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Using Disaggregate Vehicle Data to Investigate How Ride-Hailing Services Influence Personal Vehicle Use Across a Metropolitan Region

Michael A. N. Montilla
Matthew Hui
Daniel G. Chatman

National Institute for Congestion Reduction
University of South Florida
Center for Urban Transportation Research | University of South Florida

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Prepared by

Michael A. N. Montilla
Matthew Hui
Daniel G. Chatman
Department of City & Regional Planning
University of California, Berkeley

Prepared for

National Institute for Congestion Reduction
University of South Florida
Center for Urban Transportation Research

4202 E. Fowler Avenue, ENG030, Tampa, FL 33620-5375
nicr@usf.edu

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16. Abstract

App-based ride-hailing has become a popular form of urban transportation. Previous research suggests that it may in some cases enable lower reliance on private vehicles, but that it is also associated with increases in congestion and vehicle miles traveled (VMT). We examined how the introduction of the Uber ride-hailing service in the Boston area related to changes in the average daily VMT of individual vehicles. This research is unique because it focuses on the use patterns of individual automobiles instead of relying on aggregate measures of auto use, or estimates based on surveys, as done in previous research. Using data sourced from vehicle registrations and odometer readings collected during state-mandated annual inspections, we tracked changes to the average daily VMT of 1,668,215 vehicles over five years as Uber launched in the Boston area. We applied fixed-effects panel regression methods to model the relationship between Uber availability, VMT, and transit access. We also examined vehicle turnover and ownership at the Census Tract level to investigate if neighborhood change may have influenced observed changes in daily VMT. In contrast to previous studies finding associations between ride-hailing and large increases in VMT, we found that Uber availability was not related to changes in VMT in the cities of Boston and Cambridge and was significantly related to only marginally higher average daily VMT outside those core cities (0.6% increase from the mean VMT). We also found slightly lower rates of vehicle turnover and ownership in areas outside of Boston and Cambridge after Uber availability. These results suggest that ride-hailing's influence on VMT is likely smaller than indicated in other research, limited to vehicles registered outside MPO cores, and is likely not related to neighborhood change.

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Executive Summary

This report investigates the impact of ride-hailing services, specifically Uber, on personal vehicle use and vehicle miles traveled (VMT) in the Boston metropolitan area. Using disaggregate vehicle data from the Massachusetts Vehicle Census (MAVC) and applying fixed-effects panel regression methods, the study tracks changes in the average daily VMT of 1,668,215 vehicles over five years as Uber launched in the region.

Our analysis of individual vehicle level data suggests that the introduction of Uber had a small influence on VMT, and any influence was limited to vehicles registered outside the core of the metropolitan area. We also found that ride-hailing's influence on vehicle use and ownership may differ between central and peripheral areas, and is likely not related to neighborhood change, as we describe below.

In our analysis the introduction of Uber was associated with only a very small increase in VMT, and only in less-central areas of a metropolitan region. The average daily VMT of vehicles located outside of the core cities of Boston and Cambridge climbed by 0.6% above the mean of 27.6 average daily miles after the introduction of Uber, all else equal. We found similar results in the aggregate model: average vehicle mileage in Census tracts outside of Boston and Cambridge was 0.34 miles per day higher after the introduction of Uber, controlling for other factors. However, within the cities of Boston and Cambridge, we found no significant relationship between Uber availability and VMT.

Interestingly, we also found in our Census-tract level analyses that Uber availability related to 0.22 less vehicles per population, but again only outside the metropolitan core. This reduction in vehicles per population could signal lower dependence on private vehicles, and when paired with the small increase in VMT per vehicle, suggests that ride-hailing-related reductions to auto dependency could occur alongside additions to VMT in some areas.

We offer two reasons why Uber may have influences changes to VMT and ownership only outside central areas. First, in urban cores, where auto ownership and use are already lower than suburban and exurban areas, private vehicle trips that can be replaced by ride-hailing trips may be less prevalent. For example, a resident in a central city who owns a car may use non-automotive modes for most regularly occurring trips, but still keep a car for highly specific trips such as leaving the city on weekends, or large shopping trips. As such, Uber availability may not affect changes to how these residents utilize their vehicles. Second, ride-hailing drivers may be more likely to live outside urban cores; if so, VMT reductions from suburban car owners slightly reducing their auto ownership could be partly offset by the increased VMT produced by ride-hailing vehicles.

Additionally, we looked for but did not find any indication that vehicle turnover or transit service mediated how Uber's availability affected auto ownership or use. In interaction with Uber, all but one of the mode-specific transit variables were insignificant in both the individual vehicle level and Census tract level models regressing over VMT. The one transit variable in interaction with Uber availability that was significant, commuter rail station density, was significant only in the individual vehicle level model where we found evidence that Uber relates to a small reduction in the association between commuter rail station density and decreased VMT. However, this interaction was found to be significant only in Boston and Cambridge, where Uber on its own was found not to be related to VMT. This result is consistent with the hypothesis that the potential to reduce vehicle use through complementary ride-hailing and transit services may exist primarily outside central areas—perhaps because ride-hailing mainly replaces the last-mile travel related to park-and-ride transit services in peripheral areas, and these services are less common in urban cores.

Chapter 1. Introduction

Over the last decade, app-based ride-hailing has become a well-known form of urban transportation. Companies that offer ride-hailing, such as Uber and Lyft, typically provide on-demand, door-to-door services. The introduction of ride-hailing has disrupted the taxi industry and led to the development of new regulations and oversight mechanisms (Beer et al., 2017). It has also led city planners to consider whether ride-hailing services, in tandem with transit and other forms of new mobility, could fulfill transportation demands without extensive reliance on private vehicle use.

The question remains whether ride-hailing enables diminished use of automobiles or synergizes with transit and other modes. Some research has found that ride-hailing may encourage lower private vehicle use among urban and younger populations (Coogan et al., 2018). But other studies suggest that ride-hailing operations may increase vehicle miles traveled (VMT) and congestion (Erhardt et al., 2019; Henao and Marshall, 2019; Wu and MacKenzie, 2021). There is also a growing consensus that ride-hailing may complement transit only where transit availability is weak (Hall et al., 2018; Jin et al., 2019; Kong et al., 2020; Young et al., 2020). In short, research on ride-hailing raises doubts about its potential to contribute to sustainable transportation practices on an urban scale, although it may facilitate use of shared modes in some contexts.

The research on ride-hailing has primarily relied on surveys or aggregate travel data to investigate its influence on private vehicle use. Here we examine, for the first time in the literature, changes in the actual use patterns of individual automobiles as the Uber ride-hailing service launched in a metropolitan area. We analyzed disaggregate vehicle data from the Massachusetts Vehicle Census (MAVC) of 2010 to 2014, exploring how the daily VMT of individual vehicles changed and differed depending on Uber availability and access to transit in the greater Boston area. The MAVC contains records of almost all annual vehicle inspections in Massachusetts, including odometer readings and the registered storage location (Metropolitan Area Planning Council, 2016), enabling spatially-specific, direct measurement of vehicle use before and after the introduction of ride-hailing.

We built an analytical model representing how ride-hailing availability relates to the average daily VMT of individual autos and assessed how interactions between Uber availability, transit, and location of vehicles are associated with differences in VMT over time. We also supplemented this analysis by building 3 models at the Census Tract level exploring Uber's relationship with aggregate VMT, as well as vehicle turnover and ownership. Unlike previous research showing large increases in VMT related to ride-hailing (Erhardt et al., 2019; Henao and Marshall, 2019), we found that Uber availability was significantly related to only slight increases VMT, and only in metropolitan areas outside of Boston and Cambridge. In these central cities, we found no significant relationship between Uber availability and VMT, and no indications across the region of neighborhood change influencing observed changes in VMT. We also found evidence that Uber may weaken the relationship between commuter rail and VMT reductions in more urban areas, which suggests a potential substitutional relationship between transit and ride-hailing in some contexts.

Ride-Hailing and VMT

Research on ride-hailing's influence on private vehicle use has found what appears to be conflicting results. There is some evidence that ride-hailing may allow individuals to own and use private automobiles at a lower rate (Coogan et al., 2018; Bansal et al. 2020; Dong et al., 2021). But other studies argue that ride-hailing operations have led to increased VMT within their service areas (Erhardt et al., 2019; Henao and Marshall, 2019; Wu and MacKenzie, 2021).

Survey-based research has often concluded that ride-hailing may enable lower personal vehicle ownership and use but also suggests that ride-hailing's influence on VMT may vary depending on individual characteristics. A 2017 survey of residents living in U.S. ride-hailing markets found that ride-hailing customers are largely, but not solely, constituted of private vehicle users. When asked how they would complete their most regularly recurring trip if the mode typically utilized was not available, 66% of frequent ride-hailing users reported that they would have driven a car. Conversely, only 14% said they would take transit (Bansal et al. 2020). These results suggest that frequent ride-hailing users are most often replacing private vehicle trips with ride-hailing, while a minority was likely increasing their personal VMT by switching away from transit. Furthermore, about 10% of ride-hailing customers indicated that ride-hailing services allowed them to delay acquiring a personal vehicle (Bansal et al. 2020). This finding is echoed in the results of a more recent survey focusing exclusively on Philadelphia and Boston (Dong et al., 2021).

In another survey-based study, 26% of respondents reported less need for a private car because of new mobility services including ride-hailing (Coogan et al., 2018). However, this trend was not uniform across all demographics; urban commuters and single millennials were most likely to report less need for a private car. This difference in responses across groups suggests that home location and age may affect how ride-hailing shapes changes in private vehicle use and ownership (Coogan et al., 2018).

Highlighting the heterogeneous influence of ride-hailing on private vehicle use is recent research using data from the 2017 U.S. National Household Travel Survey. The authors concluded that frequent TNC users who had both driver's licenses and access to a vehicle reduced their VMT through ride-hailing, and that vehicle ownership declined among frequent ride-hailing customers more than occasional users. But the authors also estimated that at the time of the survey, ride-hailing services added 7.8 million miles of VMT nationwide daily (Wu and MacKenzie, 2021). As a whole, the study suggests that despite ride-hailing's ability to reduce private vehicle use for some users and in some contexts, it inflates VMT in most situations.

Other studies also come to the conclusion that ride-hailing operations are associated with increased VMT and congestion. One study used traffic time data alongside TNC pick-up and drop-off data from San Francisco to model changes in congestion with and without ride-hailing services. Comparing a 2010 scenario without ride-hailing to the observed conditions in 2016 with ride-hailing available, they found a 13% increase in VMT, compared to an estimated increase of 7% if ride-hailing had not been available. They concluded that ride-hailing was the main driver of new congestion in the city (Erhardt et al., 2019). These findings are mirrored by estimates from Denver indicating that ride-hailing led to 83.5% more VMT than would have been generated without ride-hailing services by replacing non-automotive trips, inducing new trips, and traveling without users aboard (Henao and Marshall, 2019).

Another important phenomenon to account for in understanding ride hailing's influence on VMT is "deadheading," a term referring to the portion of travel by ride-hailing vehicles without a paying passenger aboard, in between trips. Some studies conclude that deadheading is a significant contributor to ride-hailing VMT (Henao and Marshall, 2019; Wu and MacKenzie, 2021; Schaller, 2021). Even if a ride-hailing user traveled for fewer miles compared to driving a personal vehicle, the ride-hailing vehicle itself may produce more VMT accounting for deadheading.

Ride-Hailing and Transit

Many planners assume that ride-hailing and transit can operate alongside each other as complements resulting in a more sustainable transport system with a sizeable number of urban travelers utilizing ride-hailing to connect to or from transit. Simulation research analyzing survey data from the San Francisco Bay Area found that nearly a third of morning commuters who drive alone could reduce the generalized costs of their trips by using ride-hailing to connect to the Bay Area Rapid Transit network. The authors estimated that if all of these commuters switched, then over 600,000 miles of total daily VMT could be avoided, leading to significant reductions in vehicle emissions while bolstering the use and viability of transit services (Alemi and Rodier, 2017).

The transformative potential of ride-hailing synergizing with transit has inspired concepts for future transportation systems where most if not all private vehicle use is replaced with shared and active modes functioning in tandem. These concepts generally depend on ride-hailing and transit performing as economic complements. However, most of the existing research finds that ride-hailing typically substitutes for transit except in areas with poorly developed transit options (Tirachini, 2020).

First, there is strong evidence of an association between ride-hailing operations and declines in transit ridership. A study using longitudinal panel data from the National Transit Database found that across 22 large U.S. cities, heavy rail ridership declined 1.3% and bus ridership declined 1.7% each year after Uber launched in the area (Graehler et al., 2019). A later study using data from San Francisco similarly found that bus ridership declined roughly 10% over the first five years of Uber operations (Erhardt et al., 2022). These findings also show variation depending on transit mode; for example, in the latter study, Uber's introduction was not found to have a significant relationship with light rail ridership.

Second, numerous studies have found that ride-hailing trips rarely connect to transit, while nevertheless overlapping with transit services. A study using passenger surveys from the Denver area found that just 5.5% of Uber and Lyft riders incorporated an additional mode into their trip (Henao and Marshall, 2019). Likewise, survey research from Santiago, Chile found that among ride-hailing users, only 3.8% reported use of other forms of transportation to complement ride-hailing trips (Tirachini and del Río, 2019). Research looking at Philadelphia and Boston found that 5 to 6 percent of surveyed ride-hailing users reported using their most recent ride-hailing trip to access transit (Dong et al., 2021). Taking into account that many ride-hailing trips originate or end near transit stops (Rayle et al., 2016), these findings imply that ride-hailing often substitutes for transit services.

Despite ride-hailing appearing to act as a substitute for transit, there is also evidence indicating complementary effects in some situations. A study using Uber market penetration data in conjunction with the National Transit Database found evidence that ride-hailing may be a complement to transit in U.S. metropolitan areas with weak transit ridership. Analyzing data from every metropolitan statistical area with public transit, the authors estimated that Uber's introduction led to a 6% jump in ridership for transit agencies with ridership below the national median, and a 2.1% reduction in ridership for agencies above the median. The authors argue this result is likely because ride-hailing provides added service flexibility for riders within the context of infrequent transit services that access relatively few destinations. Altogether, the authors estimated a 5% increase in ridership for the average U.S. transit agency two years after the local launch of Uber (Hall et al., 2018).

Another study used general transit feed specification (GTFS) data and ride-hailing passenger surveys from Toronto to assess which ride-hailing trips had an alternative transit trip available. They found that about 30% of ride-hailing trips could have been completed by transit with a 15 minute or less time penalty, and they interpreted this finding to mean that these trips were substituting for transit. However, they also found that nearly 27% of the examined trips had a transit alternative that would have increased travel time by at least 30 minutes. In these cases, the authors state ride-hailing was likely complementing transit, and taken as a whole, they believe that the results show that ride-hailing acts as a substitute to transit in areas with robust transit services, and a complement where transit options are sparce (Young et al., 2020). These results reflect similar findings from New York City (Jin et al, 2019) and Chengdu, China (Kong et al., 2020).

In summary, previous studies indicate that ride-hailing substitutes for transit in many if not most situations, but there is also evidence suggesting that it complements transit where transit services are infrequent or poorly developed.

VMT and Neighborhood Change

There are of course other neighborhood and household characteristics besides access to transit or ride-hailing that likely affect travel behavior. One factor that must be considered in this research is the influence of income. Previous research has found that higher income households own and use autos at a higher rate (Crane and Crepeau, 1998; Pucher and Renne, 2003), and that lower income households rely on non-automotive modes more, and travel less overall (Chatman, 2009).

With regards to neighborhood change, many have recognized the potential for gentrification around transit improvements arguing that the arrival of new higher income households who use transit less than displaced lower income households may result in lower overall transit use (Pollack et al., 2010; Dominie, 2012). Others have identified that households in gentrified areas commute by cars more and transit less than other areas (Danyluk and Ley, 2007). While there are some indications that gentrification near transit can lead to lower VMT overall, researchers conclude that such reductions are likely not possible without densification in these areas (Chatman et al., 2019).

The Boston area has seen considerable development and change near transit services. As of January 2011, 391 development projects in Massachusetts Bay Transportation Authority (MBTA) station areas were in progress or already constructed (Reardon and Dutta, 2012). Moreover, during the study period, the MBTA enhanced their bus services, and added new commuter rail and rapid transit stations (Massachusetts Bay Transportation Authority, 2021). Given these improvements and the established connections between gentrification, income, transit access, and changes to travel behavior, it was essential that we check for signs of neighborhood change in this current study to ensure that observed changes to VMT in the MAVC were independent of changes to household wealth.

Chapter 2. Methods

The following questions guided this study: (Q1) How did the average daily VMT of individual vehicles change after the introduction of Uber? (Q2) Are those changes affected by the level of transit access? (Q3) Is the introduction of Uber associated with neighborhood change? Questions 1 and 2 are intended to answer how ride-hailing influences vehicle use, and if transit access mediates relationships between ride-hailing and VMT. The purpose of question 3 is to test if neighborhood change could explain observed relationships between ride-hailing and VMT identified by addressing questions 1 and 2.

To pursue these questions, we employed vehicle-level, disaggregate data from the Massachusetts Vehicle Census (MAVC) of 2009 to 2014 (Metropolitan Area Planning Council, 2016), temporal data representing the gradual roll out of Uber across the Boston area (Uber, 2013; Uber 2014a; Uber 2014b), year-specific locational data of MBTA transit stops and stations (Massachusetts Bay Transportation Authority, 2021), demographic data and Census Tract boundaries sourced from the U.S. Census and American Community Survey (ACS) (U.S Census Bureau 2010, 2019a, 2019b, 2019c), and additional spatial boundary data from Massachusetts planning agencies (City of Boston, 2020; City of Cambridge, 2020; Massachusetts Department of Transportation, 2019). This study is unique because of its focus on changes occurring in individual vehicles. The MAVC is a highly detailed record of state-mandated, annual vehicle inspections including odometer readings, vehicle identification numbers (VINs), and other information, allowing for calculation of the average daily VMT of individual automobiles based upon direct odometer measurements. By analyzing via panel regression the relationship between the average daily VMT of individual vehicles over time as Uber launched in the Boston area, we examined how the introduction of ride-hailing to a major metropolis with varying levels of transit access relates to personal vehicle use at a granular scale. We also utilized the disaggregate MAVC data to perform regression analyses at the Census Tract level to supplement our individual vehicle level analysis into Uber availability's relationship with VMT, and to examine if neighborhood change contributes to changes in VMT.

MAVC Disaggregate Vehicle Data

To calculate the *Average Daily VMT* of individual vehicles, we used the disaggregate Researcher Files of the MAVC as compiled by the Metropolitan Area Planning Council (MAPC). This is a comprehensive dataset of vehicle inspections merged with registration information for individual vehicles in Massachusetts from 2009 to 2014 (Metropolitan Area Planning Council, 2016). The dataset contains VINs and Massachusetts property tax parcel numbers (*Parcel IDs*) for each inspection record, and we used these identifiers to track vehicle mileage and registered location over time. For each inspection record, the dataset provides odometer readings (mileage), emissions data, and other vehicle characteristics such as make, model, model-year, and curb weight. Using the MAVC dataset, we identified mileage records for each unique *VIN-Parcel ID* pair corresponding to each year from 2009 to 2014. We then weighted these mileage records by the number of days within each year to obtain yearly averages of daily VMT for each unique *VIN-Parcel ID* pair. Note that a vehicle that moved from one registered location to another would have more than one *VIN-Parcel ID* pair, and would produce a unique observation in the resulting average daily VMT data for each *VIN-Parcel ID* pair within any given year it moved. 1,668,215 vehicles were included in this study as were 1,873,996 unique *VIN-Parcel ID* pairs. In total, the dataset has 6,309,506 observations due to multiple observations of the same vehicles in the same locations over the five-year observation period.

To generate a proxy measure of the wealth/income of each vehicle's owner, we calculated a *Depreciated MSRP* variable via a function based on the vehicles' manufacturer suggested retail price (*MSRP*) and *Vehicle Age* as reported in the MAVC. We used a linear depreciation method assuming that vehicle values are fully depreciated in 12 years. We then rescaled this variable by subtracting its median. We also rescaled the adjusted miles per gallon (*Adjusted MPG*) variable, and repurposed vehicle characteristics such as *Vehicle Type* and *Fuel Type* as dummy variables for use in model construction.

Finally, we utilized the parcel IDs to confirm the registered Census Tract for every *VIN-Parcel ID* pair. Later on, we utilized the Census Tract information to associate the MAVC data with other spatially defined information such as Uber availability, transit access density, and population demographics. We also utilized the vehicle-level MAVC data to calculate Census Tract aggregate measures of VMT per vehicle-days, as well as vehicle turnover and vehicles per population.

Uber Availability Data

Boston is one of Uber's oldest markets, beginning operations within the city on October 27th, 2011 (Uber, 2016). In their earliest years of operation, Uber maintained a relatively small service area limited to the cities of Boston and Cambridge. A few trips in these early years did extend out of this zone, but Uber avoided expanding their service area until July 2013 when they expanded operations into nearby suburbs south of the urban core (Uber, 2013). In January 2014, they similarly expanded to the north (Uber, 2014a). Finally, by October 2014, Uber operations had expanded to the west of Boston's inner suburbs towards central Massachusetts (Uber, 2014b).

Using the publicly available history on Uber's expansion in the Boston area, we created a dummy variable indicating whether individual vehicles reported in the MAVC were registered to an address both within the Boston Region MPO (the spatial extent of this study), and within a Census Tract with Uber availability for each year of the study. We decided to use April 1st of each year as the critical date determining Uber availability because April 1st is the reference day for U.S. Census data, and we used Census data in our model as control variables. If a Census Tract fell within Uber's service area on April 1st of a specified study year, then it was designated as such using the dummy variable. Therefore, for 2010 and 2011, none of the vehicles were designated as being registered in an area with Uber availability. For 2012 and 2013, only vehicles registered in Boston or Cambridge were designated as having Uber availability because Uber did not expand out of the core urban area until later in 2013. In 2014, all vehicles registered in the Boston Region MPO were designated as having Uber availability as Uber services had expanded to areas outside the MPO by later in 2014. While we are not certain that every area in the MPO had Uber availability by April 1st, 2014, we are confident that most if not all did. A map highlighting Boston, Cambridge, and MPO boundaries is shown in Figure 1 (City of Boston, 2020; City of Cambridge, 2020; Massachusetts Department of Transportation, 2019).

It should be noted that other ride-hailing TNCs besides Uber, namely Lyft, began operating in the Boston area near the end of the study period. These are unaccounted for in our analysis but played a minor role. Note that because of Uber's gradual roll-out in the area, only vehicles registered within Boston or Cambridge have multiple years of records with Uber availability.

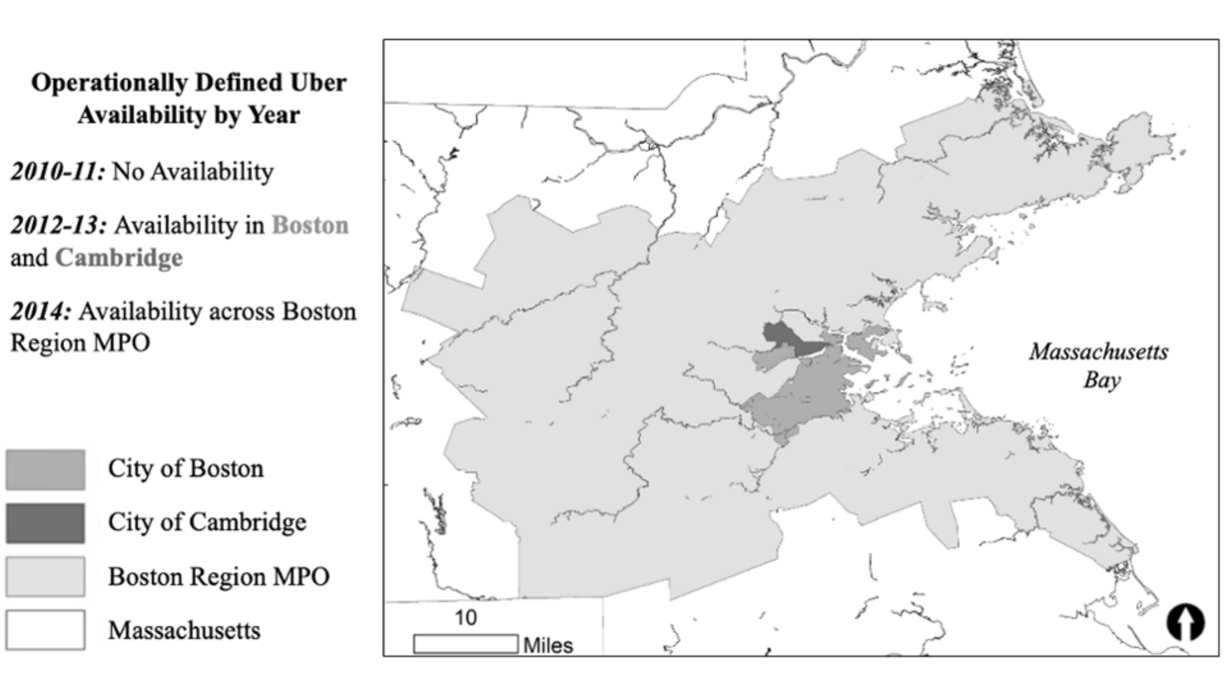

Figure 1. Boston, Cambridge, and Boston Region MPO Boundaries

Transit Density Data

To measure transit accessibility, we created scores representing the relative density of transit access nodes (stops and stations) for each Census Tract in the Boston Region MPO for each year of the study. To locate transit nodes, we accessed date-specific spatial data of MBTA facilities from the agency's GTFS archive (Massachusetts Bay Transportation Authority, 2021), and utilized the record closest to April 1st of each year to create shapefiles in ESRI's ArcGIS representing the location of MBTA facilities for each study year. We examined the data, and removed non-access nodes (such as maintenance facilities), ferry docks, airport shuttle bus stops, and duplicate entries. We reviewed the accuracy of the data by comparing it to a written history of MBTA service changes (Belcher, 2021), and then updated the data to reflect which of three types of services operate at each stop or station: traditional bus, rapid transit (including heavy rail, light rail, and bus rapid transit), and commuter rail. Finally, we spatially joined the remaining transit node points onto a polygon shapefile of Census Tracts (U.S. Census Bureau, 2010), and calculated the density of transit points in each Census Tract. While most of the variation in the transit density scores can be seen between Census Tracts, there is some variation within Census Tracts as well since some bus stop locations changed over time, and other transit nodes closed or opened. The transit density scores were then merged onto the MAVC data by Census Tract. Transit density scores and node locations for 2014 are shown in Figure 2.

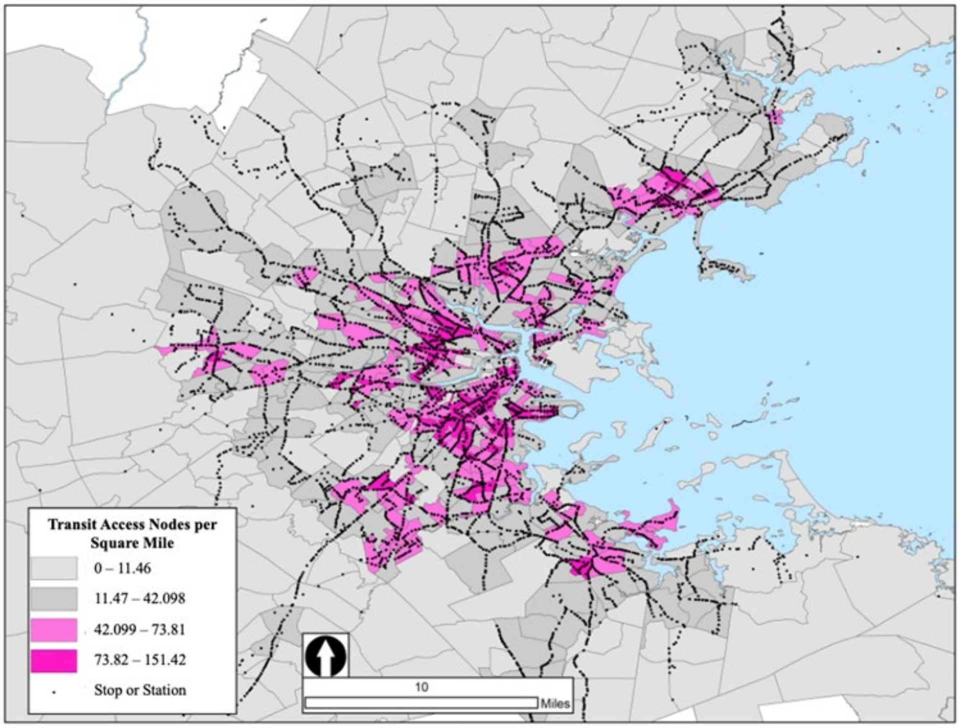

Figure 2. Distribution and Density of Transit Access Nodes by Census Tract, 2014

Demographic Data

Because we do not observe demographic characteristics of vehicle owners (these are not available in the MAVC data), we used year-specific, U.S Census and American Community Survey demographic characteristics of the Census Tract in which the vehicle is registered as a crude proxy for average population characteristics of the vehicle owners. We created a *Population Density* variable based on the square mileage of each Census Tract, as well as 5-year estimates of *Median Household Income*, the *Proportion of Owner-Occupied Housing Units*, the *Percent of Residents Younger than 25*, the *Percent of Residents Older than 65*, and the percent of residents reported in the Census defined race and ethnic categories as *White Alone* for every year of the study (U.S Census Bureau 2010, 2019a, 2019b, 2019c). These data were then merged onto the MAVC data by Census Tract.

Individual Vehicle Level Analysis

We performed negative binomial fixed-effects panel regressions using Stata with *VIN-Parcel ID* as the panel variable, *Year* as the time variable, and *Average Daily VMT* as the dependent variable. Descriptive statistics for all the variables utilized in model specification and selection are shown in Table 1. We first performed linear fixed-effects panel-regressions, but they resulted in a significant number of negative predicted *Average Daily VMT* values. This issue was addressed by using negative binomial fixed-effects panel regressions, which is left-censored at 0 and accounts for over-dispersion.

We added independent variables progressively starting with the geographic and transportation variables of interest, systematically adding vehicle-specific variables, and then more demographic control variables measured at the Census Tract level. A precursor study to the current research included transit access density as a single variable representing all modes (Montilla and Chatman, 2022). To further understand the effects of different types of transit, we separately included *Rapid Transit Density*, *Commuter Rail Density*, and *Bus Stop Density* here. We also interacted these transit density variables with Uber availability and whether or not the vehicle was registered or stored in Boston or Cambridge.

Table 1. Descriptive Statistics at the Individual Vehicle Level, 2014

	Mean	Std. Dev.	Min.	Max.
Dependent variable:				
Average Daily VMT	27.570	18.2173	0	199.921
Geographic variable:				
Boston and Cambridge^	0.157	0.363	0	1
For Vehicles in Boston and Cambridge:				
Rapid Transit Stop Density*	1.783	5.143	0	55.761
Commuter Rail Stop Density*	0.462	1.677	0	15.919
Bus Stop Density*	52.156	29.566	0	151.422
For Vehicles Not in Boston and Cambridge:				
Rapid Transit Stop Density*	0.136	1.021	0	16.808
Commuter Rail Stop Density*	0.117	0.389	0	3.827
Bus Stop Density*	14.009	21.544	0	139.762
Vehicle Characteristics:				
Adjusted MPG	21.526	5.710	8.200	55.610
MSRP	26,970	10,584	0	470,000
Depreciated MSRP†	-0.285	11.028	-11.25	420
Vehicle Age	8.029	4.93	0	33
Census Tract Characteristics:				
Percent Under 25 Years Old	29.873	6.748	11.7	90.1
Percent Above 65 Years Old	14.500	4.813	0	40
Median Age	40.038	5.760	18	56.1
Median Income (in thousands)	87.589	34.425	12.813	226.181
Homeownership Rate	67.743	22.772	0	100
Population Density#	7.737	10.188	0.174	108.682
Percentage White	82.105	18.295	4.6	99.8

Notes: Uber is available across the entire study area in Year 2014.
^ Dummy variable indicating if the vehicle is registered within Boston or Cambridge
* *Transit Density* variables are in units of stops per square mile
\# *Population Density* is in units of people per square mile
† The variable is rescaled for regression analysis

Only a limited number of time-variant vehicle characteristics were available to be included in the fixed-effects models. As such, we included the *Adjusted MPG* variable hypothesizing that the fuel economy of the vehicle likely relates to vehicle use, with owners purchasing more fuel-efficient vehicles when they intended to drive longer distances. We also included Vehicle Age as proxy measures of the income of vehicle owners.

Table 2 shows the preferred model which includes Uber availability and transit variables, vehicle characteristic variables from the MAVC, and population characteristic variables from the US Census. The preferred model was chosen based on the log-likelihood ratio, Akaike Information Criterion (AIC) and Bayesian Information Criterion

(BIC) test scores. Because of the large number of observations, we defined significance at the 99% Confidence Interval, and report exponentiated coefficients as incidence risk ratios (IRR) in Table 2 to ease in interpretation of the negative binomial model.

Table 2. Individual Vehicle Level Fixed-Effects Panel Regression on Average Daily VMT with Incidence Risk Ratios Reported (Negative Binomial Model)

Independent Variables	
Geographic and Transportation Variables	
Boston and Cambridge × Uber Availability	0.9964 (-2.38)
Boston and Cambridge × Rapid Transit Stop Density*	**1.004†** **(4.28)**
Boston and Cambridge × Commuter Rail Stop Density*	**0.9897†** **(-8.31)**
Boston and Cambridge × Bus Stop Density*	**0.9996†** **(-6.22)**
Boston and Cambridge × Rapid Transit Stop Density* × Uber Availability	1.000 (0.704)
Boston and Cambridge × Commuter Rail Stop Density* × Uber Availability	**1.002†** **(3.55)**
Boston and Cambridge × Bus Stop Density* × Uber Availability	1.000 (-0.495)
Not Boston and Cambridge × Uber Availability	**1.006†** **(6.51)**
Not Boston and Cambridge × Rapid Transit Stop Density*	**1.017†** **(8.10)**
Not Boston and Cambridge × Commuter Rail Stop Density*	1.004 (0.806)
Not Boston and Cambridge × Bus Stop Density*	**0.9997†** **(-5.39)**
Not Boston and Cambridge × Rapid Transit Stop Density* × Uber Availability	1.000 (1.44)
Not Boston and Cambridge × Commuter Rail Stop Density* × Uber Availability	1.000 (0.577)
Not Boston and Cambridge × Bus Stop Density* × Uber Availability	1.000 (1.38)
Vehicle Characteristics	
Adjusted MPG	**1.025†** **(70.1)**
Vehicle Age	**0.9285†** **(-214)**

Independent Variables	
Census Tract Characteristics	
Percentage Under 25 Years Old	1.000 (1.91)
Percentage Above 65 Years Old	1.000 (0.518)
Median Age	1.000 (1.17)
Median Income	**1.000**† **(9.08)**
Homeownership Rate	**1.000**† **(7.08)**
Population Density#	1.000 (0.687)
Percentage White	**1.000**† **(6.47)**
Year	
2011	**1.051**† **(101)**
2012	**1.098**† **(117)**
2013	**1.147**† **(123)**
2014	**1.205**† **(112)**
Other Results	
Constant	**31.91**† **(302)**
LL	-1.32e+07
Chi-2	155,811
AIC	2.650e+07
BIC	2.650e+07
Total Observations	6,309,506
Unique VIN-Parcel ID Pairs	1,873,996

Notes: Coefficients are displayed as incidence risk ratios (IRR)
Z-statistics are derived using maximum likelihood estimation (MLE)
Uber Availability and *Boston and Cambridge* are dummy variables
† Variables that are significant at the 99% Confidence Interval are bolded
* *Transit Density* variables are in units of stops per square mile
# *Population Density* is in units of people per square mile

Census Tract Level Analyses

To examine neighborhood level changes, we also built 3 models at the Census Tract level. We first aggregated the vehicle-level MAVC data by Census Tract locating individual vehicles to Tracts based on the vehicle's parcel location. Three dependent variables are derived at the aggregate level: [1] *Vehicle Turnover,* [2] *VMT per Vehicle-Days*, and [3] *Vehicles per Population*.

Vehicle Turnover (also called churn) is intended as a proxy for neighborhood change. It is a measure of the total number of vehicles that move into or out of the Census Tract relative to the total number of vehicles in the Census Tract. We identified vehicles moving in or out by the continuity of the unique *Vin-Parcel IDs* in each Census Tract. For example, if a unique *Vin-Parcel ID* record began in 2012, then that vehicle is classified as moving into the Census Tract in 2012. If a unique *Vin-Parcel ID* record ended in 2013, then that vehicle is classified as having moved out of the Census Tract in 2014. A limitation of this methodology is that vehicles moving within a Census Tract are overcounted.

VMT per Vehicle-Days is a measure of average daily VMT at the Census Tract level. The measure uses the total VMT by the vehicles registered within the Census Tract normalized by the number of vehicles in the Census Tract and the number of days a vehicle resided in the Census Tract (vehicle-days). This is an aggregate level *Average Daily VMT* measure that accounts for vehicles moving in and out of the Census Tract and weights them accordingly.

Lastly, *Vehicles per Population* measures vehicle ownership rates. It is defined as the total number of vehicles registered in a Census Tract for the year divided by the population of the Census Tract. We found that vehicle counts in some areas of the Boston metropolitan area are disproportionately low in the processed MAVC dataset. This error is likely due to missing parcel records or geocoding issues that are systematic geospatially but likely not temporally. This issue is mitigated to some degree by the use of fixed-effects panel regression methods which account for geospatial errors (errors over the panel variable) better than random-effects models because fixed-effects regressions consider each geospatial observation (*Census Tract ID*) as expressing a unique categorical variable.

For each of these three dependent variables, we performed ordinary least squares (OLS), fixed-effects panel regressions using Stata with *Census Tract ID* as the panel variable and *Year* as the time variable. Descriptive statistics for all the variables utilized in model selection are shown in Table 3. The three models are shown in Table 4. We specified the models in a similar way as the individual vehicle level analysis, which interacted *Uber Availability*, *Boston and Cambridge*, and transit stop densities variables. The same set of Census Tract characteristics are used, but individual vehicle characteristics variables were removed as they are non-applicable at the aggregate level.

Table 3. Aggregate Descriptive Statistics at Census Tract Level, 2014

Variables	Mean	Std. Dev.	Min.	Max.
Dependent Variables:				
Turnover	0.406	0.089	0	1.013
Mileage per Vehicle Days	26.520	4.082	14.889	64.460
Vehicles per Population	0.432	0.165	0.011	1.319
Geographic Variable:				
Boston and Cambridge^	0.315	0.465	0	1
For Vehicles in Boston and Cambridge:				
Rapid Transit Stop Density*	2.413	6.454	0	55.761
Commuter Rail Stop Density*	0.436	1.737	0	15.919
Bus Stop Density*	50.558	31.923	0	151.422
For Vehicles Not in Boston and Cambridge:				
Rapid Transit Stop Density*	0.216	1.309	0	16.808
Commuter Rail Stop Density*	0.137	0.462	0	3.827

Variables	Mean	Std. Dev.	Min.	Max.
Bus Stop Density*	18.715	25.451	0	139.762
Census Tract Characteristics:				
Percent Under 25 Years Old	30.878	10.043	0	90.1
Percent Above 65 Years Old	13.580	6.304	0	100
Median Age	37.959	6.855	18	66.7
Median Income	79,905	35,677	12,813	226,181
Homeownership Rate	58.191	26.293	0	100
Population Density#	12.013	14.058	0	108.682
Percentage White	76.703	22.120	4.6	100

Notes: Uber is available across the entire study area in Year 2014.
^ Dummy variable indicating if the vehicle is registered within Boston or Cambridge
* Transit Density variables are in units of stops per square mile
# *Population Density* is in units of people per square mile

Table 4. Census Tract Aggregate Level Fixed Effects Panel Regressions (OLS Models)

Independent Variables	Dependent Variables		
	Turnover	VMT per Veh.-Days	Veh. per Population
Geographic and Transportation Variables			
Boston and Cambridge × Uber Availability	-0.014 (-1.980)	-0.208 (-1.061)	-0.004 (-0.488)
Boston and Cambridge × Rapid Transit Stop Density*	**-0.012†** **(-8.773)**	**0.317†** **(6.517)**	**0.003†** **(3.217)**
Boston and Cambridge × Commuter Rail Stop Density*	**0.009†** **(6.793)**	-0.009 (-0.229)	-0.000 (-0.844)
Boston and Cambridge × Bus Stop Density*	-0.000 (-1.114)	-0.007 (-1.019)	-0.000 (-1.099)
Boston and Cambridge × Rapid Transit Stop Density* × Uber Availability	-0.001 (-2.264)	0.016 (0.977)	0.000 (0.805)
Boston and Cambridge × Commuter Rail Stop Density* × Uber Availability	-0.000 (-0.350)	0.008 (0.378)	0.001 (1.720)
Boston and Cambridge × Bus Stop Density* × Uber Availability	-0.000 (-0.565)	0.003 (1.385)	0.000 (0.775)
Not Boston and Cambridge × Uber Availability	**-0.013†** **(-3.225)**	**0.344†** **(3.250)**	**-0.022†** **(-6.674)**
Not Boston and Cambridge × Bus Stop Density*	0.000 (0.416)	-0.005 (-0.732)	0.000 (0.141)
Not Boston and Cambridge × Rapid Transit Stop Density* × Uber Availability	-0.001 (-1.456)	-0.031 (-1.600)	0.000 (0.189)
Not Boston and Cambridge × Commuter Rail Stop Density* × Uber Availability	0.005 (2.241)	-0.122 (-1.612)	-0.001 (-0.300)

Independent Variables	**Dependent Variables**		
Not Boston and Cambridge × Bus Stop Density* × Uber Availability	0.000 (0.606)	-0.002 (-2.200)	**0.000†** **(7.382)**
Census Tract Characteristics			
Percentage Under 25 Years Old	0.000 (0.465)	-0.029 (-1.944)	-0.001 (-2.092)
Percentage Above 65 Years Old	0.000 (0.132)	-0.018 (-0.978)	-0.000 (-0.555)
Median Age	0.001 (1.153)	-0.026 (-1.236)	0.001 (1.182)
Median Income	0.000 (0.471)	-0.000 (-1.441)	**-0.000†** **(-5.494)**
Population Density#	-0.001 (-0.890)	0.027 (1.289)	**-0.007†** **(-8.813)**
Percentage White	0.000 (0.568)	-0.007 (-1.179)	-0.000 (-0.397)
Year			
2011	**-0.037†** **(-24.978)**	**-0.342†** **(-10.077)**	**0.028†** **(26.905)**
2012	**-0.088†** **(-54.100)**	**-0.686†** **(-17.429)**	**0.032†** **(20.651)**
2013	0.002 (1.301)	**-0.557†** **(-12.649)**	**0.037†** **(18.697)**
2014	**-0.040†** **(-10.546)**	**-0.435†** **(-4.540)**	0.003 (1.152)
Other Results			
Constant	**0.440†** **(10.957)**	**29.128†** **(19.552)**	**0.583†** **(9.987)**
R2 within	0.632	0.133	0.448
R2 between	0.224	0.0337	0.416
R2 overall	0.0249	0.0268	0.418
AIC	-14,350	6,505	-15,381
BIC	-14,210	6,646	-15,241
Total Observations	3,264	3,264	3,264

Notes: Z-statistics are derived using maximum likelihood estimation (MLE)
Uber Availability and *Boston and Cambridge* are dummy variables
* Transit Density variables are in units of stops per square mile
# *Population Density* is in units of people per square mile
† Variables that are significant at the 99% Confidence Interval are bolded

Chapter 3. Results and Discussion

The results of our models suggest that the introduction of ride-hailing significantly relates to only a small increase in VMT, and only in inner suburban and other less central areas of a metropolitan region. Holding other variables constant, the individual vehicle level model found that the *Average Daily VMT* of vehicles located in metropolitan areas outside of the core cities of Boston and Cambridge climbed by 0.6% above the mean after introduction of Uber. This result is supported by the Census Tract level model of *VMT per Vehicle Days*, which estimates that vehicles outside of Boston and Cambridge drove 0.344 more miles per day after introduction of Uber ceteris paribus. Within the cities of Boston and Cambridge, we found no significant relationship between Uber availability and VMT at the 99% confidence interval in both our individual vehicle level and Census Tract level analyses.

Small Uber-Related Increases in VMT Outside MPO Core

Likely the most important outcome from this study is that we find a much weaker-in-magnitude relationship between ride-hailing and VMT than previous studies have. Previous research relying on city-wide trend data, surveys, and/or TNC service patterns estimate that ride-hailing nearly doubled the growth of congestion and VMT in some cities (Erhardt et al., 2019). One study concluded that ride-hailing contributed to 83.5% more VMT in Denver than would have been generated without ride-hailing services (Henao and Marshall, 2019). In contrast, we found only a 0.6% increase from the mean *Average Daily VMT* when looking at changes occurring in individual vehicles. This difference may be because those other methods are less reliable, or because we looked at changes occurring in individual vehicles registered in the MPO, and Boston has commuters from outside the region including interstate commuters. There may have been a substantial number of ride-hailing drivers with high VMT who registered their cars outside the study area. Alternatively, it may also be because the timeframe of our study ended in 2014. As such, this study may be accounting for solely immediate changes related to Uber availability whose influence may grow or transform over time. That said, Boston was one of Uber's earliest markets, and as of 2017, use of ride-hailing in the Boston metropolitan area was one of the highest in the country (Schaller, 2018). We would expect an analogous, or more substantial relationship between ride-hailing and VMT in Boston compared to most other cities, and we found a more muted association instead.

Overall, it seems as if other factors may influence vehicle use more than the availability of ride-hailing. The individual vehicle level model indicates that certain vehicle characteristics had stronger-in-magnitude relationships with *Average Daily VMT*. Of note, our model suggests that for every additional mile of *Adjusted MPG*, vehicles on average traveled 2.5% more than the mean VMT holding other variables constant. Conversely, we found that for every year of *Vehicle Age*, vehicles traveled 7.15% less than the mean holding other variables constant. Interestingly, the Census/ACS demographic variables detailing Census Tract *Median Income*, *Homeownership Rate*, and *Percentage White* population, were all found to be highly significant in our individual level model, but their exponentiated coefficients suggest that they are almost inconsequential in influencing changes off the mean VMT. This result may be an outcome of using Census Tract aggregates as input variables in a model describing changes occurring in individual cases. Nevertheless, the results of the individual vehicle level model on whole indicate that other factors besides ride-hailing influenced changes in VMT more than Uber availability, and that ride-hailing's influence on VMT in the Boston region was rather miniscule and limited to areas outside of Boston and Cambridge during the study period.

No Evidence for Density of Transit Stops Affecting Ride-Hailing's Relationship with VMT

We did not find any indications of the density of transit stops and stations mediating Uber availability's relationship with VMT. In interaction with Uber, all but one of the transit variables were insignificant in both the individual vehicle level and Census Tract level models regressing over VMT. Furthermore, the one variable that was significant, commuter rail station density in interaction with Uber, is significant only in the individual vehicle level model, and only in Boston and Cambridge where Uber on its own was found insignificant with *Average Daily VMT*. However, the significance of this term suggests that ride-hailing, transit and VMT do relate in some situations.

The individual vehicle level model found that Uber was associated with a slightly weaker relationship between the density of commuter rail stations and reductions in VMT within Boston and Cambridge. In these cities, commuter rail density related to a 1% decrease in VMT from the mean for every stop per Census Tract square mile, but the combination of commuter rail and Uber availability was associated with a smaller net decrease of about 0.8%. These results suggest that in the areas of Boston and Cambridge served by commuter rail, auto use declined less than it could have without Uber availability.

Previous research as a whole suggests that ride-hailing substitutes for transit in many if not most contexts (Graehler et al., 2019; Henao and Marshall, 2019; Tirachini and del Río, 2019; Tirachini, 2020; Erhardt et al., 2022), but may compliment transit where transit is week. While we do not find any direct evidence for a substitutional relationship, the individual vehicle level model does suggest that ride-hailing could weaken transit's ability to reduce private vehicle use in more central areas. Given that many commuter rail users also consider auto use, it is not unreasonable to contend that the observed changes in commuter rails' relationship with VMT indicates that transit may be less appealing to potential auto users if ride-hailing is available, and thusly substitutes with ride-hailing in urban contexts.

No Indications of Neighborhood Change Influencing Increased VMT

To check if the observed changes in VMT could be related to neighborhood change, we built analytical models at the Census Tract level using *Vehicle Turnover* and *Vehicles per Population* as dependent variables. The results of these models in tandem suggest that neighborhood change did not influence the variations to VMT seen after Uber introduction in either the individual vehicle level, or Census Tract level analyses. The aggregate models at the Census Tract level indicate that outside of Boston and Cambridge, Uber was associated with 0.013 fewer vehicles turning over per existing vehicle, and 0.022 fewer *Vehicles per Population*. Reduced turnover implies reduced neighborhood change or displacement, and reductions in *Vehicles per Population* suggest that the individuals living in these Tracts gave up some vehicle ownership or that any incoming population did not bring vehicles with them. Either way, the results indicate that neighborhood change likely did not affect Uber-related changes to VMT over the study period.

Evidence for Increased VMT and Reduced Vehicle Ownership in the Same Data

Previous research has produced evidence for a relationship between ride-hailing and both increased VMT (Erhardt et al., 2019; Henao and Marshall, 2019; Wu and MacKenzie, 2021) and reduced auto dependency (Coogan et al., 2018*;* Bansal et al., 2020; Dong et al. 2021), but evidence for either outcome typically comes from separate studies. Here we find evidence for both within the MAVC data, but only for areas outside of Boston and Cambridge. The Census Tract level models find that Uber availability was associated with an increase in VMT (0.344 more miles per vehicle day), as well as 0.022 fewer *Vehicles per Population* and less vehicle turnover compared to without Uber availability. The reduction in *Vehicles per Population* could signal lower dependence on private vehicles, and when paired with the small increase in VMT, suggests that ride-hailing-related reductions to auto dependency could occur alongside additions to VMT in certain areas such as inner suburbs and metropolitan peripheries.

One noteworthy study that identifies both trends in the same data comes from Wu and MacKenzie (2021). However, their study based VMT and ownership estimations on 2017 National Household Travel Survey data. In the current study, we provide similar evidence but using data from direct vehicle measurements. While Wu and MacKenzie (2021) find evidence that deadheading is a likely influence on increased VMT, they also find that access to a driver's license and household vehicle influence ride-hailing's relationship with VMT. Ultimately, they contend that ride-hailing propensity to lower VMT exists only within specific groups of potential users: those with driver's licenses and access to a household vehicle who frequently use ride-hailing. This conclusion suggests that certain population factors shape ride-hailing's potential to reduce VMT, and that prospective reductions in VMT exist within groups who can meaningfully reduce the number and length of their private vehicle trips by utilizing ride-hailing. We identify a comparable potential resting within potential users living in non-central parts of a metropolitan area—areas where private vehicle trips are more likely to be the norm.

Differences Across the Metropolitan Area

A consistent finding across our study is that ride-hailing on its own relates to VMT outside of Boston and Cambridge but not within. This distinction between whether a vehicle is registered in Boston or Cambridge and elsewhere suggests there is a geographical element to ride-hailing's relationship with passenger vehicle use that may affect ride-hailing's influence over VMT within metropolitan markets. We offer two possible reasons why this may be the case. First, automobile users who live in highly urban areas may not be replacing many personal vehicle trips with ride-hailing trips. In urban cores, where auto dependency is already lower than suburban and exurban areas, private vehicle trips that can be replaced by ride-hailing trips may be less prevalent. For example, a resident in a central city who owns a car may use non-automotive modes for most regularly occurring trips, but still keeps a car for some highly specific trips such as leaving the city on weekends, or large shopping trips. Previous research from Boston suggests that ride-hailing draws users from multiple modes including driving, transit, biking, and walking (Dong et al., 2021). It may be that for urban car owners, ride-hailing may replace some of their non-automotive trips, but not many of their personal vehicle trips. Second, ride-hailing drivers may be more likely to live near urban cores; if so, VMT reductions from urban car owners replacing car trips with ride-hailing could be offset by the increased VMT produced by vehicles used by ride-hailing drivers.

Additionally, the disparity in results within Boston and Cambridge and elsewhere in the MPO indicates that ride-hailing, transit, and private vehicle use all interrelate differently (if at all) within urban cores compared to inner suburban, and peripheral areas. Our results are consistent with the hypothesis that the potential to reduce vehicle use through complementary ride-hailing and transit services may exist primarily outside central areas—perhaps because ride-hailing mainly replaces the last-mile travel related to park-and-ride transit services in peripheral areas, and these services are less common in urban cores.

Chapter 4. Conclusion

We find that ride-hailing's influence on VMT is small and limited to vehicles registered outside the MPO core. Moreover, we identify that ride-hailing's influence on vehicle use and ownership may differ between central and peripheral areas and is likely not related to neighborhood change. The results of this study also suggest that ride-hailing may simultaneously relate to less vehicle ownership and slightly more vehicle use. When considering how ride-hailing can be utilized to influence travel behaviors across a metropolitan area, planners must identify community transportation goals. If goals include reducing auto dependency, then the results of this study support actions to encourage use of ride-hailing outside of metropolitan cores. Conversely, if goals include reducing VMT, then government supported use of ride-hailing should be more heavily scrutinized, but not necessarily avoided. Within cities, this study suggests that ride-hailing has no significant impact on the use of vehicles owned by residents of core areas, and that promoting the use of other modes besides ride-hailing or personal vehicles may be an appropriate course of action for either goal.

Use of individual vehicle level data is an underutilized avenue to investigate ride-hailing's impact on travel behaviors. Future studies should strive to include such data whenever possible. Ideally, more recent data from the time period up until and through the Covid-19 pandemic would be used. Research is also needed into ride-hailing's potentially variable influence across a metropolitan area, as well as into locating where TNC drivers live as their auto use heavily impacts aggregate level VMT data. In all, this study found much smaller influences of ride-hailing upon vehicle use than survey-based research, research using aggregate data, or travel-model-based simulation studies. Using actual vehicle mileage data is a fruitful area for future research and is arguably more reliable than these other methods.

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