlined by the U.S. EPA, see https://tinyurl.com/2dasabdc), only four are treated counties.

14. This reasoning holds with greater strength for pollution outcomes. While congestion contributes to pollution levels, they are also strongly affected by geography and climatic factors and weather patterns. Consequently, it is unlikely that Uber chose to enter a county on a specific date based upon the county's pollution outcome, meaning that Uber's date of entry to a county can be considered essentially (conditionally) random.

where traffic$_{cht}$ represents one of the following three weekday-only traffic outcomes for county c during hour h and date t: VMT, vehicle delay in seconds at a travel speed of 60 mph, and travel efficiency, with VMT and delay (which represent county-level totals) normalized by population. The independent variable of interest is $uber$ which is a dummy variable equal to 1 if Uber is active in county c on date t. We also include county fixed effects ($county$) and in **time**, we include a dummy variable for federal holidays and hour-of-day fixed effects, week fixed effects, month fixed effects, day-of-week fixed effects, and year fixed effects. We also include a linear date trend, county-year trends ($county \times year$) and weather variables, specifically daily precipitation and a quadratic in maximum temperature (**weather**).[15]

We also include several county-year-level variables representing socioeconomic characteristics (**SES**) that could influence traffic outcomes, including median age, population density (population per mile^2), number of people with at least a high school degree by age 25 and number of unemployed civilians who are 16 years or older (both normalized by population), and median income per capita. Finally, the error term, ϵ, represents other factors that affect our dependent variables that are unaccounted for in eq. (1). Standard errors are clustered at the county-year level (with 239 clusters in total) to account for serial correlation in a given county and year.

Our set-up in eq. (1) differs slightly from the standard panel data DiD set up with all treated units subject to contemporaneous treatment. Of the 37 counties in California for which we have data in 2015, Uber eventually entered only 19 (see Table 1), and at different points in time. Thus, the coefficient of interest, α_1, is identified from both the differential timing of entry for the treated counties and from the presence of counties that Uber did not enter (i.e. the variation used is both in timing and the occurrence of entry). Thus, control counties at time t include not only "never treated" counties but also all counties that Uber had not entered at time t but did so subsequently,[16] a framework that has been used in empirical studies more recently.[17] Two underlying assumptions ensure identification of the coefficient of interest, α_1. First, Uber's

15. Alternative specifications using cubic splines for temperature and precipitation yielded identical results.

16. Were Uber to have entered all counties eventually, then the only source of identification would be differential timing of entry while if Uber entered only a few counties but did so on the same date, identification would have been on the basis of differential traffic outcomes between treated and control counties.

17. For example, Novan and Smith 2018 investigate the effect of energy efficiency rebates for households, who receive rebates at different times, in the Sacramento region in California.

decision to enter a county and the precise timing of that entry is not based upon unobserved and transitory factors, but is (at least partly) idiosyncratically determined.[18] This approach of leveraging Uber's entry as an identifying source of variation has been used many times to explore a range of outcomes (see footnote 5). We also note that our specification accounts flexibly for policies or institutions that are fixed over space and time by including fixed effects along spatial and different temporal dimensions. As a result, omitted variable bias, driven by factors that affect traffic and correlate with the timing of Uber's entry, is unlikely to be of much concern. The second is the "common trend" assumption, which for our setting, requires that neither treatment timing nor selection into treatment are allowed to depend upon anticipated shocks to untreated potential outcomes in any period.[19] We evaluate this aspect subsequently and provide evidence suggesting that these conditions are very plausible.

Our study differs from previous work relating RH services to congestion in two important ways. First, we measure traffic outcomes across a large cross-section of counties in California, leading to an arguably increased possibility that the effect of Uber's entry will vary based on population size or other characteristics (e.g., transit accessibility). Second, our focus is on traffic and congestion on freeways, as opposed to surface streets, the latter of which has been the focus of previous work. Uber's entry may affect freeway congestion differently than on surface streets for many reasons. For instance, "deadheading", which represents travel undertaken while waiting for a customer or driving to and from a customer, may be less of a concern on freeways than on surface streets. Furthermore, in counties with limited public transit, buses are typically a better substitute for travel along surface streets than on freeways, which could affect the decision to use RH services. While these aspects make it more challenging to assess if α_1 should have a positive or negative sign, findings in the prior literature suggest there is greater reason to assume that Uber has a positive effect on vehicle delay, our main measure of congestion, meaning an expectation of $\alpha_1 > 0$.

18. Observed and known factors (such as differences in levels and patterns of traffic congestion across counties) are allowed to influence Uber's decision to enter a county (and its timing) without affecting identification. Furthermore, previous studies report that Uber's entry decision (i.e. choice of metropolitan region to enter) is largely a function of population and economic size, an observable accounted for in all our specifications.

19. §2.3 of Callaway and Sant'Anna (2019) (p.12) summarise this: "the parallel trend assumption does not permit units to select into treatment in period t because they anticipate a negative 'shock' to their untreated potential outcomes in that period". See also §II.B, Goodman-Bacon (2018)

3.2 Results

Regression results for our main specification (eq. (1)) are presented in Table 3, where odd-numbered columns show coefficients without socioeconomic controls while even-numbered columns show coefficients with those controls included. Columns 1 and 2 show the effect of Uber's entry on weekday freeway travel efficiency, for which we see a statistically significant ($p < 0.05$) increase of 1.65 and 1.52 mph (resp.) at the hour-date-county level in the treated counties. To understand the magnitude of this effect, we note that 1.65 represents 2.6% of the pre-2013 mean travel efficiency in treated counties.[20] Next, columns 3 and 4 show effects of Uber's entry on our preferred measure of freeway congestion, weekday per capita vehicle delay in seconds (at a free-flow speed of 60 mph). We find a statistically significant reduction in delay of 0.19 seconds in column 4, which represents approximately 13% of the pre-2013 mean vehicle delay in treated counties, suggesting a sizeable improvement in freeway traffic congestion on average. Finally, column 6 shows a statistically significant increase of 0.024 miles in VMT per capita, our measure of traffic volume, which represents 8% of the pre-2013 VMT per capita mean in treatment counties. We note that the size of coefficients for all traffic outcomes measures are unaffected by the inclusion of socioeconomic characteristics.

Next, we evaluate the plausibility of the "common trend" assumption and provide suggestive evidence that the effects upon traffic we observe relate specifically to treatment and to treated counties. In particular, if Uber's entry into a county was systematically related to observed changes in traffic (as we assume in our main specification), then traffic outcomes in periods prior to Uber's entry ought to be indistinguishable between treatment and control counties. To observe dynamic changes in traffic before and after Uber's entry, we use an event-study approach. We allow Uber's entry to exert an effect on traffic prior to and after entry into a county and evaluate this hypotheses using the framework below, which is similar to our main specification in eq. (1).

$$\text{traffic}_{ct} = \sum_{k=-5}^{4} \theta_k U_{ct}^k + \mathbf{time}_t + \mathbf{weather}_{ct} + \text{county}_c + \eta_{ct}, \tag{2}$$

where $\{U_{ct}^k\}$ represent indicator variables that equal 1 during k 90-day window(s) after (before,

20. The 2009-2012 ("pre-2013") period means for all traffic outcomes are presented in Table A6. We use pre-2013 means as a point of comparison (here and later on) since these data are "uncontaminated" by Uber's entry given that the first entry of Uber occurred towards the second half of 2013.

if $k < 0$) Uber enters county c.[21] In other words, U_{ct}^{1} takes the value 1 for the first 90-day window after entry and is 0 otherwise. If $k = 2$, then U_{ct}^{2} equals 1 on days 91 to 180 after Uber's entry. We use 90-day windows, which is approximately a quarter, to account for macroeconomic changes and because previous work suggests Uber's popularity grew slowly over time after entry dates.[22] The coefficients of interest are the $\{\theta_k\}$, which represent the effect of each 90-day window on congestion in treatment counties. Specifically, the coefficient, θ_1, shows the effect of Uber on traffic in treated counties one 90-day window after Uber's entry ($k = 0$), relative to periods more than 450 days prior to ($k = -5$) or 360 days post ($k = 4$), Uber's entry. We also include county fixed effects and the same time fixed effects (**time**) and weather variables (**weather**) as defined in eq. (1). Standard errors are clustered at the county-year level. If our identification strategy is valid, then we anticipate that the effects of Uber on traffic congestion are observed after or near Uber's entry period.

The coefficients of interest (θ_k) are plotted with 95% confidence intervals in Figure 1, for up to four 90-day windows (or 360 days) post-entry and five 90-day windows prior to entry. The horizontal red line represents zero and the dashed vertical line separates pre-entry from post-entry periods. This figure reveals that for all 90-day windows prior to Uber's entry, all three traffic outcomes of interest are statistically indistinguishable between the treated and untreated counties. Following Uber's entry ($k = 1$), treated counties experienced a statistically significant increase in both travel efficiency (panel A) and VMT (panel C), while the decrease in vehicle delay (panel B) occurred after a single 90-day period. We then test for the joint significance of the pre-entry and post-entry coefficients for each traffic measure: for all three traffic measures, we can reject the null of no effect post-entry but are unable to reject the null for pre-entry periods.

We also are unable to reject the null of equality of post-entry coefficients for all three outcomes, suggesting that there is no significant change in the effect of Uber over the time period of our sample. In light of recent findings that treatment effects based on differences in

21. We note that since we exclude weekends from our sample, we only consider weekdays in our 90-day windows.

22. For example, Barreto, Silveira Neto, and Carazza (2021) find that Google Trend searches for "Uber" grew slowly after Uber's entry, but increased more rapidly three quarters to 1 year after the entry date. Hall, Palsson, and Price (2018) shows that effects of Uber's entry on public transit ridership are not immediate, but also grew slowly over many months post-entry.

treatment timing can be biased in the presence of heterogeneous treatment effects over time (Sun and Abraham 2021), this finding provides a measure of comfort that our treatment effects are unlikely to be biased on this count.

3.3 Robustness Checks

We next assess the degree to which our main results in Table 3 are robust to different specifications and falsification tests. We note that all specifications considered here include socioeconomic variables. We turn first to addressing concerns that "control" counties are not comparable in many observable ways to counties where Uber entered, as seen in the summary statistics between the "treated" and "never treated" (Table 2), with the latter counties constituting a larger part of the "control" counties towards the end of the sample period. To illustrate these differences, we note that the average population in a treated county, at 1.95 million, is nearly twice that of the never-treated counties. These differences can affect many aspects, such as transit provision, that has a bearing upon traffic congestion. We are particularly interested in addressing the threat to identification posed by time varying changes in some of these differences, since they may lead to unobservable differences related to Uber's entry decision.

We present two different specifications whose results suggest that these differences do not substantively affect our main findings. First, we explicitly control for differences in population levels by restricting our sample to counties and years with populations over 100,000 and 250,000. Regression results for these specifications are presented in panel A of Table 4, where columns 1-3 show results for counties with $>$ 100,000 people and columns 4-6 show findings for population $>$ 250,000 people. These results are qualitatively very similar to those for our main specification, the only noteworthy changes being that the effect on VMT becomes marginally significant and smaller while the effect of travel efficiency is halved in size. Overall, our results suggest that the treatment effects we find are robust to the exclusion of smaller counties, although effect size may vary across traffic outcomes. Second, we evaluate the degree to which accounting for differences in population affects the magnitude of our estimates of congestion relief. We evaluate this using a variant of eq. (1), where we substitute an interaction between 2009 baseline population levels and a year trend for county-year trends. Estimates from this specification are presented in panel B of Table 4 and are larger (at 0.36) than those found using our main specification in Table 3.

A related concern is the order of treatment: early or late treated units may differ in specific ways along key dimensions that could challenge conditional random assignment. We evaluate the relevance of this threat by excluding the first three and last four counties entered by Uber in turn. The regression results from these two restricted samples are presented in panel C of Table 4. Columns 1 to 3 show results obtained when the first three counties Uber entered (Los Angeles, San Francisco, and San Diego) are excluded while columns 4 to 6 show results when the last four counties entered (Butte, Tulare, San Luis Obispo, and Ventura)[23] are excluded. These results are again similar to those in Table 3, though the point estimates for vehicle delay and VMT per capita become only marginally significant in columns 2 and 3.

We also check to see that specific treatment groups or treatment times and the order of Uber's entry are not a key driver of our results. To this end, we carry out a permutation test, wherein Uber's entry date is randomly assigned to counties Uber entered. Results are in Figure 2, where the distribution of these coefficients over 999 replications are plotted, together with the coefficient estimated for the actual entry date and a p-value for the hypothesis that the treatment effect estimated using actual entry dates arises purely by chance. The fact that we can reject this null clearly suggests that the size of the effects of Uber's entry we find for all traffic outcomes are too large to arise purely by a chance realisation of treatment time.

To ensure that our findings are not very sensitive to outliers in the traffic outcomes, we carry out the following two types of checks: one, winsorize or trim the top and bottom 1% of observations on the dependent variable, and two, expunge outliers identified using standard metrics (i.e. Cook's distance). The coefficient on Uber with these samples, as well as those of our main specification for reference (light blue dashed line), are provided in Figure 3. For both travel efficiency and delay, winsorizing (solid blue line) and trimming (solid red line) both lead to almost no change in the effect size, while expunging outliers identified using Cook's distance (dashed orange line) leads to the effect size being reduced for travel efficiency and vehicle delay (to half or three-fourths, respectively), while being significant. For VMT, trimming leads to a slight reduction in the effect size but wisorizing and expunging outliers leads to substantively

23. Uber entered two of these counties, Ventura and San Luis Obispo, on the same date, leading us to choose the final four–instead of three–counties entered.

similar effects as the main specification. Overall, outliers and extreme observations do not affect our estimated effect size in a substantive way.

In this same graph in Figure 3, we also present results from a specification restricting our sample to only treated counties, meaning that the differences in treatment timing are the only source of identification. Results are represented by "Treated Counties only" (green dashed line) and are very similar to those of the main specification, with only the effect on VMT being half the size of the main result.[24]

Next, we assuage concerns that our results are sensitive to functional form. To do so, we use the natural log of the dependent variable and note that the size of the effects obtained, in panel A of Table 5, are unchanged qualitatively from those of our main specification: a statistically significant increase in travel efficiency and a reduction in delay, though there is no significant effect on VMT. Finally, we evaluate whether the relative change in populations across treatment and control groups, and the use of a per-capita version of delay and VMT, affect some of our findings. We show that population changes are not a key driver of our findings by examining specifications with annual population as a control variable, instead of population density, in eq. (1) and using levels of delay and VMT as the dependent variable. In order to minimize the effect of scale (levels of VMT, delay and population vary significantly across counties), we use the log of the levels of delay and VMT as our dependent variable, and add log of population as an independent variable. Regression results for these specifications are presented in panel B of Table 5, which suggest a statistically significant reduction in vehicle delay, but the effect on VMT loses significance. The interpretation of the coefficient in column 2 suggests vehicle delay will decrease on average by approximately 16% following Uber's entry.

3.4 Heterogeneity in effect of Uber on traffic outcomes

Our main specification, eq. (1), assumes homogeneous effects across hours and counties. However, congestion is often localised both spatially and temporally, so in this section we evaluate the question of which travel periods during a day and counties or regions within California are

24. We also carry out a falsification test using the event-study specification from eq. (2) with three socio-economic characteristics that should be unaffected by Uber's entry (higher education, median income, and population density). For all three variables, Uber's entry does not appear to affect their pattern of evolution, and no set of pre- or post-coefficients are (jointly) significant (see Figure A3 in Online Appendix).

most affected by Uber's entry.

3.4.1 Intra-day variation

If Uber's entry has a greater effect on congestion during peak travel periods, such as the morning or evening rush hour, then the marginal benefits or costs of Uber's entry are likely larger than would be suggested by the estimates derived from eq. (1), which specifies a single effect over an average hour. To examine the within-day variation of the effect of Uber's entry on weekday traffic outcomes, we use a variant of our main specification, where we partition the day into five periods, generate an indicator variable for each period, interact it with the $Uber$ indicator, and include it in the specification in eq. (1). The five periods are: an afternoon period (10am to 1:59pm), PM peak period (i.e. evening rush hour, 2 to 7:59pm), the nighttime period (8 to 11:59pm), and a late-night period (12am to 06:59am), with the base period being the AM peak period from 7 to 9:59am. The definition of these these time periods, specifically the AM and PM peak periods, are based on when traffic is expected to be greatest. By having the evening rush hour cover a long period of six hours (which may be longer than the actual peak in many counties), the estimated effect of Uber's entry will likely underestimate the "true" effect in a given county if the actual peak period is shorter than defined here.

The total effects of Uber's entry on traffic outcomes throughout the day (i.e. the sum of the coefficients on $Uber$ and its the interaction terms) are displayed in Figure 4. Panels A, B, and C show the effects upon travel efficiency, vehicle delay, and VMT (resp.) during the AM peak, afternoon, PM peak and nighttime.[25] During the AM peak period, there is no significant effect on travel efficiency nor vehicle delay, and a marginally significant effect on VMT of 0.30 miles per capita. During the PM peak period, there is a significant *increase* in vehicle delay of 0.85 seconds per capita (or 25% of the average delay during the PM peak[26]), but no effect on the other two traffic outcomes. This suggests that freeway congestion worsened after Uber's entry during evening rush hour, with the size of this increase being more than four times larger than the average reduction shown in the main results. During the less congested time periods, the afternoon and nighttime, we find a statistically significant increase in travel efficiency, of 1.98

25. The late-night period is not as relevant for congestion and pollution outcomes, so these results are not shown.
26. See Table A1 for mean traffic outcomes during different time periods in the day.

mph, and reduction in vehicle delay of 0.68 seconds per capita, both of which are larger in size than those in the main results. The effect on VMT is positive and marginally significant during the afternoon and statistically significant during the nighttime.

3.4.2 Inter-regional variation

Given the physical extent of California and the significant variation in socioeconomic characteristics, transportation-related infrastructure, and urban sprawl across its counties, there is likely significant heterogeneity across counties in the effect of Uber on freeway traffic outcomes. Most of the previous literature has focused on major metropolitan areas, with little known regarding effects across urban agglomerations of varying sizes. Furthermore, higher congestion likely exerts a greater marginal cost in more populated cities and counties, which presumably already have worse congestion, especially if public transit is scarce. The variation across counties in traffic outcomes (as discussed in appendix A.2) follows expected patterns: the more populated counties (including Los Angeles, Orange, San Diego, and a few counties in the Bay Area near San Francisco) tend to experience worse vehicle delay, while VMT per capita is a function of many characteristics including population size. Motivated by the evident heterogeneity in traffic outcomes, we explore next whether this heterogeneity carries over into the effects of Uber's entry on traffic outcomes.

We consider two particular groupings of counties in California, with the first one being Southern California, which not only includes the most populated counties in California but is also often characterized as a region of urban sprawl suffering from high congestion. For example, vehicle delay is 50% higher in these counties versus counties outside southern California (see Table A2). Southern California includes the following eight counties, all of which Uber entered (although not all at once): Los Angeles, Orange County, Riverside, San Bernardino, San Diego, San Luis Obispo, Santa Barbara, Ventura.[27] For our empirical specification, we use eq. (1) and include an interaction term between our treatment indicator, $Uber$ and an indicator variable that takes the value 1 for all counties within southern California. The estimated treatment effects of Uber's entry in southern California (i.e. the sum of the coefficient on $Uber$ and its interaction term) are displayed in Figure 5 with 95% confidence intervals, as well as the effect outside of

27. Our definition of "southern California" is from https://tinyurl.com/em568nhk

southern California. We discuss statistically significant results only, unless otherwise noted.

These estimates suggest a high degree of heterogeneity: increases in travel efficiency (panel A) in Southern California ("SoCal") is much smaller, at 0.85 mph (and only marginally significant) compared to change outside the region ("Not SoCal"), at 2.03 mph. For vehicle delay (panel B), these differences are even stronger: a marginally significant increase in delay of 0.2 seconds for counties in Southern California, and a decline in delay outside Southern California of 0.48 seconds, which is more than twice the effect on an average county and 22% of the pre-2013 average for these counties.[28] For VMT (panel C), there is a small increase of 0.04 miles in southern California counties, but no significant effect outside. Overall, reductions in congestion and VMT are concentrated in counties outside of Southern California, while there is some evidence of a small increase in both for counties located within.

The second grouping consists of the five most populated counties in California, all of which are in southern California, with each having a population of at least 2 million: Los Angeles, San Diego, Orange, Riverside, and San Bernardino. Any additional congestion (relief) resulting from Uber's entry in these counties could impose significantly higher marginal costs (benefits) in these counties. The specification used is identical to that for Southern California: an indicator for this county grouping interacted with the treatment indicator, $Uber$. The treatment effect is displayed in Figure 5, where the right side of the vertical line in each panel represents the total effects of Uber's entry in the five most populated counties ("Top 5") and counties outside ("Not Top 5"). Our findings here are virtually identical to those for the southern California specification: increases in delay (panel B) of 0.22 seconds in the "Top 5" counties, with reductions of 0.35 seconds in counties outside. There is a smaller increase in travel efficiency (panel A) of 1.25 mph in the Top 5 versus the 1.63 mph at counties outside. Finally, for VMT (panel C) there is an increase of 0.054 miles per capita in the Top 5 counties, which is twice the magnitude of the average county (or about 14% of the pre-2013 average in the Top 5 counties), but no significant change in the other counties.

28. See Table A6 for mean traffic outcomes for the pre- and post-2013 periods.

3.5 Discussion

Our main results in Table 3 show higher travel efficiency and reduced vehicle delay following Uber's entry, suggesting RH services improved freeway congestion for the average county entered. However, at busier time periods, specifically the PM peak period, and in more populated counties, we find that freeway congestion worsened, varying in magnitude between being similar to and up to four times as large as our main results. We also find traffic volume (VMT) increased both in our main results and in the more populated counties (SoCal and Top 5), where the magnitude of this increase in the latter is twice that in our main results. Findings during off-peak periods, specifically the afternoon and nighttime, and in less populated counties better reflect our main results, showing improvements in freeway congestion and travel efficiency, but no significant increases in VMT. These findings suggest not only that the effect of Uber's entry upon freeway congestion and volume is sensitive to county characteristics and time-of-day, but also that the "average effect", being weighted towards congestion relief, can provide a misleading indication of the effects in specific types of counties.

4 Causal mechanisms

While equilibrium responses at many scales may have led to changes in freeway traffic and congestion, we next explore the direct macro-scale effects that are most naturally analysed in our county-level setting: public transit and vehicle ownership. While a detailed analysis of the effects of Uber on these outcomes is beyond the scope of our study, we provide suggestive evidence that these channels serve to explain, at least partially, our findings regarding traffic patterns.

4.1 Public transit

One possible mechanism underlying our findings is the role of public transit: If Uber's entry caused individuals to shift from Uber to public transit, then one would anticipate vehicle delay and VMT would both decrease, as seen in our main findings. To examine the relationship between Uber's entry, transit usage and traffic patterns, we gather data on unlinked passenger trips (UPT), a commonly used measure of transit usage, at the month-year level from the

National Transit Database over the sample period.[29]

We recall that our findings in section 3.4 suggest significant heterogeneity in effects upon congestion, and we hypothesize that one reason for this difference is that counties with greater transit accessibility, and consequently, ridership, experienced different effects from Uber's entry than counties with lower transit usage. We examine this hypothesis in two different ways: first, by evaluating whether the effects of Uber varied significantly among counties with "high", "medium", and "low" transit usage based on UPT; and second, examining whether the effects of Uber varied by type of transit, with rail transit in particular being considered complementary to RH services. If counties with greater transit usage/presence or rail-based transit experience improved (worsened) traffic outcomes, such as reduced (increased) vehicle delay, then we may surmise that Uber acts to complement (substitute for) public transit.

To explore the first channel, we use a variant of eq. (1) with an interaction term between Uber and two indicator variables based on a county's pre-2013 average UPT per capita. Pre-2013 averages are used since they are not "contaminated" by Uber's entry. The indicator variables identify counties with "high" and "medium" UPT per capita, based on whether a county's pre-2013 average exceeds the 75th percentile of the pre-2013 average for all sample counties or lies between the 25th and 75th percentile (resp.) (appendix A.2 discusses summary statistics by transit and auto ownership category). The omitted category consists of counties with "low" UPT per capita, defined as those counties with a pre-2013 average below the 25th percentile. The results of this regression specification are presented in panel A of Table 6 and the total effects of Uber show a statistically significant reduction in congestion (and increase in travel efficiency) in the medium and high UPT counties, relative to low UPT counties.[30] There is no statistically significant effect on VMT per capita. While not definitive, these results are suggestive of a complementary relationship between Uber and public transit usage for counties where transit usage was already relatively high and could help explain our findings in Table 3 and Figure 5.

29. Transit agencies report these data, which captures the majority of trips in the U.S., to the FTA (Federal Tranist Administration), which are then aggregated to the county-month-year level (they are unavailable at finer time-scales).

30. Sample sizes in panels A and B of Table 6 are identical, but differ from the main specification since not all counties in our sample have UPT data.

We next consider the effect of rail-based transit, which can carry more passengers, move at a greater speed than buses, often covers larger distances, and may serve as more of a complement to Uber's services than buses along freeways. Counties with rail-based transit include Los Angeles, Sacramento, San Diego, Santa Clara, Sonoma, Alameda, and San Joaquin, of which Uber entered the first five. We allow for the effects of Uber to differ in these counties by including an interaction term in eq. (1) between Uber and an indicator for the presence of rail-based transit. The regression results for this specification are presented in Panel B of Table 6 and show that in counties with access to rail, there is a statistically significant increase in the total effect of Uber on travel efficiency of 1.19 mph and a reduction in vehicle delay of 0.44 seconds. In counties lacking rail transit, there is a significant increase in travel efficiency of 0.81 mph and in VMT of 0.023, but no significant effect on vehicle delay.

Altogether, our results here provide some support for the hypothesis of a complementary relationship between Uber and public transit, at least for counties that have high transit ridership or rail-based transit, and are consistent with those in the prior literature for major metropolitan areas nationally (e.g., Hall, Palsson, and Price 2018, Nelson and Sadowsky 2018).[31]

4.2 Vehicle ownership

The entry of Uber into a county can be anticipated to affect both short- and long-run household decisions related to personal vehicles, in particular, vehicle usage and ownership. In the short-run, individuals may alter their vehicle usage decisions while over the longer-run, and depending upon the interaction with public transit, Uber's entry and easy availability may lead to altered ownership patterns. There is limited evidence related to the ownership effect in the literature (e.g. Ward, Michalek, and Samaras 2021). In view of these suggestive findings, we examine if car ownership prior to Uber's entry influences the relationship between traffic outcomes and Uber's entry, using annual, county-level vehicle registration data (these data are unavailable at a finer resolution). To do so, we use our main specification in eq. (1), but interact $Uber$, our treatment indicator, with a dummy variable equal to 1 if the average annual pre-2013

31. We note that our finding that high UPT counties and counties with rail transit experience a greater reduction in congestion is consistent those regarding inter-regional heterogeneity (in section 3.4), since the overlap between counties in "Top 5" and in southern California, and those in high UPT/with rail transit, is low (i.e. not all large counties/counties in SoCal either have rail based transit or significant UPT per capita).

registrations per capita for a county exceeds the 66th or lies within the 33rd and 66th percentiles, which constitute respectively counties with “high” or “medium” automobile ownership.

We hypothesise that the effect of Uber’s entry is greater in counties with lower car ownership (i.e. per capita registrations below the 33rd percentile), since RH services are likely in greater demand. The regression results for the specification detailed are provided in panel C of Table 6 and show that the entry of Uber in “low” registration counties (represented by the coefficient on “Uber”) led to a statistically significant increase in VMT per capita of 0.03 and a reduction in vehicle delay of 0.26 seconds. Both these coefficients are larger than those in the main results in Table 3. While in counties with “medium” and “high” auto registrations, we only find a statistically significant increase in travel efficiency at 2 mph.

In summary, our results suggest that counties with low automobile ownership per capita, which are also typically counties with higher transit ridership levels, experience greater reductions in vehicle delay following Uber’s entry.[32]

5 Air pollution

5.1 Empirical Specification

Examination of the raw pollution levels data in section 2.2 suggested that greater reductions in air pollution may have occurred in treated counties, relative to never treated counties. To examine this hypothesis more rigorously, we use the panel fixed-effects DiD specification in eq. (3) below to assess the effects of Uber’s entry on weekday air pollution. We note that the identifying assumptions and most variables used (along with their definitions) are similar to those for traffic outcomes in section 3, with the only changes occurring to account for daily (as opposed to hourly) effects, since only daily data are available. The specification we use is:

$$\text{pollution}_{ct} = \beta_1 uber_{ct} + \beta_2 date_t + \mathbf{time}_t + \mathbf{SES}_{ct} + \mathbf{county} \times \mathbf{year}_{ct} + \mathbf{weather}_{ct} + \mathbf{county}_c + \nu_{ct} \tag{3}$$

where pollution represents weekday concentrations of PM2.5, NO_2, CO, and O_3 in county c on date t. The independent variable of interest is $uber_{ct}$, which takes the value 1 if Uber was

32. We note that data on automobile registration are available for many more counties (36) than data for UPT (25). Consequently, despite the significant overlap between “low” automobile ownership and high UPT counties, the differences in the two samples ensure that our findings regarding transit usage and vehicle ownership provide complementary perspectives.

active in county c at time t and 0 otherwise. A linear date trend is also included in *date*, as well as several time fixed effects, specifically day-of-week fixed effects, month fixed effects and week fixed effects to account for seasonality in pollution levels, year fixed effects to control for annual trends and a dummy variable for federal holidays. Socioeconomic factors, weather, and county fixed effects are defined as in eq. (1). Standard errors are clustered at the county-year level, with the number of clusters varying by pollutant since the number of time periods and counties varies over pollutants.

The coefficient of interest is β_1. If Uber's entry is associated with reductions in air pollution (e.g., from reduced congestion), then we expect $\beta_1 < 0$, but if it is associated with increases in air pollution (e.g., from increased VMT), then we expect $\beta > 0$. In view of our main results on freeway traffic outcomes showing reduced vehicle delay, but higher VMT, the net effect on air quality is unclear. Similar to eq. (1), identification in eq. (3) relies on the timing of Uber's entry to a county being (conditionally) uncorrelated with other factors that affect air pollution (as discussed in footnote 14).

One concern with considering pollution at the daily level is the dynamics involved in pollutant concentration over adjacent days. Several factors, such as precipitation or pollution from the previous day, could contribute to today's air quality. One way to account for this dependence is to include a lagged (by a day) pollutant concentration variable to the specification in eq. (3). Estimation of this specification raises certain challenges however, since least-squares estimates from lagged dependent variables with fixed effects are known to be inconsistent (i.e. the Nickell bias). One way to deal with these challenges is to exploit the so-called "bracketing" property (Guryan (2004)) between the county fixed-effects regression without the lagged dependent variable in eq. (3) ("FE") and the lagged dependent variable regression without county fixed effects ("LDV"): if the coefficient on Uber is negative, then the FE DiD without the lagged dependent variable in eq. (3) will underestimate the true coefficient while a lagged-dependent-variable model without county fixed effects (in eq. (4) below) will overestimate the true coefficient. Thus, the true effect of interest in our case will lie between these two estimates. The specification with a lagged dependent variable ("LDV") is:

$$
\begin{aligned}
\text{pollution}_{ct} = & \gamma_1 uber_{ct} + \gamma_2 pollution_{c,t-1} + \gamma_3 date_t + \textbf{time}_t \\
& + \textbf{SoCal} \times \textbf{year}_{ct} + \textbf{SES}_{ct} + \boldsymbol{\Omega}\textbf{weather}_{ct} + \nu_{ct},
\end{aligned} \tag{4}
$$

where $pollution_{c,t-1}$ represents a 1-day lag of the outcome variable and instead of county-year trends, we include year trends for the region of southern California (**SoCal**) as defined in section 3.4.2.[33]

The interpretation of the coefficient of interest (γ_1) is similar to that of β_1 in eq. (3). We also explore an alternative approach to lagging pollution outcomes: aggregation of pollution to a higher temporal scale, seen in other studies to reflect seasonal changes in air pollution (e.g. Neidell 2004). Therefore, in an alternative specification, we use weekly average pollutant concentration, and produce a weekly version of our fixed effects specification in eq. (3), excluding the linear date trend, day-of-week fixed effects, and the dummy variable for a federal holiday.

5.2 Results

Our estimates on the effect of daily weekday pollution from Uber's entry are presented in Panel A of Table 7. Odd-numbered columns show estimates from eq. (3), the "FE" or county-fixed-effect specification (without lagged air pollution) and even-numbered columns present estimates from the "LDV" specification in eq. (4) that excludes county fixed effects but includes the 1-day lagged pollutant concentration. Estimates show statistically significant reductions in PM2.5, a key metric of urban air pollution, in columns 1 and 2 between 0.3 and 1 μg/m^3 (resp.) per day after Uber's entry into a county. To provide context, these estimates represent between 2.9 and 10% of pre-2013 average PM2.5 in treated counties (pre-2013 pollution averages are presented in Table A7). For the remaining three pollutants (NO_2, O_3 and CO), our estimates show no statistically significant effect of Uber. Panel B in Table 7 presents estimates using weekly aggregate pollution concentration, an alternative measure of exposure, and we find a statistically significant reduction of 1.1 μg/m^3, almost identical in magnitude to the FE specification from Table 7. Similar to the bracketing approach, however, no significant reduction in pollution is

33. Considerations similar to those related to the inclusion of county fixed effects (in the LDV framework) preclude the use of county-year time trends (as in eq. (1)), leading to the use of region-specific time trends. We also consider two alternative specifications: (i) using the five-most-populated counties (instead of counties located in southern California) as an alternative definition of region; and (ii) excluding time trends altogether. Both specifications yield very similar results to those of our main specification in eq. (4).

observed for the other three pollutants.

We note that robustness checks for pollution are presented in Appendix A.6, where we carry out the same checks as for traffic outcomes in section 3.3, suggest. They suggest that our main findings regarding the effects of Uber on pollutant concentration are robust to specification checks, permutation tests and different ways of dealing with outliers.

5.3 Heterogeneity in effects of Uber on pollutant concentration

Similar to the reasoning for traffic congestion, we anticipate that there may be a degree of heterogeneity across counties in the effects of Uber's entry based on population (see section 3.4). Our analysis here closely parallels that for traffic outcomes: we focus on the two regional classifications, southern California ("SoCal") and the five-most-populated counties ("Top 5"); and interact indicators for these regions with the Uber indicator in their respective specification (FE, LDV and weekly aggregate). The effects of Uber in southern California are presented in Figure 6, from which a few findings follow. First, we find that the weekly and "FE" specifications yield nearly identical results for all pollutants. Second, in southern California, we show a statistically significant small increase in O_3 (panel C) of 0.91 ppb (about 3% of these counties' pre-2013 mean counties) using the "FE" and weekly specifications, but find no effect on PM2.5. However, we also show a larger reduction in O_3 outside southern California ("Not SoCal") at 1.35 ppb (or about 5% of the pre-2013 average in these counties). Additionally, we find counties in "Not SoCal" experience a statistically significant reduction in PM2.5 of up to 1.36 μg/m^3 (which is about 40% larger than the main result). Results for the "Top 5" grouping are displayed in Figure 7, and our findings are very similar to those for the "SoCal" grouping for PM2.5 and O_3, with the only difference being a statistically significant increase (across all three specifications) in NO_2 in the "Top 5" up to 1.25 ppb (which is a sizeable 8% of the pre-2013 average for the top 5 most populated counties). There is no significant effect in the other counties.

Overall, patterns in air quality associated with Uber's entry closely mimic those of our freeway traffic outcomes, specifically for vehicle delay (as opposed to VMT) which decreased on average, but worsened in more populated counties. Similarly, we show reductions in daily weekday PM2.5 on average, but show other pollutants (O_3 and NO_2) actually increased in more populated counties. These results reinforce how aggregate average effects of Uber's entry can provide an incomplete accounting of its true effect on freeway traffic and air quality.

6 Valuing the Effects of Uber's entry

Previous studies have documented the effects of the entry of RH services on transit usage (Hall, Palsson, and Price (2018)), automotive fatalities (Barreto, Silveira Neto, and Carazza (2021) and Barrios, Hochberg, and Yi (2020)), labour markets (Hall and Krueger (2017)) and congestion (Tarduno (2021)) among others. We attempt a modest and simple exercise aimed at exploring the potential magnitude of costs and benefits arising from Uber's entry based upon our empirical estimates.

6.1 Value of Uber's entry on congestion

We begin by quantifying the effect of Uber on congestion in the average county Uber entered. To do so, we use the coefficient on the vehicle delay measure from our main specification, in column 4 of Table 3 of 0.19 seconds per capita (at an ideal speed of 60 mph) per hour on weekdays. This figure is then multiplied by half the current median hourly wage in California ($11.74) (U.S. BLS 2021), which represents the value of travel time per hour of delay per capita. We multiply this figure by a quarter of the total population in treated counties in 2013, the first year of Uber's entry into counties in California, to represent the population affected by Uber in a given hour (approximately 15.3 million).[34] This results in aggregate congestion benefits of $4,598 in a given hour and date in California. This number is then multiplied by 260, the approximate number of weekdays in a year, yielding the annual hourly benefit from the reduction in delay of $1.2 million. We then multiply this by 12 hours to capture the time during which the majority of cars are on the road, so the annual daily benefits of reduced delay on freeways in treatment counties is $14.3 million. The only comparable study to ours, Tarduno (2021), finds that for Austin alone, congestion related costs of RH services amounted to $33 to $52 million annually. The spatial aggregation of vehicle delay involved in our analysis at the county-level will smooth out congestion peaks on the most congested freeways in every county

34. We use a quarter of the population to account for a large fraction that does not drive at any given hour, encompassing populations that cannot drive (e.g., anyone under the age 15), users of public transit and in general all non-drivers at an average hour. While this figure will overstate road users at non-peak hours, it is likely to understate users at peak, meaning that overall, it is likely an appropriate estimate.

(with associated congestion cost spikes), so the magnitude of benefits we find for California appear reasonable.

However, the average benefits estimated above fail to account for the heterogeneous effects of Uber's entry upon congestion, so we also explore how accounting for heterogeneity in Uber's effects influences the value of congestion-related benefits.[35] We begin with heterogeneity across hours of the day, for which our results showed statistically significant results during the PM peak period (2-7:59pm), afternoon (10am-1:59pm) and nighttime (8-10:59pm) (Figure 4). First, we estimate congestion costs associated with increased vehicle delay during the PM peak period, modifying the approach used for average congestion effects in two ways: by multiplying the annual hourly cost/benefit from a change in delay by the number of hours during that time period (e.g. the PM peak period is a 6-hr period); and, for the PM peak period, using a third of the population of treated counties, since more drivers are likely to be on the road during these hours. We find annual congestion costs of approximately \$42.8 million during the PM peak period in treated counties. During the afternoon and night-time, on the other hand, we find congestion relief benefits of \$17.1 and \$13.6 million (resp.).

Next, we explore differences in congestion costs and savings by region, where Figure 5 shows more-populated county groupings experiencing worsened congestion. We use a similar approach to calculating heterogeneous effects throughout the day and find annual congestion costs of \$11 million resulted from Uber's entry in southern California counties and congestion benefits of \$9.9 million in counties outside this grouping. Turning to the second categorisation, the five-most populated counties in California, we estimate congestion costs of \$11.2 million resulting from Uber's entry, while counties outside realised benefits amounting to \$8.6 million. The main reason for the larger effects in these two county groupings is the larger population concentrations.

In summary, our findings suggest that Uber's entry may have reduced welfare by increasing congestion at the most congested times of the day and in counties already experiencing the greatest congestion. The net heterogeneous effect of Uber's entry (from Table A8) is a congestion cost between \$1.1 and \$12.1 million, which differs significantly from the congestion reduction

35. The value of congestion relief across different dimensions (county groupings and time periods) discussed here, and the simple net effect (i.e., the unweighted sum across heterogeneous effects) are summarized in Table A8.

benefits computed using the average treatment effect.

6.2 Value of Uber's entry on pollution and health

Following many epidemiological studies assessing the relationship between health outcomes and pollutants, we evaluate the effects of pollution by focusing on changes in health risks resulting from Uber's entry. We use figures from two widely-cited studies that that focus on exposure to PM2.5. The first study, by Pope et al. (Pope et al. 2002), found that a 10 μg/m^3 increase in PM2.5 is associated with an increase in risk of all-cause mortality by 4%. The second, a meta-analysis of over 100 studies focused on short-term exposure (Atkinson et al. 2014), found that a 10 μg/m^3 increase in PM2.5 was associated with a 1.04% increase in risk of death (which varied by region). Our estimates in panel A of Table 7 associate Uber's entry with a reduction in (average daily weekday) PM2.5 concentration of between 0.3 (LDV) and 1.09 (FE) μg/m^3. Using estimates from our preferred specification (FE) and assuming a linear relationship between pollution and risk of death, on average, Uber's entry is associated with a 0.1% to 0.4% reduction in risk of death in treated counties. In counties outside southern California or the top 5 most populated counties, the effect is slightly larger, between 0.2% and 0.6%.[36]

However, Figure 6 and Figure 7 show increases in daily or weekly O_3 and NO_2 concentrations up to 1.2 and 1.26 ppb (resp.) in southern California or the five-most populated counties. Outside these counties, daily or weekly O_3 concentrations decreased up to 1.35 ppb. To put these results for O_3 in perspective, a long-term study of O_3 and mortality in almost 100 U.S. cities by Jerrett et al. 2009 found an increase between 2.9% and 4% in the risk of death from respiratory causes due to a 10 ppb increase in exposure to O_3, with greater effects in cities with very high O_3 concentrations, a category that includes many cities in California (e.g., Los Angeles, San Francisco, Sacramento). Based on these figures, Uber's entry to southern California and the five-most-populated counties in California is associated with a 0.4 to 0.5% increase in risk of death from respiratory disease. This is partly offset by the decline in risk of death between 0.4 and 0.6% in less populated counties. Turning to the effects of increased NO_2, another study

36. For the LDV specification, treated counties on average experience a 0.03% to 0.1% reduction in risk of death and a 0.05% to 0.2% reduction outside southern California or the top 5 most populated counties.

showed that an increase in 12-month NO_2 exposure of 10 ppb among those on Medicare, which primarily includes those aged 65 years or older, is associated with increased mortality from respiratory disease of 3% (Eum et al. 2019). Using our estimates of increased NO_2, these findings suggest that Uber's entry to the five-most populated counties is associated with an increase in mortality from respiratory disease of 0.4% among elderly adults.

7 Conclusion and Policy implications

We find that the entry of Uber to a county in California is associated, on average, with reduced freeway congestion (vehicle delay falls by 13%, travel efficiency increases by 2.5%) and increased freeway traffic volume (VMT increases by 8%). This congestion relief is in line with our finding that, on average, Uber's entry is estimated to reduce PM2.5 by at least 3%. These average effects, however, mask rather significant variation across different county types and time periods: the most populated counties and evening rush hour showed an increase in congestion and VMT. In these more populated counties, we also show corresponding increases in NO_2 and O_3 (at 8% and 2% respectively). Simple calculations suggest there are both social costs and benefits from the resulting changes in congestion and air pollution. Our results also suggest that the accessibility of public transit, especially rail-based transit, is an important determinant of the relationship between freeway traffic outcomes and Uber's entry. Our results using annual vehicle registration data also show a similar pattern: counties with "low" registrations, which typically have higher transit ridership, experience preferential vehicle delay reductions following Uber's entry.

Apart from cautioning against the use of a single, average "effect of Uber" across space and time, our findings also have implications for policy design. They suggest that policies addressing traffic-related externalities arising from RH services should target more populated cities or counties or periods of a day when Uber worsens traffic. Outside these counties and during non-peak hours, Uber's effects appear more beneficial, with improvements in air quality and congestion along highways. Consequently, a statewide one-size-fits all policy, without careful considerations of how RH services affect air quality and congestion in affected areas, could impose greater social costs than policies tailored to local circumstances. Policy decisions regarding RH services may therefore be better targeted at the local level (e.g., by cities, counties) to complement their transportation needs and economic circumstances.

Our findings also suggest future directions for research around RH services, and shared mobility services in general, with a view to better understanding the implications for traffic congestion and volume. First, our study focused on freeway congestion, an understudied, but important component of commuting and travel in California. However, given the significant variation in pattern of freeway use and traffic across the U.S., further research examining congestion along different dimensions (e.g., freeways, surface streets) in contexts outside California would help establish the external validity of our findings. Such evaluations should also focus on areas outside major metropolitan regions, in view of the heterogeneity we report. Second, detailed studies along the most congested routes at specific urban agglomerations (and not just at the largest metropolitan areas) are needed to highlight the local consequences related to congestion and air pollution associated with RH services. Third, RH services represent only one small component of the growing and broader shared mobility service landscape, with other modes (e.g., bikeshares, e-scooters) becoming more prevalent. While these services have a stated intention of improving overall urban mobility, current work has been focused more on mode split, with little known regarding environmental or traffic-related outcomes (e.g., Hamilton and Wichman (2018)), particularly using micro-data. More rigorous empirical research exploring how shared mobility services influence congestion, vehicle ownership, public transit and each other would provide more information for policymakers and urban planners looking to leverage such services.

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Tables

Table 1: UberX entry date for counties in California (2009 to 2015)

County	City	Entry date
San Francisco	San Francisco	1/18/2013
Los Angeles	Los Angeles	3/14/2013
San Diego	San Diego	5/9/2013
Santa Clara	San Jose	7/24/2013
Orange County	Orange County	9/13/2013
Sacramento	Sacramento	9/30/2013
Santa Barbara	Santa Barbara	10/31/2013
Monterey	Monterey Bay City	2/4/2014
Santa Cruz	Santa Cruz	2/4/2014
Fresno	Fresno	2/5/2014
Stanislaus	Modesto	4/2/2014
Riverside	Palm Springs	4/3/2014
Sonoma	Santa Rosa	5/12/2014
San Bernardino	San Bernardino	5/29/2014
Kern	Bakersfield	6/14/2014
San Luis Obispo	San Luis Obispo	7/17/2014
Ventura	Oxnard and Simi Valley	7/17/2014
Tulare	Visalia	12/1/2014
Butte	Chico	10/8/2015

Notes: Table shows the entry dates for UberX in California's cities and its associated county.While UberX had a "soft" entry date in San Francisco of July 3, 2012, we focus instead on the official entry date since this is when we anticipate its services being more widely utilized.

Table 2: Summary statistics by treatment status

		Never treated counties			Treated counties			Never treated-treated
	1	2	3	4	5	6	7	8
	Mean	2009-2015	2009	2015	2009-2015	2009	2015	Diff (tstat)
Panel A: Annual socioeconomic characteristics								
Population density (Pop. per mi^2)	1180	507	534	490	1,813	2,153	1,590	-1306*** (260)
Median income (US$)	63,895	65,593	76,242	59,164	62,297	73,396	56,514	3296*** (114)
Median age (years)	37	39	39	39	35	36	35	3.90*** (466)
High school graduates per capita	0.56	0.58	0.59	0.58	0.53	0.55	0.52	0.048*** (335)
Number unemployed per capita	0.05	0.05	0.03	0.06	0.05	0.03	0.06	-0.00096*** (35)
Panel B: Weekday hourly traffic								
Travel efficiency (mph)	61	60	63	56	62	62	62	-1.82*** (120)
Vehicle Delay (seconds) per capita	1.6	1.6	1.1	2.4	1.6	1.5	1.9	-0.015*** (2.74)
Vehicle miles traveled (VMT) (miles) per capita	0.3	0.33	0.29	0.35	0.29	0.25	0.33	0.045*** (99.1)
Panel C: Weekday daily air pollution								
PM2.5 ($\mu g/m^3$)	9.9	10.2	13	9.5	9.7	14	9.0	0.48*** (6.65)
NO_2 (parts per billion (ppb))	10	9.4	10	8.7	11	12	10	-1.5*** (27.4)
O_3 (ppb)	30	30	26	31	29	26	31	0.2** (2.32)
CO (ppb)	353	370	398	358	343	383	337	26.7*** (13.4)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents means for all counties (column 1), never treated counties (i.e. counties that Uber did not enter) (columns 2-4) and counties that were treated (i.e. that Uber entered at some point between in 2009 and 2015) (columns 5-7). Column 8 shows results from t-tests for differences between never treated and treated counties (t-statistic in parentheses). Of the 58 counties in California, data related to traffic outcomes are available for 31 and 37 counties in 2009 and 2015 respectively. Pollutant concentration data availability varied across time and pollutant, but data are available for at least 27 counties for all pollutants (see appendix table A5 for details).

Table 3: Effects of Uber's entry on weekday freeway traffic (2009-2015)

	1	2	3	4	5	6
	Travel Efficiency (MPH)		Delay (vehicle seconds) per capita		VMT per capita	
Uber	1.65***	1.52***	-0.17*	-0.19**	0.024**	0.024**
	[0.56]	[0.51]	[0.092]	[0.094]	[0.010]	[0.010]
Median age		-0.56		-0.036		-0.017
		[1.16]		[0.098]		[0.016]
Population density		-0.012		-0.0031*		-0.000092
		[0.0079]		[0.0017]		[0.00020]
High school graduates per capita		35.1		-1.92		0.8
		[45.6]		[4.53]		[0.78]
Unemployed per capita		51.5		2.3		0.27
		[40.3]		[4.33]		[0.84]
Median income per capita		-0.000048		-0.00001		8.60E-07
		[0.000096]		[0.000013]		[1.6e-06]
N	1,369,135	1,369,135	1,369,135	1,369,135	1,369,135	1,369,135
R^2	0.529	0.53	0.432	0.432	0.814	0.814
Number of clusters	239	239	239	239	239	239
Socioeconomic variables	NO	YES	NO	YES	NO	YES

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in brackets and clustered at the $county \times year$ level. Columns 1, 3, and 5 show results from the specification in eq. (1) without socioeconomic variables on weekdays freeway traffic between 2009 and 2015 in California at the county-hour-date level. Results in columns 2, 4, and 6 include socioeconomic variables, specifically median age, population density (population/mile^2), the number of high school graduates per capita, the number of people unemployed per capita and median income per capita in the same specification. All regressions also include: a linear date trend, hour fixed effects, week fixed effects, month fixed effects, day-of-week fixed effects, year fixed effects, a dummy variable for federal holidays, county-year trends, daily precipitation, and a quadratic in daily maximum temperature. The independent variable of interest is the treatment indicator, $Uber$, a dummy variable equal to 1 if Uber entered a county on a given date. Columns 1 and 2 show effects on travel efficiency (mph). Columns 3 and 4 show impacts on vehicle delay (relative to an ideal speed of 60 mph) on freeways per capita. Columns 5 and 6 shows effects on vehicle miles traveled (VMT) per capita. Computation of travel efficiency and delay are detailed in the text (see appendix A.4).

Table 4: Robustness checks for Traffic outcomes: Restricted samples of counties

	1	2	3	4	5	6
	Travel Efficiency (MPH)	Delay (vehicle seconds) per capita	VMT per capita	Travel Efficiency (MPH)	Delay (vehicle seconds) per capita	VMT per capita
Panel A: Restricted samples- Counties with populations > 100,000 or 250,000						
	Population > 100k			Population > 250k		
Uber	0.77***	-0.21**	0.015*	0.64***	-0.31***	0.015*
	[0.26]	[0.093]	[0.0090]	[0.22]	[0.10]	[0.0093]
N	1,199,712	1,199,712	1,199,712	1,007,016	1,007,016	1,007,016
R^2	0.447	0.453	0.836	0.529	0.473	0.848
Number of clusters	207	207	207	173	173	173
Panel B: Include 2009 population*year trend instead of county-year trends						
Uber	4.11***	-0.36***	0.053***			
	[1.10]	[0.11]	[0.018]			
N	1,369,135	1,369,135	1,369,135			
R^2	0.364	0.424	0.764			
Number of clusters	239	239	239			
Panel C: Restricted samples- Drop first 3 counties or last 4 counties Uber entered						
	Drop first 3 counties Uber entered			Drop last 4 counties Uber entered		
Uber	1.60***	-0.21*	0.023*	1.93***	-0.24**	0.028**
	[0.61]	[0.11]	[0.012]	[0.62]	[0.11]	[0.012]
N	1,245,511	1,245,511	1,245,511	1,247,023	1,247,023	1,247,023
R^2	0.531	0.405	0.811	0.549	0.44	0.815
Number of clusters	218	218	218	216	216	216

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the county-year level, in brackets. Table presents results from a regression specification similar to that in table 3, but differing in: restricting the sample to exclude counties not meeting populations cut-offs (Panel A) or those that Uber entered very early or very late (Panel C); and in using 2009 population-year trends instead of county-year trends (Panel B). In Panel A, five (Mariposa, Nevada, San Benito, Tuolomne, and Yuba County) counties had populations below 100,000 people and eleven (a further six from the first cut-off: Butte, El Dorado, Kings, Madera, Napa, Yolo) counties below 250,00 people. In panel C, Columns 1 to 3 show results after dropping the first three counties Uber entered (Los Angeles, San Francisco, and San Diego) and columns 4 to 6 show results after dropping the last four counties entered (Butte, Tulare, San Luis Obispo, and Ventura).

Table 5: Robustness checks: natural log specification of key variables

	1	2	3
	Travel Efficiency (MPH)	Delay (vehicle seconds) per capita	VMT per capita
Panel A: Log of per capita traffic outcome variables			
Uber	0.013***	-0.20**	0.048
	[0.0041]	[0.086]	[0.045]
N	1,351,881	1,259,883	1,351,881
R^2	0.471	0.727	0.895
Panel B: Log of levels of dependent variables			
		Delay (vehicle seconds)	VMT
Uber		-0.20**	0.048
		[0.086]	[0.045]
N		1,259,883	1,351,881
R^2		0.727	0.895

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in brackets and clustered at the $county \times year$ level. Panels A and B show variants of the regression in eq. (1). Panel A shows results of a version with the log of the traffic outcomes as the dependent variable. Panel B presents results from a specification differing from that in Panel A in using log of traffic outcomes in level, instead of normalized (per capita) versions, as the dependent variable for VMT and delay, and the inclusion of log of population as an independent variable. Sample sizes in Panels A and B differ from those from the main specification presented in Table 3 due to the exclusion of zero values for dependent variables. Both regression specifications have the same number of clusters, 239.

Table 6: Causal Mechanisms: Public transit and automobile registration

	1	2	3
	Travel Efficiency (MPH)	Delay (vehicle seconds) per capita	VMT per capita
Panel A: Effect of Uber varying by level of UPT per capita			
Uber	0.098	0.20	0.033*
	[0.34]	[0.13]	[0.018]
Uber × Medium UPT	0.97*	-0.62***	-0.011
	[0.50]	[0.19]	[0.023]
Uber × High UPT	0.87*	-0.41**	-0.033
	[0.44]	[0.16]	[0.023]
Total effect in high UPT-counties (tstat)	0.97*** (3.13)	-0.21** (-1.83)	0.026 (0.022)
Total effect in medium UPT-counties (tstat)	1.07*** (2.63)	-0.42** (-2.86)	0.022* (1.63)
Panel B: Counties with rail-based transit			
Uber	0.81**	-0.17	0.023**
	[0.37]	[0.11]	[0.010]
Uber× All rail	0.38	-0.26	-0.0063
	[0.43]	[0.24]	[0.023]
Total effect in counties with rail transit (tstat)	1.19*** (4.23)	-0.44**(2.09)	0.017 (0.84)
Panel C: Automobile registration			
Uber	1.13*	-0.26***	0.30
	[0.61]	[0.097]	[0.012]
Uber × Medium Auto	0.91	0.13	-0.022
	[0.73]	[0.17]	[0.019]
Uber × High Auto	0.18	0.095	0.0064
	[0.70]	[0.25]	[0.022]
Total effect in high auto counties (tstat)	2.02** (2.02)	-0.16 (0.68)	0.037* (1.83)
Total effect in medium auto counties (tstat)	2.03*** (2.96)	-0.13 (0.9)	0.007 (0.49)

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors, clustered at the county-year level, in brackets, with t-statistics for total effects in parentheses. Table presents regression results from three variants of the specification in eq. (1). In the first (Panel A), the treatment indicator, Uber, is interacted with two indicator variables,"High UPT" and "Medium UPT", corresponding respectively to pre-2013 average UPT per-capita exceeding its 75th percentile or lying between 25th and 75th percentile. Panel B is similar, but Uber is interacted with an indicator variable for the presence of all rail-based transit. Sample size (952,656) and number of clusters (164) are identical in Panels A and B. Panel C shows regression results from a variant of the specification in eq. (1) with the Uber interacted with two indicator variables,"High auto" and "Medium auto", corresponding respectively to pre-2013 county average automobile registration exceeding its 66th percentile or lying between the 33rd and 66th percentiles (N=1,368,631, 238 clusters). All regressions include the full set of socioeconomic variables. Sample size differs from Table 3 since counties that did not report public transit ridership or vehicle registration for a given year-month or year were not included.

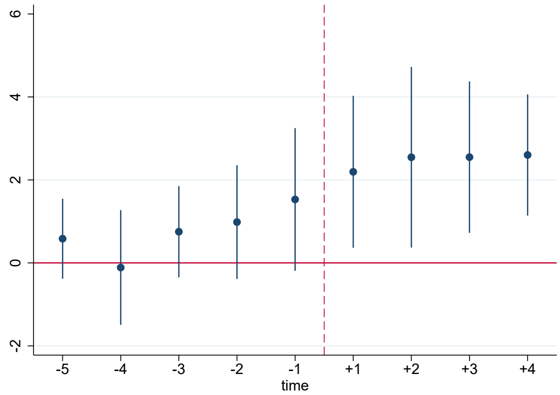
Table 7: Effect of Uber's entry on weekday air pollution (2009-2015)

	1	2	3	4	5	6	7	8
	PM2.5	PM2.5	NO_2	NO_2	O_3	O_3	CO	CO
Panel A: Daily weekday pollutant concentration								
Uber	-1.03**	-0.30**	-0.024	0.097	-0.35	-0.073	6.41	6.7
	[0.51]	[0.15]	[0.29]	[0.19]	[0.39]	[0.24]	[12.5]	[4.54]
N	48,578	48,578	54,721	54,721	79,002	79,002	40,991	40,991
R2	0.277	0.584	0.682	0.764	0.681	0.794	0.593	0.75
Number of clusters	254	254	229	229	335	335	254	42
County fixed effects	YES	NO	YES	NO	YES	NO	YES	NO
Lag of dependent variable	NO	YES	NO	YES	NO	YES	NO	YES
Southern California-year trend	NO	YES	NO	YES	NO	YES	NO	YES

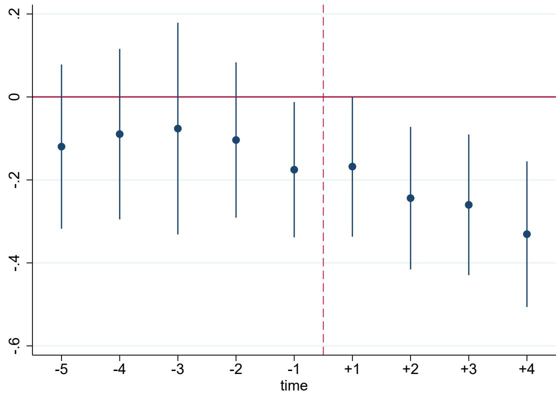
Panel B: Aggregated weekly pollutant concentration	PM2.5	NO_2	O_3	CO
Uber	-1.09**	-0.011	-0.33	6.04
	[0.44]	[0.28]	[0.38]	[12.4]
N	13,372	11,021	16,112	8,219
R^2	0.389	0.802	0.793	0.687
Number of clusters	299	229	335	171
County fixed effects	YES	YES	YES	YES

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in brackets and clustered at the $county \times year$ level. The outcome variables, PM2.5 ($\mu g/m^3$), NO_2 (ppb), O_3 (ppb), CO (ppb), represent average daily pollutant concentrations in county c and on date d (Panel A) and average weekly pollutant concentration (Panel B) in county c and week w. Only weekdays are included. Panel A presents results using eq. (3) (the DiD with county fixed effects (FEs) specification) in columns 1, 3, and 5 and eq. (4) (which substitutes lagged concentration for county FEs and includes a southern California-year trend instead of county-year trends) in columns 2, 4, and 6 (see notes for Figure 5 to see how southern California is defined). The coefficient on the treatment indicator Uber, for both Panels A and B represents the effect of Uber's entry on (respective) pollution concentrations. Other control variables included in eq. (3) are day-of-week-, month-, week- and year fixed effects, a dummy variable for federal holidays, a linear date trend, daily precipitation and a quadratic term in maximum temperature, county-year trends, and county fixed effects. The same set of annual socioeconomic variables as in eq. (1) are also included in both daily and weekly specifications. The weekly average specification in Panel B uses weekly average pollution concentrations and includes the same control variables as eq. (3), excluding the linear date trend, day-of-week fixed effects, and the dummy variable for federal holidays.

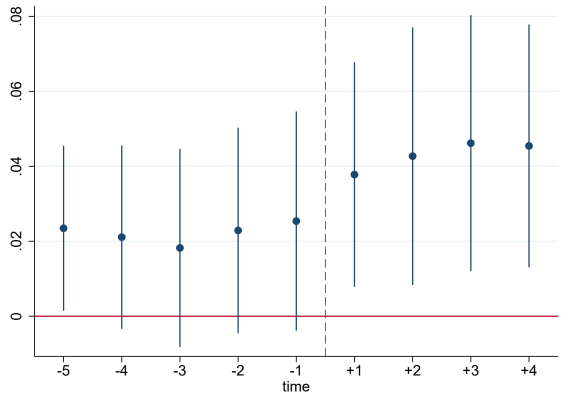
Figures



(a) Travel efficiency (MPH)

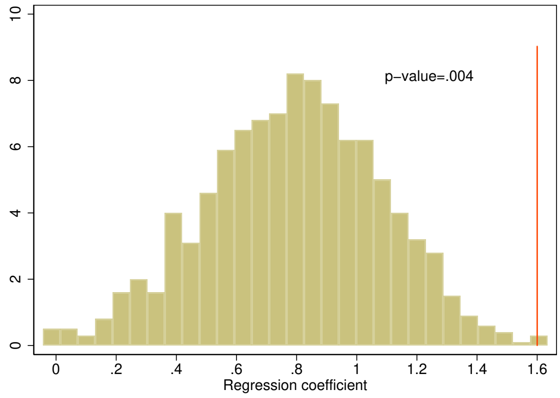


(b) Delay per capita (vehicle seconds)

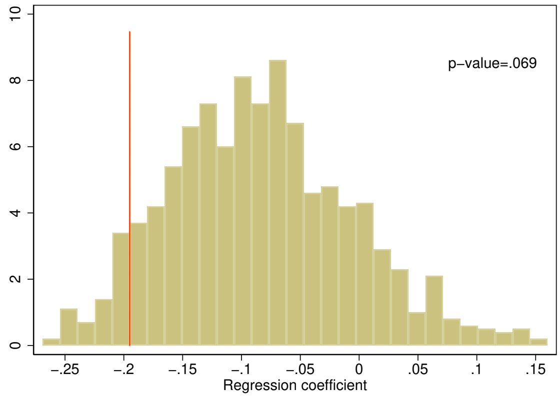


(c) VMT per capita

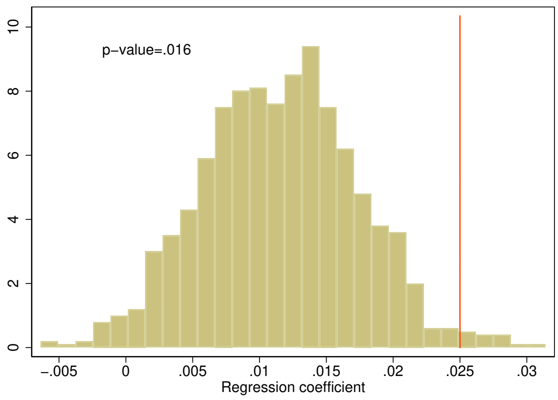
Figure 1: Event study estimators using 90-day windows for weekday freeway traffic outcomes
This figure shows point estimates and 95% confidence intervals from eq. (2). Each tick on the x-axis represents a 90-day window either before or after Uber's entry. For example, the first 90-day window prior to Uber's entry date is denoted "-1", while the first 90-day window after Uber's entry date is denoted "+1". Each point estimate shows the effect of Uber's entry on the relevant weekday traffic outcome of interest. The control group is never-treated counties and periods more than 450 days prior to Uber's entry date or 360 days after Uber's entry date. The horizontal line represents 0 and the dashed vertical line represents Uber's entry date (or t=0).



(a) Travel efficiency (mph)



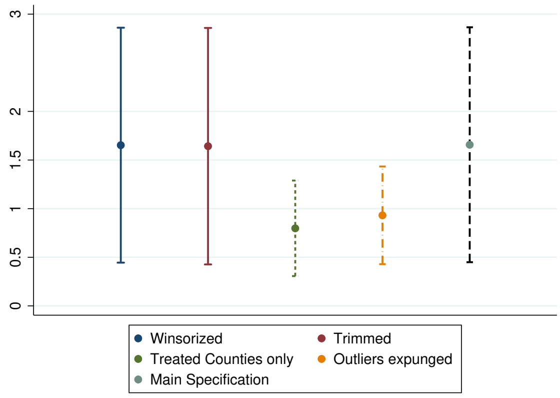
(b) Vehicle delay per capita (seconds)



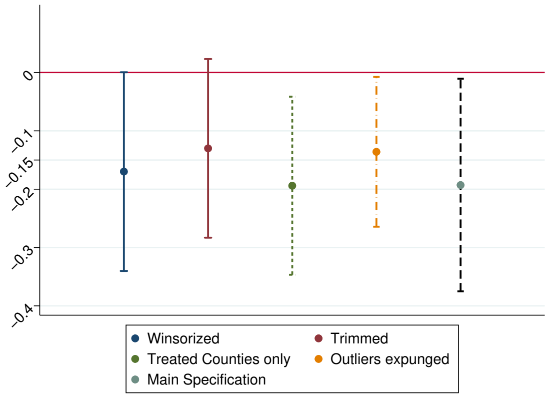
(c) VMT (miles per capita)

Figure 2: Permutation test for Traffic outcomes.

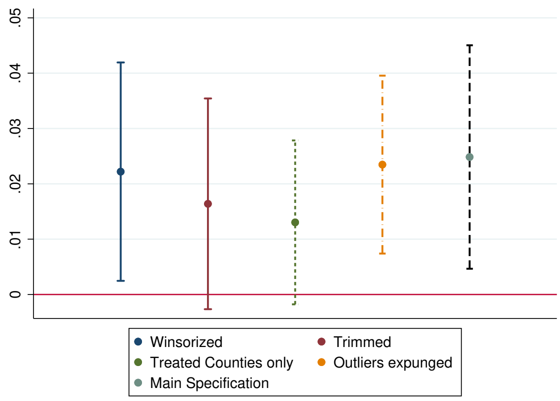
Notes: Each figure presents a histogram of the distribution of coefficients from 999 separate regressions, with the respective traffic outcome as the dependent variable. Each regression involves randomly permuting the date of Uber's entry at counties it entered and running the main regression specification. The null hypothesis for each outcome is that the coefficient estimated in the main regression (represented by the red vertical line) is obtained purely by chance (i.e. it is zero). The p-value for this hypothesis test, which is the proportion of (absolute value of) permuted coefficients larger than that estimated with the actual Uber entry date, is provided in the text in each figure.



(a) Travel efficiency (mph)



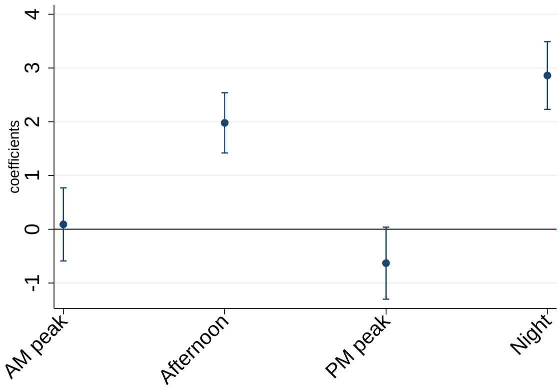
(b) Vehicle delay per capita (seconds)



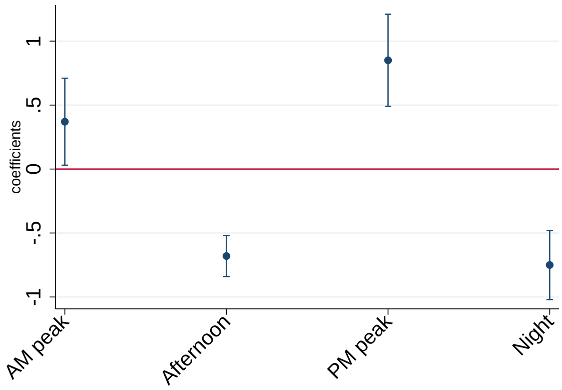
(c) VMT per capita

Figure 3: Uber's effects on Traffic: Sensitivity to outliers.

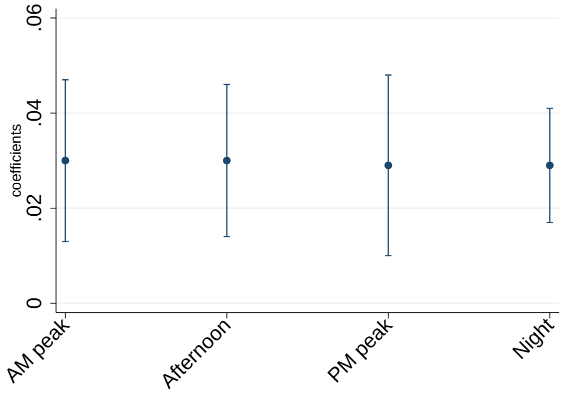
Notes: Figure shows coefficient on Uber and 95% confidence intervals from difference-in-differences specification from eq. (1) for the following sub-samples: the top and bottom 1% of observations are winsorized (in blue) or trimmed (red); only counties eventually treated are included in the sample (i.e. never-treated counties are excluded) (green, short-dash); and "outliers" in the dependent variables, identified using Cook's distance, are excluded (orange, dashed). The "Main Specification" (light blue, dash-dot) refers to our preferred specification from Table 3 and is provided for reference. The red horizontal line represents the zero effect.



(a) Travel efficiency (mph)



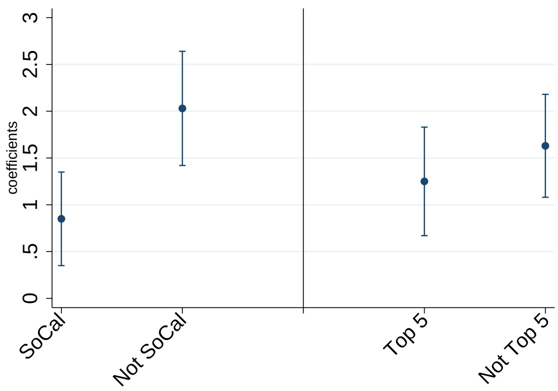
(b) Vehcile delay (seconds per capita)



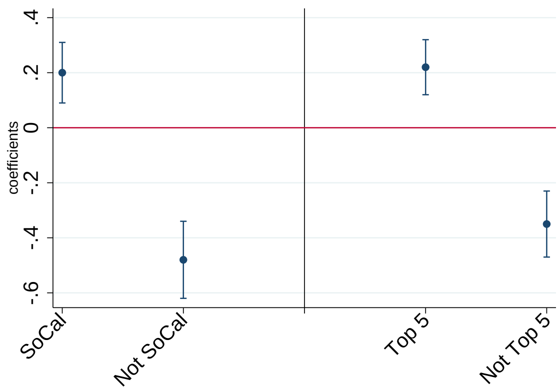
(c) VMT per capita

Figure 4: Intra-day effects of Uber on traffic outcomes

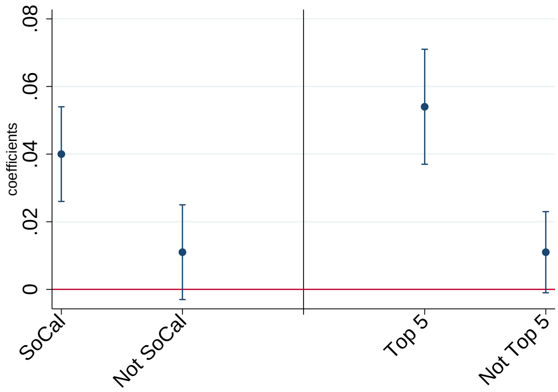
Notes: Figures show effects across different time periods in a given weekday for the relevant traffic outcome. Each point represents the total effect of Uber on a respective outcome for the respective time period, with the bars representing 95% confidence intervals. The four periods presented are: the "AM peak" (i.e. morning rush hour), 7:00-9:59am; "Afternoon" period, 10am-1:59pm; "PM peak", represents evening rush hour, and consists of the hours between 2pm and 7:59pm; and "Night"time, 8:00-10:59pm. "late night", 11pm-6:59am, is not shown. These estimates are based on an alternative specification of eq. (1), with the treatment variable, $Uber$ interacted with an indicator variable for each time period. The coefficients represent the total effect of Uber's entry during this time period (i.e., a sum of the interaction and main effect for each time period) after adjusting standard errors. All regressions include socioeconomic variables; see notes to table 3 for further details.



(a) Travel efficiency (VMT/VHT)



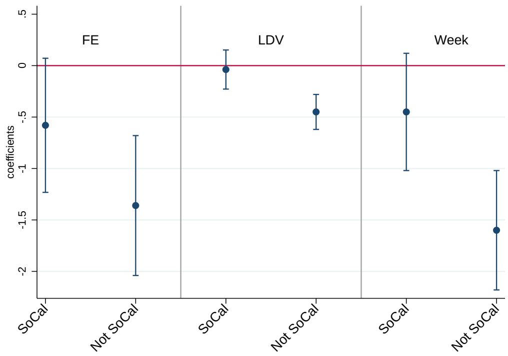
(b) Vehicle delay per capita (vehicle seconds)



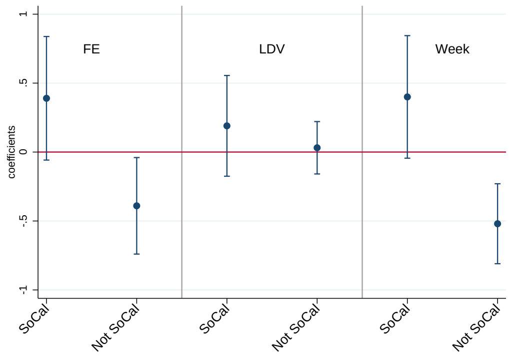
(c) VMT per capita

Figure 5: Heterogeneous effects of Uber on Traffic outcomes across California's counties.

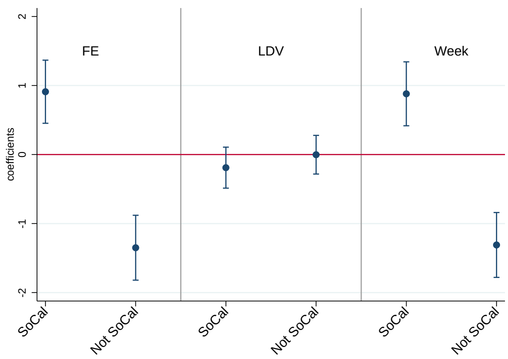
Notes: Figure shows effects across two different categorizations of California's counties for the three traffic outcomes. Each point represents the total effect of Uber on an outcome for the respective category, with the bars representing 95% confidence intervals. For each of the two categorizations, results pertain to a modification of the main specification in eq. (1) that includes an interaction term between the treatment indicator, Uber, and an indicator variable for the categorization (see text for further details). On the left side of each figure, we present the effect of Uber on counties lying within Southern California ("SoCal"), which includes Orange County, Riverside County, Los Angeles County, San Diego County, Santa Barbara County, San Luis Obispo County, San Bernardino County, or Ventura County, and those lying outside ("Not SoCal"); on the right side, we present the effect of Uber's entry on the five most populated counties ("Top 5"), which includes Los Angeles, San Diego, Orange, Riverside and San Bernardino, and the remaining counties in California ("Not Top 5"). All regressions include socioeconomic variables' see notes for Table 3 for further details.



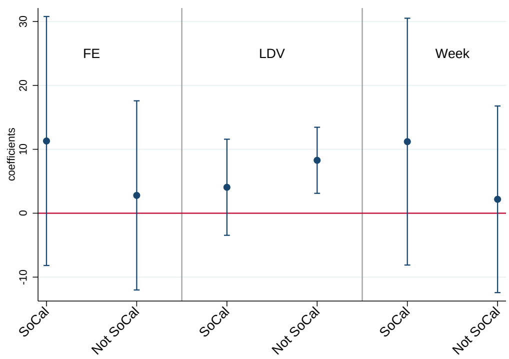
(a) PM 2.5 concentration–SoCal



(b) NO_2 concentration–SoCal



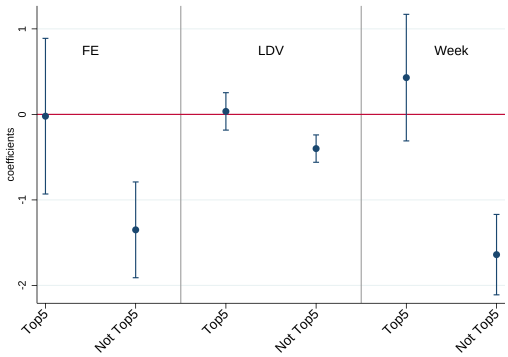
(c) Ozone concentration–SoCal



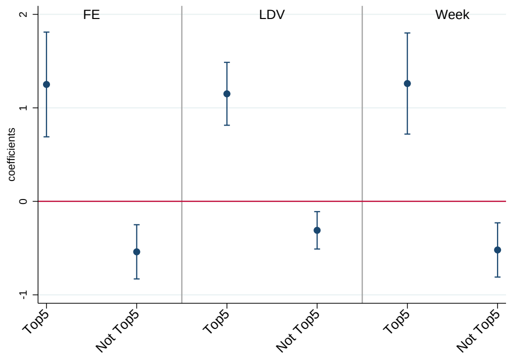
(d) Carbon monoxide concentration–SoCal

Figure 6: Heterogeneous pollution effects: Southern California

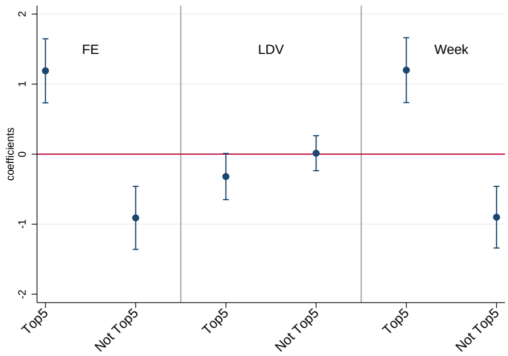
Notes: Figures represent effects of Uber's entry (along with 95% confidence intervals) on counties within southern California ("SoCal") and outside of southern California ("Not SoCal"). Definition of counties within Southern California and computation of the effects of Uber on counties are in the notes for Figure 5. All regressions include socio-economic variables; see notes to Table 7 for details. "FE", "LDV" and "Week" represent respectively specifications: with county fixed effects (FEs) (eq. (3)); without county FEs but with a lagged pollutant concentration (eq. (4)); and weekly average pollution concentration and county FEs.



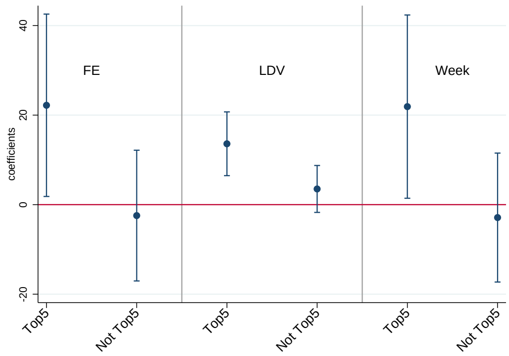
(a) PM 2.5 concentration–Top 5



(b) NO_2 concentration–Top 5



(c) Ozone concentration–Top 5



(d) Carbon monoxide concentration–Top 5

Figure 7: Heterogeneous pollution effects: Top 5 counties

Notes: Figures represent effects of Uber's entry (along with 95% confidence intervals) within the top 5 most populated counties ("Top5") and outside ("Not Top5") (see notes for Figure 5 for more information). All regressions include socioeconomic variables; see notes to Table 7 for details. "FE", "LDV" and "Weekly" represent respectively specifications: with county fixed effects (FEs) (eq. (3)); without county FEs but with a lagged pollutant concentration (eq. (4)); and weekly average pollution concentration and county FEs.

Appendix A Online Appendix (Not for Publication)

Subsection A.1 Public Transit and Automobile Ownership Data

We obtain information on public transit ridership using data from the National Transit Database, which has information on unlinked passenger trips (UPT) for different modes of public transit in various cities and counties at the month-year level. Data from the FTA's NTD are based on an "urbanized area". For public transit systems spanning multiple counties, UPT was assigned to the most populated county among those served to avoid double counting. This was done for three urbanized areas. The Los Angeles-Long Beach-Anaheim urbanized area was counted as Los Angeles County, which means Long Beach County was dropped from the sample. Additionally, Anaheim is in Orange County, however, Orange County was not dropped from the sample because there is another urbanized area in Orange County (i.e., Mission Viejo-Lake Forest-San Clemente). The Riverside-San Bernardino urbanized area was counted as Riverside County, and another urbanized area located in San Bernardino (i.e., Victorville-Hesperia) was used to represent the county. The San Francisco-Oakland urbanized area was replaced with Alameda County and San Francisco County was dropped. In an alternative specification, the public transit system is represented by San Francisco County instead of Alameda County and the results are very similar (available upon request). Other counties that did not include urbanized areas that reported to the NTD were dropped from our study, which includes El Dorado, Madera, Marin, Mariposa, Nevada, Placer, San Benito, San Francisco, San Mateo, Tulare, Tuolumne, and Yuba, most of which are smaller counties.

Subsection A.2 Additional Summary Statistics

By time-period: Summary statistics for the outcomes of interest separated by the AM peak (7am to 9:59am), afternoon (10am to 1:59pm), PM peak (2pm to 7:59pm) and finally by nighttime (8pm to 11:59pm) are in Table A1. They show that delay per capita is consistently greater during the AM and PM peak period, almost twice that of the afternoon or nighttime. Travel efficiency is also lower, though the difference is not as great while VMT per capita is of similar magnitude during the AM and PM peak periods as in the afternoon, though much lower at nighttime.

Inter-regional variation in traffic outcomes: The heterogeneity and variation across counties in traffic outcomes is presented visually in Figure A1 and Figure A2 for vehicle delay and VMT (resp.) during the morning (7 to 9:59am) and evening (2 to 7:59pm) rush hour (panels A and B resp.). Each circle represents average vehicle delay or VMT over the study period in a given county, with the size of the circle representing magnitude. The blue and orange counties are treated and never treated counties (resp.). As surmised, the more populated counties (including Los Angeles, Orange, San Diego, and a few counties in the Bay Area near San Francisco) tend to experience worse vehicle delay, while VMT per capita is a function of many characteristics including population size.

Transit: As a reference point, average UPT per capita during the study period and for relevant counties is approximately 2 with a standard deviation of 4.7. Treated counties have a mean of 1.3 while untreated counties have a (statistically significantly) larger mean of 3.84. There is also evidence of statistically significant increase in UPT per capita in treated counties before (at 1.19) and after (at 1.56) treatment (see Table A3.

Further, high UPT counties (as evident from table A3) in general have higher congestion levels, are significantly more densely populated and have higher levels of economic activity (not shown) and of automobile ownership. They are however not more likely to have rail-based transit, however, meaning that the High UPT-based classification differs from the rail-transit-based classification.

Automobile registration: We note that counties with "high ownership" differ from those without along expected dimensions: having significantly lower UPT, fewer counties entered by Uber, slightly lower delay, similar population densities, but with significantly lower median income (see table A3).

Subsection A.3 Further details regarding the Transit and Automobile registration regressions

Transit: We note that in light of previous studies reporting a relationship between Uber's entry and transit usage, congestion and transit usage are likely both affected by Uber. Consequently, a specification of the form of eq. (1) with transit usage as a control variable potentially suffers from an endogeneity problem. Nonetheless, using UPT as a control variable in our main regression (eq. (1)) yielded estimates of the effects of Uber that were almost identical to those of our main specification, with the only difference being a smaller (but still significant) increase in travel efficiency (see Panel C of Table 6). We also note that it is highly unlikely that the entry of Uber influenced whether a county moved from being a low UPT per-capita to a high UPT-per-capita (or vice-versa) category over the short time period under consideration, as evidenced by the largely static UPT shares over the sample period (as evident from an inspection of the average UPT over time–not presented).

We also note that the overlap between counties in Southern California and the five most populated counties and the counties included in transit-related analysis is essentially only L.A and San Diego. These are the only counties in Southern California that Uber entered and has either rail transit or is a "high UPT" county.

Finally, we also note that the qualitative insights of our findings in section 4.1 are robust to using an alternative definition of "high" and "medium" UPT counties (using the third and second terciles), using only "high UPT counties", or categorising counties into "above" and "below" median UPT per capita. These results are available upon request.

Automobile Ownership: As for the case of transit, using a simpler classification of counties into those with above- and below-average (per capita) ownership (based upon pre-2013 data) or into those with high ownership and those without (i.e. using only a "high ownership" indicator), yielded similar qualitative findings (results available upon request).

We note that in view of previous findings that vehicle registrations are affected by Uber's entry, its use as a dependent variable in a regression of the effects of Uber on traffic patterns can suffer from endogeneity. The approach we follow, of categorising counties by pre-entry registration average, provides a way of avoiding these endogeneity-related challenges.

Subsection A.4 Definition of Traffic Outcomes

PEMS defines the three traffic outcomes we use as follows:

Vehicle Hours of Delay (VHD): is computed as $F \times \left(\frac{L}{V} - \frac{L}{V_t}\right)$ where F is flow, L is length of segment, V is the speed of travel and V_t is the threshold speed (PeMS, 2009). It is calculated as the VHT at the speed of travel minus the VHT at the threshold speed (taken here to mean the typical freeway speed of 60 m.p.h). To enhance readability, we multiply VHD by 3600 seconds so it is now measured in seconds.

Vehicle Hours of Travel (VHT): is the total amount of time spent by all vehicles over a freeway segement during a certain time period (Caltrans 2020). At the aggregate level, it is the sum of VHT from individual detectors, so at the county-level, it is the sum of VHT across individual detectors in a given county.

Vehicle Miles Travelled (VMT): is calculated in PeMS by multiplying the number of cars that drove over a detector in a given period (i.e., flow) by the segment length. It does this for each detector in a given county and then sums the miles to obtain total VMT.

Subsection A.5 Data-related Challenges

Transit data: We note that traffic outcome data are not available for all counties in California: of the 58 counties, data are available for 37 in 2015 and 31 in 2009 (data are largely missing for the more sparsely populated counties). Figure A1 shows a map of counties with average vehicle delay during different time periods in our study over the sample period (2009-2015), where colored counties represent those with data available. Counties colored blue are treated (i.e., counties Uber eventually entered) while those colored orange are never-treated counties (i.e., counties Uber did not enter during our study period).

Pollutant data: As for traffic outcomes, not every county collects (or is required to collect) air quality data, though the most populated counties typically do. Further, the number of counties with data varies over time since pollutant concentration data were not recorded for all counties and years. The number of observations for each pollutant varies since the number of counties monitoring each pollutant depends partly on whether a county falls within an EPA-notified "non-attiainment" area (see https://www3.epa.gov/airquality/greenbook/ancl.html for further details). Most commonly, certain counties either do not monitor certain pollutants at all (particularly true for CO) or begin monitoring post-2009 (or to a lesser extent end monitoring pre-2015), as illustrated for the regression sample in Table A5. We also note that counties with missing data are usually sparsely populated, so (traffic and) pollution are less of a major concern. Finally, we note that using stricter criterion for data availability (e.g. retaining only counties that are monitored in 2009, 2012, and in 2015) does not lead to discernible changes of our estimates of the effects of Uber on pollution (results available upon request).

Weather Data: Wind speed is also arguably an important factor in understanding pollution concentrations (and, to a lesser extent, traffic). However, since average wind speed is not available at $> 90\%$ of weather stations in California, we do not include it in our analysis. We also note that for one county, Sutter County, unavailability of consistent weather data led us to use data from the adjacent county of Yuba.

ACS Data: Some counties, specifically Amador, Calaveras, Colusa, Del Norte, Glenn, Inyo, Mariposa, Plumas, San Benito, Siskiyou, Tehama, Trinity and Tuolumne did not have information available in the 1-year American Community Survey, in which case, we used data from the 5-year ACS, where data from the 2009-2013 5-year ACS represented the years 2009 to 2012 and data from the 2013 to 2015 5-year ACS represented 2013 to 2017.

Finally, we point out that data on automobile registration are available for many more counties (36) than data for UPT (25). Consequently, despite the significant overlap between "low" automobile ownership and high UPT counties, the differences in overall sample ensure that our findings regarding transit usage and vehicle ownership provide complementary perspectives.

Subsection A.6 Robustness checks for pollutant concentration

We carry out a series of robustness and specification checks to ensure the validity of our findings related to pollutant concentrations. First, we evaluate whether our findings are influenced by the degree to which our control ("never treated") counties represent valid controls, by restricting attention to only the treated counties (meaning identification is now entirely a result of the differential timing of Uber's entry). The results of this specification are summarised in Figure A4 ("Only Treated Counties" represented by the dashed orange line on the right of each graph), where the horizontal red line represents zero. As is evident, the only change from the main specification (the dashed light blue line on the far right) is for O_3, which now shows a statistically significant reduction in treated counties. In other words, after Uber's entry into a county, O_3 concentration falls by about 1 ppb, or 2% of the pre-2013 mean in treated counties, relative to counties yet to be treated.

Next in Figure A4, we evaluate the degree to which outliers in the dependent variables affect our results, for which we use our main specification but deal with outliers in the following two ways: one, either winsorize (the solid blue line on the far left of each graph) or trim the top and bottom 1% of observations of the dependent variable (the solid red line on the left), and two, expunging outliers identified using standard metrics (e.g. Cook's distance) (the dashed green line in the center). The coefficient on Uber with these samples are provided in Figure A4. For PM2.5, the only change we see is that in the trimmed and outlier-expunged samples (that lose a fraction of the sample), the effect of PM2.5 shrinks by a third and turns insignificant. As already mentioned, estimates from the "treated only" sample are almost identical to those of the main specification. Overall, outliers do not significantly affect our estimate of Uber on county-level pollution outcomes.

As for traffic congestion, we also check to ensure that specific treatment groups or treatment times are not a key driver of our results. To this end, we carry out a permutation test by randomly assigning treatment dates to treated counties with a view to ensuring that the magnitude of our Uber effects (regression coefficients) are large enough to rule out their being largely a result of a chance realisation of treatment time. Figure A5 plots the results of this test, together with the distribution of these coefficients and the coefficient estimated for the actual treatment date and a p-value for the null. The fact that we can reject this null for all pollutants clearly suggests that the size of the effects of Uber we find for all pollutants, in particular for PM2.5, are too large to arise by chance. Similarly, we also evaluate whether the first or last few counties entered overwhelmingly differed from the remaining and drive our results. We do so by re-estimating equations 3 and 4 where we exclude the first three and final four counties entered. The results of these specifications, presented in Table A4, are almost identical to those of our main specification, suggesting that changes in pollution outcomes did not drive the order of Uber's entry into a county.

Similar to the case of traffic congestion, we also check to ensure that specific treatment groups or treatment times are not a key driver of our results. To this end, we carry out a permutation test by randomly assigning treatment dates to treated counties with a view to ensuring that the magnitude of our Uber effects (regression coefficients) are large enough to rule out their being largely a result of a chance realisation of treatment time. Figure A5 plots the results of this test, together with the distribution of these coefficients and the coefficient estimated for the actual treatment date and a p-value for the null. The fact that we can reject this null for all pollutants clearly suggests that the size of the effects of Uber we find for all pollutants, in particular for PM2.5, are too large to arise by chance.

Similarly, we also evaluate whether the first or last few counties entered overwhelmingly differed from the remaining and drive our results. We do so by re-estimating equations 3 and 4 where we exclude the first three and final four counties entered. The results of these specifications, presented in Table A4, are almost identical to those of our main specification, suggesting that changes in pollution outcomes did not drive the order of Uber's entry into a county.

Subsection A.7 Figures

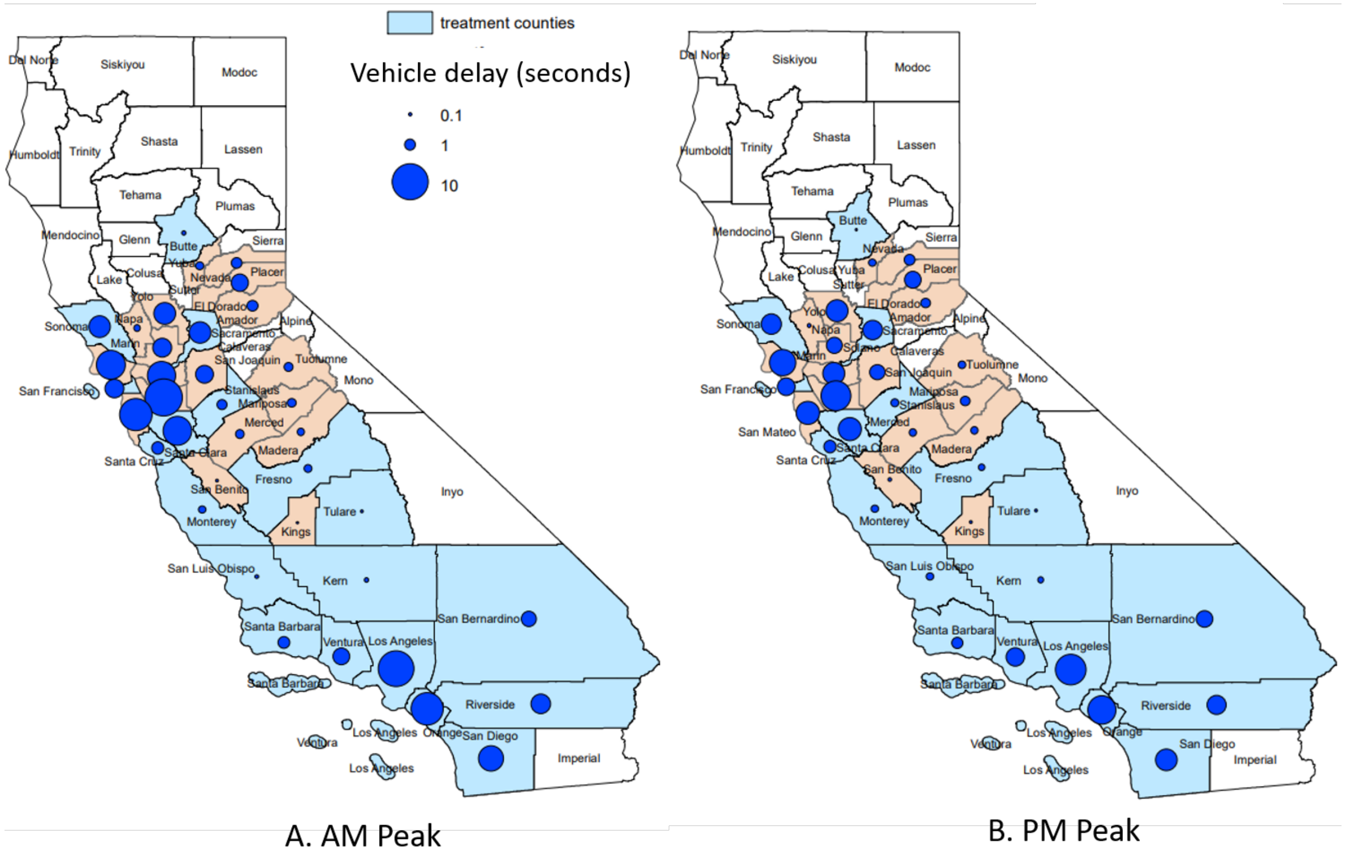
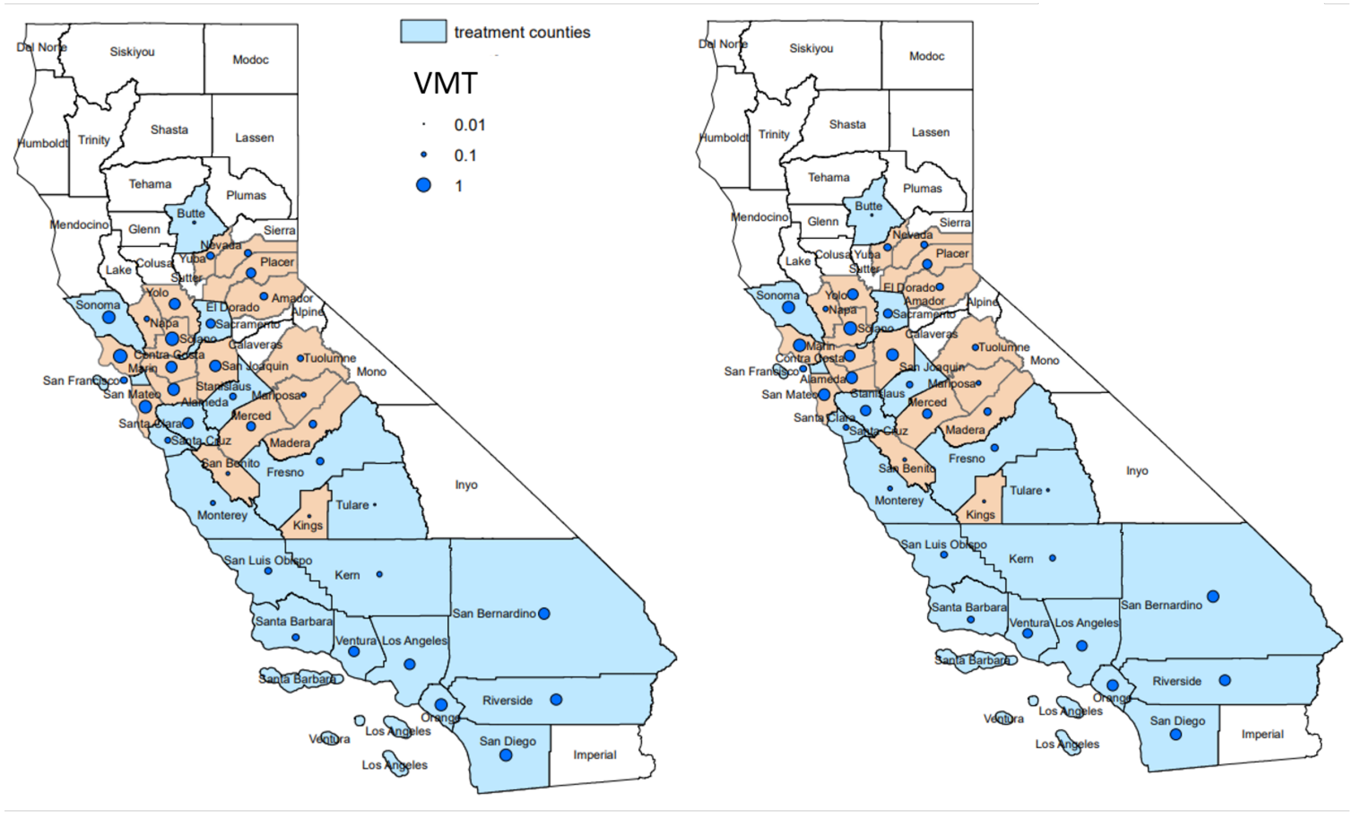


Figure A1: County-level delay at peak periods

Notes: Figure shows vehicle delay in seconds per capita at a free flow speed of 60 mph during the AM (7:00-09:59 AM) and PM (2:00-7:59 PM) peak periods in panels A and B (resp.). The size of the circles are in proportion to the magnitude of delay. Data on traffic for the non-shaded counties are missing. All colored counties are those included in our dataset, 37 in total. Blue counties are treated counties (i.e. counties Uber entered at some point during our study period between 2009 and 2015) and the orange counties are "never treated" counties, which Uber never entered during our study period.

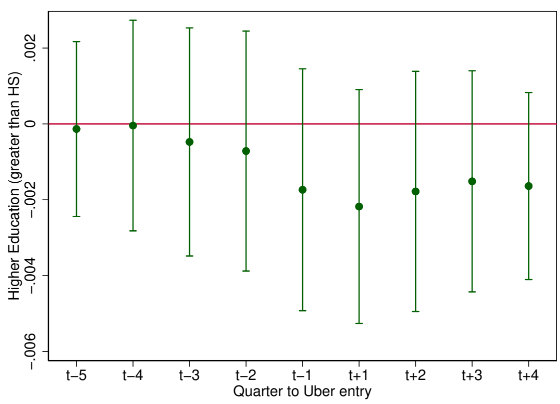


A. AM Peak

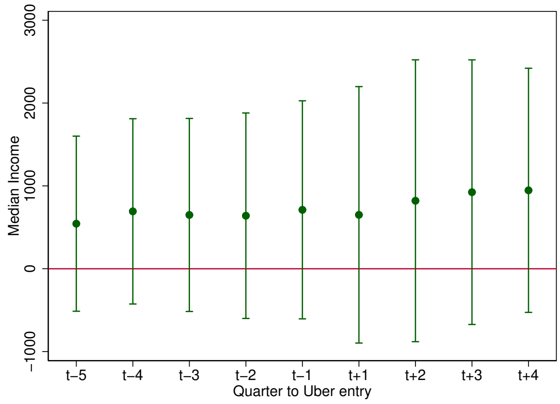
B. PM Peak

Figure A2

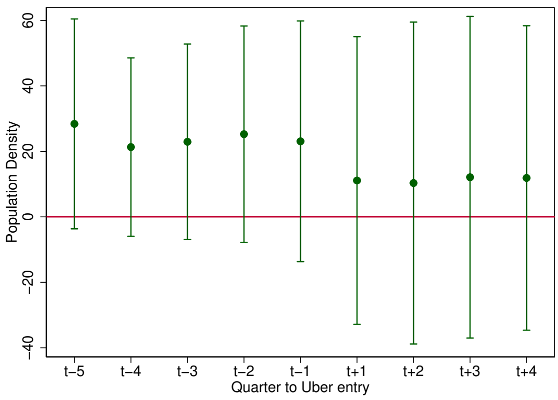
Figure shows vehicle miles traveled (VMT) per capita at the AM and PM peak period. See Figure A1 for more information.



(a) Higher Education



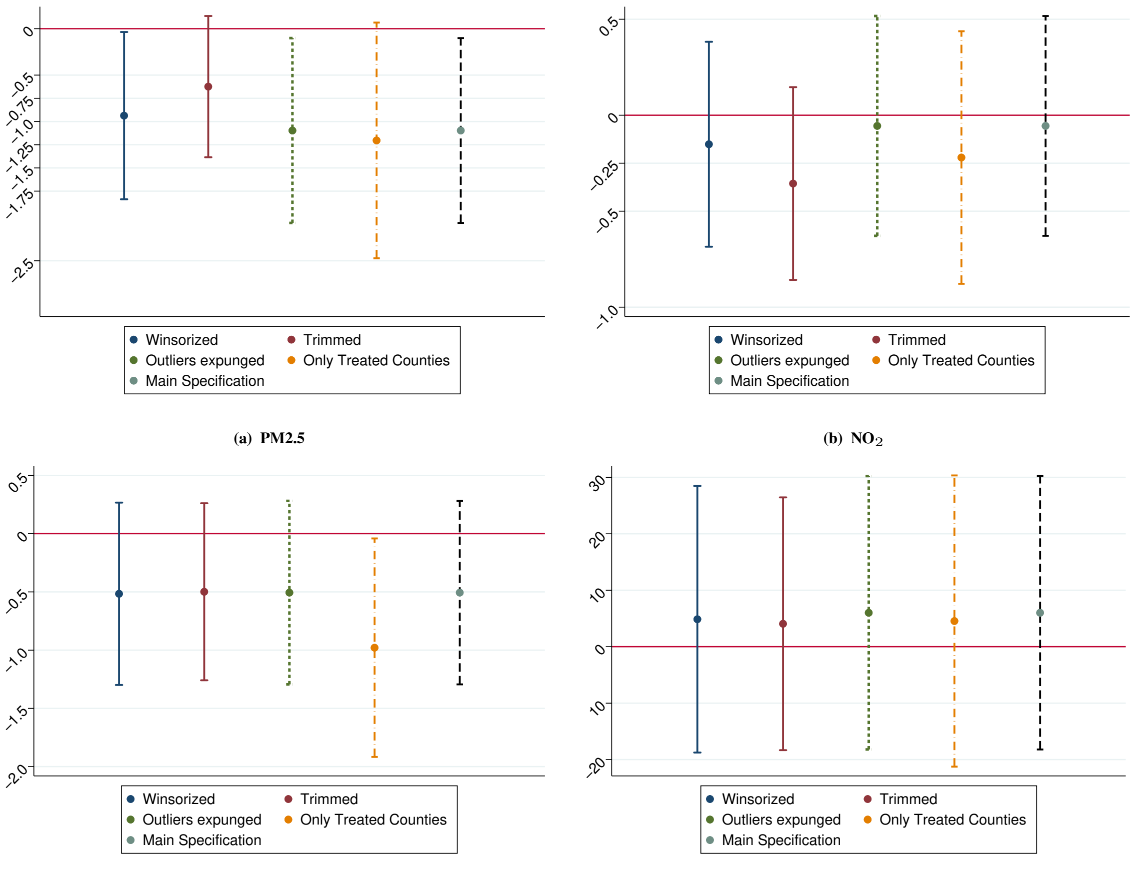
(b) Median Income



(c) Population Density

Figure A3: Falsification test: County characteristics before- and after-Uber entry.

Notes: Figure shows coefficient on Uber and (90%) confidence intervals from event study regressions of county characteristics before and after Uber's entry. All specification-related details are as for prior event studies (see fig. 1). Panel (a) shows higher education (share of county population with above higher secondary education), Panel (b) shows county median income while Panel (c) shows county population density (population divided by sq. miles).



(a) PM2.5

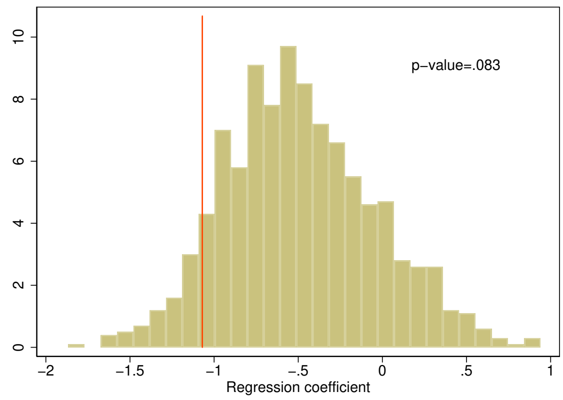
(b) NO_2

(c) Ozone

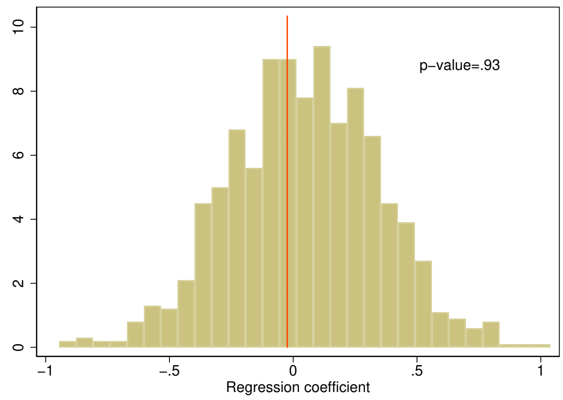
(d) CO

Figure A4: Sensitivity of Uber entry effects on Pollution to outliers.

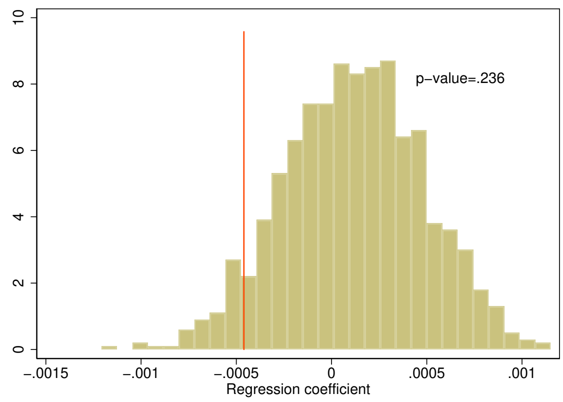
Notes: Figure shows coefficient on Uber and (95%) confidence intervals from difference-in-differences specification for daily pollution concentrations from the county FE specification in eq. (3) for the different sub-samples (detailed in Figure 3).



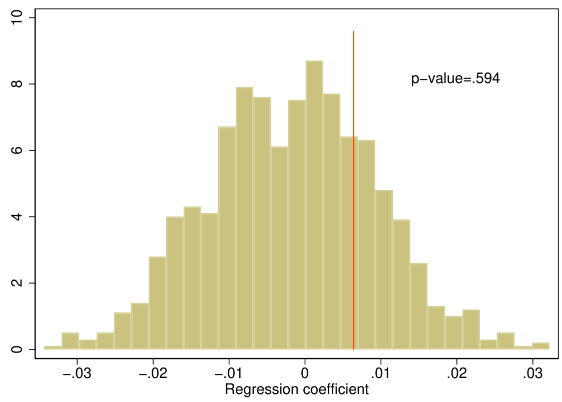
(a) PM2.5



(b) NO_2



(c) O_3



(d) CO

Figure A5: Permutation test for daily Pollution outcomes.

Notes: Each figure presents the distribution of coefficients from 999 separate regressions (our main specification with county FE, from eq. (3)), with respective daily pollutant concentrations as the outcome. All other aspects are identical to those detailed in fig. 2.

Subsection A.8 Tables

Table A1: Mean traffic outcomes across different time periods within a day

	AM Peak	Afternoon	PM Peak	Night time
Travel efficiency (VMT/VHT) (mph)	59	61	59	64
Treated Counties	59	62	59	66
Never Treated Counties	58	60	59	63
Delay (vehicle seconds per capita at 60 mph)	3.0	1.5	3.3	0.3
Treated Counties	3.0	1.4	3.5	0.3
Never Treated Counties	3.0	1.7	3.1	0.4
Vehicle miles traveled (VMT) per capita	0.4	0.4	0.5	0.2
Treated Counties	0.4	0.4	0.4	0.2
Never Treated Counties	0.5	0.4	0.5	0.2

Notes: Mean traffic outcomes at different times of the day for all weekdays in the sample. The four time periods are defined as follows: "AM peak" is the period between 7am and 9:59am, "Afternoon" represents hours between 10am and 1:59pm, "PM peak" consists of the hours between 2pm and 7:59pm and "Night time" corresponds to the period of 8pm to 10:59pm.

Table A2: Summary statistics by region

	Southern Calif.	Outside Southern Calif.	Top 5	Outside Top 5
	Socio-economic characteristics			
Population density	1148.74	1188.61	1526.99	1118.54
Median age	35.63	37.74	35.09	37.67
Median Income	63694.15	63950.31	61771.14	64271.3
	Traffic Outcomes			
Delay (vehicle seconds per capita)	2.32	1.38	2.93	1.35
Travel Efficiency(MPH)	62	61.21	61.49	61.36
VMT (per capita)	0.39	0.29	0.45	0.29
Number of counties	8	29	5	32
Number of observations	295368	1073767	206040	1163095
	Pollutant Concentration			
PM2.5	9.68	9.91	10.44	9.77
NO2	11.71	9.82	15.38	9.35
Ozone	31.05	29.19	31.28	29.3
CO	344.41	356.22	375.11	347.5
	Transit and Vehicle ownership			
UPT per capita	1.57	2.33	1.87	2.15
Automobile ownership per capita	0.6	0.59	0.59	0.6

Table A3: Key sample characteristics by Transit and Automobile ownership

Panel A: By unlinked passenger trips (UPT) category				
	High UPT		**Not high UPT**	
	Untreated	*Treated*	*Untreated*	*Treated*
UPT per capita	23	2.83	0.69	0.68
Vehicle Delay (seconds per capita)	4.74	2.7	1.6	1.16
VMT (per capita)	0.50	0.35	0.41	0.27
Travel efficiency (mph)	60.23	60.52	63	63
Population density	2168.5	1381.2	519	578.2
Median Income	78305.22	68280.23	62485.14	57866.46
Number of counties with rail transit	1	2	2	2
Number of counties	1	5	6	13
Automobile registration (per capita)	0.625	0.612	0.572	0.56
Panel B: By auto ownership category				
	High Car		**Not high Car**	
	Untreated	*Treated*	*Untreated*	*Treated*
Auto ownership (per capita)	0.70	0.65	0.54	0.54
UPT per capita	0.46	0.78	4.45	1.52
Vehicle delay (seconds per capita)	1.76	1.34	1.38	2.30
VMT (per capita)	0.39	0.25	0.28	0.40
Travel efficiency	60.72	61.98	60.18	62.36
Population Density	624.33	1978.35	377.32	1360.73
Median Income	59771.88	56906.39	72111.41	77041.69
Number of counties	8	5	9	14

Notes: "High UPT" and "Not high UPT" represent counties with pre-2013 average UPT per capita > and < the 75th percentile (resp.). "High car" and "Not high car" represent counties with pre-2013 average county automobile ownership per capita > and < the 66th percentile (resp.) (i) Total number of counties with non-missing UPT data for years 2009-2012 is 25. Note that most mean differences across treated and untreated (e.g. auto registration) are significant at the 1% level. (ii) Of the 25 counties for which we have UPT data, the following six are high UPT counties: LA, Sacramento, San Diego, Santa Barbara, Santa Clara (Treated) and Alameda (untreated). (iii) Of the eight counties that are in the High car category, only one (Santa Clara) is in the High UPT category (and only three more are included in the sample with UPT data).

Table A4: Robustness checks for pollution: Restricted sample of counties

	1	2	3	4	5	6	7	8
	PM2.5	PM2.5	NO_2	NO_2	O_3	O_3	CO	CO
Panel A: Excluding first three counties entered								
Uber	-1.20**	-0.22*	0.031	0.007	-0.27	-0.082	6.92	-0.26
	[0.58]	[0.12]	[0.33]	[0.10]	[0.43]	[0.13]	[13.0]	[4.94]
N	43,759	43,759	49,589	49,589	73,870	73,870	35,855	35,855
R2	0.282	0.595	0.664	0.779	0.684	0.814	0.558	0.755
Number of clusters	233	233	208	208	314	314	150	150
Panel B: Excluding the final four counties entered								
Uber	-1.00*	-0.16	0.29	0.032	-0.086	-0.023	5.56	2
	[0.59]	[0.13]	[0.35]	[0.13]	[0.44]	[0.13]	[14.0]	[4.68]
N	45,236	45,236	47,904	47,904	72,139	72,139	39,351	39,351
R2	0.286	0.595	0.692	0.79	0.683	0.813	0.574	0.76
Number of clusters	233	233	201	201	307	307	164	164
County fixed effects	YES	NO	YES	NO	YES	NO	YES	NO
(1-day) Lag of dependent variable	NO	YES	NO	YES	NO	YES	NO	YES

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in brackets and clustered at the county-year level. Table presents regression results from a specification differing from that in table 7 only in restricting the sample to exclude counties that Uber entered very early (Panel A) or very late (Panel B). Odd- and even-numbered columns show results using the county FE (eq. (3)) and LDV (eq. (4)) specifications (resp.).

Table A5: Pollutant data availability across counties for different regression specifications

	1	2	3
	Main Specification	Excluding counties missing data for	
		year 2009	years 2009 or 2012 or 2015
PM2.5	42	39	39
NO2	35	34	31
O3	48	48	48
CO	26	25	24

Notes: Number of counties included in different regression specifications by pollutant. Regression specifications differ in exclusion criteria for counties, ranging from using the entire sample of counties ("main specification"), to excluding counties missing data for 2009 only, and missing data for any of 2009, 2012 or 2015. All (county FE) regression specifications yielded qualitatively similar (if not identical) results to those in Table 7 (Panel A).

Table A6: Pre-2013 and Post-2012 means for traffic outcomes

	1 Pre-2013	2 Post-2012
Panel A: Travel efficiency (VMT/VHT) (mph)		
Overall	63	60
Treated counties	63	62
Southern California	62	62
Never treated counties	63	57
Outside Southern California	63	59
Top 5 most populated counties	62	61
Outside Top 5 most populated counties	63	59
AM peak	61	57
Afternoon	62	59
PM peak	61	57
Nighttime	66	63
Panel B: Delay if ideal speed is 60 mph (vehicle seconds) per capita		
Overall	1.3	1.9
Treated counties	1.5	1.7
Never treated counties	1.2	2.0
Southern California	2.2	2.6
Outside Southern California	1.1	1.8
Top 5 most populated counties	2.5	3.6
Outside Top 5 most populated counties	1.1	1.7
AM peak	2.6	3.4
Afternoon	1.3	1.7
PM peak	2.8	3.9
Nighttime	0.2	0.4
Panel C: VMT (miles) per capita		
Overall	0.3	0.3
Treated counties	0.3	0.3
Never treated counties	0.3	0.3
Southern California	0.4	0.4
Outside Southern California	0.3	0.3
Top 5 most populated counties	0.4	0.6
Outside Top 5 most populated counties	0.3	0.3
AM peak	0.4	0.4
Afternoon	0.4	0.4
PM peak	0.4	0.5
Nighttime	0.2	0.2

Notes: Table shows pre-2013 and post-2012 means (columns 1 and 2 resp.) for the traffic outcomes of interest, where "pre-2013" includes all years prior to 2013 (i.e. 2009-2012) and "post-2012" includes all years after 2012 (i.e. 2013-2015). This includes means overall (across all counties in the sample), in treated counties only, never treated counties, and across different regions and time bands of interest to this study. See notes from Table 2 for more information.

Table A7: Pre-2013 and Post-2012 means for pollution outcomes

	1	2
	Pre-2013	Post-2012
Panel A: PM2.5 (ug/m3)		
Overall	10.2	9.7
Treated counties	10.0	9.4
Never treated counties	10.4	10.0
Southern California	10.3	9.4
Outside Southern California	10.5	9.3
Top 5 most populated counties	11.0	10.3
Outside Top 5 most populated counties	10.3	9.2
Panel B: NO_2 (parts per billion (ppb))		
Overall	10.6	9.9
Treated counties	11.4	10.5
Never treated counties	9.7	9.2
Southern California	12.4	10.1
Outside Southern California	10.1	9.1
Top 5 most populated counties	16.3	14.5
Outside Top 5 most populated counties	9.7	8.7
Panel C: O_3 (ppb)		
Overall	28.4	30.8
Treated counties	28.3	30.7
Never treated counties	28.5	30.9
Southern California	29.8	32.9
Outside Southern California	27.9	30.8
Top 5 most populated counties	29.8	33.6
Outside Top 5 most populated counties	28.0	30.8
Panel D: CO (ppb)		
Overall	361.5	343.6
Treated counties	350.4	334.4
Never treated counties	379.4	358.5
Southern California	361.3	328.6
Outside Southern California	365.6	341.3
Top 5 most populated counties	396.3	354.1
Outside Top 5 most populated counties	356.0	334.2

Notes: Table shows pre-2013 and post-2012 means (columns 1 and 2 resp.) for the pollutants of interest. See notes for Table A6 for more information.

Table A8: Welfare implications of Uber's entry on freeway congestion in California

Estimates	Annual welfare effects (US$ millions)
Average effect	**14.3**
Heterogeneous effects	
Over time	
Afternoon (10 am-1:59 pm)	17.1
PM peak period (2-7:59 pm)	-42.8
Nighttime (8-10:59 pm)	13.6
Net effect	**-12.1**
Across county groupings	
In Southern California	-11.0
Outside Southern California	9.9
Net effect	**-1.1**
At Five most populated counties	-11.2
Outside five most populated counties	8.6
Net effect	**-2.6**

Notes: Table presents results from the back-of-the-envelope welfare computations discussed in section 6, using estimated effects of Uber's entry on freeway congestion in California (between 2009 and 2015). The "Average effect" is based on estimates in Table 3, while the heterogeneous effects "over time" and "across county groupings" are based on estimates from Figure 4b and Figure 5 (resp.). The "Net effect" in bold is the direct sum of the annual welfare effects during these different time periods or across different regions.