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Abstract

Ridesharing services such as Uber and Lyft are increasingly popular with many travelers. Yet little is known about the effects of this mode on travel behavior and other social effects, such as public transit use, traffic, and pollution. In this paper, we estimate the effects of the availability of ridesharing on travel mode choices in a large sample of metropolitan areas. We do so by estimating a discrete choice model of household mode choice using nationally representative data on travel behavior and simulating household mode choices in a setting where ridesharing was not available. We find that a majority of travelers would have used a car or taxi or walked had ridesharing not been available. In some large cities, however, ridesharing displaces a significant portion of public transit trips. We find that the availability of ridesharing has led to modest increases in total vehicle miles traveled and greenhouse gas emissions. Moreover, the effects of ridesharing could be heterogeneous across cities because of the differences in each city's drivability and public transit use.

Keywords: ridesharing, mode choice, substitution

JEL classification: L91, Q48, Q51

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1 Introduction

The transportation sector is undergoing several significant transformations that change the way people travel. One transformation is the increasing availability of ridesharing services such as Uber and Lyft. Ridesharing – which we define as all application-based ride hailing services other than traditional taxi services – has created a new mode for private travel. These services lower the transaction cost between vehicle owners and travelers through a user-friendly phone application.

The growth of ridesharing undoubtedly has raised private welfare. The overall social welfare effects, however, hinge on ridesharing externalities, such as congestion, air pollution, noise, and traffic accidents. The magnitude of these external costs critically hinges on what modes travelers would have taken had ridesharing been unavailable. For instance, if travelers would have driven their own private vehicle instead of using ridesharing, then the external cost would be modest given that the ridesharing is basically replacing another vehicle. On the other hand, if travelers using ridesharing would have traveled by a mode that produces fewer external costs, such as walking, then the external cost could be significant.

The potential increase in external costs due to ridesharing has led to several efforts at the state and local levels to internalize these costs. Beginning in 2017, Austin, Texas, required ridesharing drivers to be fingerprinted and undergo background checks. In Massachusetts, ridesharing vehicles, unlike taxis, are prohibited from cruising for passengers. Each ridesharing trip is taxed at 20 cents, where the tax revenue is allocated to state and local governments. Certain cities, including Vancouver, British Columbia, have banned ridesharing apps.

In this paper, we estimate the modes that would have been taken had ridesharing been unavailable and calculate the resulting external costs of this new mode. We do so by estimating a discrete choice model of travel mode selection using the most recent wave of the National Household Travel Survey (NHTS), then simulating mode choices under a counterfactual scenario where ridesharing is not available. A strength of our approach is that we are able to estimate mode choice substitution for about 100,000 households living in roughly 300 core business statistical areas (CBSAs). In addition to determining mode substitution patterns at the National level, we are able to disaggregate our results at a relatively refined geographical level and across several relevant household demographics, such as income and age.

Our empirical result is that travelers would have used their own vehicle, a taxi or walked for most of their trips in place of ridesharing. In particular, about 60 percent of ridesharing trips would have been taken by a privately owned vehicle or taxi. In certain areas, however, the substitution between ridesharing and using one's own car or walking is quite different. For example, in Los Angeles, the majority of ridesharing trips would have been taken by a private car or taxi. Whereas in Washington D.C., we found that ridesharing displaced a significant amount of walking. As a result, Washington D.C. likely experienced a significant increase in vehicle miles traveled (VMT) and a proportional increase in VMT-related externalities, such as congestion and air pollution. This differential effect across cities suggests that local targeting of externality-reducing policies is necessary for achieving socially optimal outcomes.

We find that ridesharing has slightly increased VMT and emissions. The increase is due to ridesharing replacing some trips where travelers would have either walked, biked, or taken public transit. The fact that we find a small increase is partly due to our estimated substitution pattern that ridesharing primarily replaces private vehicle or taxi trips. This result is also due to ridesharing being a relatively expensive and unpopular mode of travel: during our sample period, ridesharing is used for well less than 1 percent of all trips taken.

The effects on VMT and emissions, however, vary considerably by city. San Francisco, a city where many travelers would have walked, biked, or taken public transit had ridesharing been unavailable, sees VMT increase by 1.38 percent. But VMT in many smaller cities increases by less than 0.05 percent. We find that this heterogeneity is partly caused by underlying city-specific mode preferences and access to public transit.

Our paper is related to several strands of literature, including a growing body of literature related to the ridesharing economy. Some studies compare ridesharing with conventional taxi services and examine the effect of ridesharing on the taxi industry. Berger et al. (2018) exploit the staggered rollout of Uber across the United States over 2009 to 2015 to estimate the effect of Uber on the employment and earnings of workers in conventional taxi service, and they find that the labor supply of taxi drivers increases in cities where Uber was introduced relative to cities where it was not. Angrist et al. (2017) use an experiment that offered random samples of Boston Uber drivers opportunities to lease a virtual taxi medallion that eliminates or reduces the Uber fee to estimate the intertemporal substitution elasticity, and to compute the average compensation required to make drivers indifferent between ridesharing and a traditional taxi compensation contract. They find that ride-hailing drivers gain considerably from the opportunity to drive without leasing.

Other studies aim to quantify the effects of ridesharing on consumers and drivers. Cohen et al. (2016) rely on a regression discontinuity design based on Uber's surge pricing algorithm to estimate demand elasticities at several points along the demand curve and then use the elasticity estimates to measure consumer surplus. They find that for each dollar spent by consumers, about $1.60 of consumer surplus is generated.[1] Zoepf et al. (2018) use data on self-reported revenue and vehicle choices from 1,100 Uber and Lyft drivers with detailed vehicle operational cost parameters to estimate costs, profit, and tax rates for ridesharing drivers. They find that 30 percent of drivers lose money once vehicle expenses are included per hour worked, and the median gross revenue less operating expenses is 29 cents per mile. Chen et al. (2019) use data on hourly earnings for Uber drivers and estimate the drivers time-varying reservation wages and find that Uber drivers benefit significantly from real-time flexibility, earning more than twice the surplus they would in less flexible arrangements. By exploiting the staggered rollout of ridesharing into different markets between 2012 and 2016, Koustas (2018) examines how the reduction of frictions on hours brought by ride hailing affect households ability to smooth consumption in response to income shocks. The results show that debt and high credit card use are major predictors of participation in ridesharing, and that ridesharing income replaces 73 percent of income losses from main payroll jobs. Cook et al. (2019) examine the labor supply choices and earnings among more than a million ridesharing drivers on Uber and find gender a earnings gap of 7 percent among drivers. Even in the flexible labor markets, women's relatively high opportunity cost of non-paid-work time and gender-based differences in preferences and constraints can sustain a gender pay gap. Loginova et al. (2019) build a theoretical model of a ridesharing market to examine the welfare implication of multi-homing in the ridesharing market, particularly how it affects the average pickup time on both sides of the market. They find that multi-homing drivers potentially benefit themselves at the cost of single-homing drivers because of stolen rides. Multi-homing riders benefit themselves as well as single homing riders because of the reduced waiting time.

A few studies examine the interaction of ridesharing with public transportation. Schwieterman (2019) investigate how service attributes affect choices between ridesharing and public transit in Chicago. Their results show that when accounting for both monetary and nonmonetary costs (including a desire to avoid walking and perceived difference in comfort), an average commuter is six times less likely to rideshare when the public transit experience is considered favorable rather than unfavorable. Hall et al. (2018) estimate the effect of ridesharing on public transit ridership by exploiting the spatial and temporal variation of Uber penetration in the US market and find that Uber complements public transit by solving the "last mile

[1] The authors find that the UberX service in the United States in 2015 generated $6.8 billion of consumer surplus.

problem." They mention that Uber would increase pollution and congestion no matter whether it complements or substitutes public transit because it increases travel demand. However, their analysis does not consider the substitution between ridesharing and public transit or private vehicle driving. If it complements public transit, ridesharing could encourage more consumers to switch from driving to using public transit and thus reduce on-road emissions. Therefore, to investigate the overall environmental effect, we need to estimate consumer travel demand for all mode choices.

This paper proceeds as follows. In the next section, we discuss the data used in the analysis. Section 3 describes the empirical strategy. Section 4 presents the estimation results. We illustrate the robustness of our results by estimating two alternative forms of our model in the Appendix. Section 5 presents estimates of the effect of ridesharing on VMT and emissions. We then show and discuss how ridesharing affects cities differently in Section 6. Section 7 discusses caveats, and Section 8 concludes.

2 Data

The primary data set that we use in our analysis is the 2017 NHTS. The 2017 NHTS, a nationally representative survey of households living in the United States, was administered from 2016 to 2017. The survey is meant for understanding broad travel behavior among Americans and contains such statistics as household annual vehicle miles traveled, annual uses of other travel modes, e.g., public transit, and stated travel preferences. The survey also contains a rich set of household characteristics and demographics, such as the city that each household lives in, household income, age and marital status of head of households, and the number of individuals in each household.

We combine three parts of the survey to construct mode choices for each household. In the first part, respondents provide the number of times that they use a certain travel mode in a given year. For example, the survey asks respondents how often they use a bus for travel. The survey has separate questions for the following modes: walk, bike, car, rideshare/taxi, bus, and rail. Respondents can answer this question as daily, a few times a week, a few times a month, a few times a year, or never. Based on these responses, we can impute the total number of times a household uses each mode. We make these imputations by multiplying each response by a constant factor. For example, for respondents who state that they use a particular mode daily, we assume that they use that mode twice per day for a total of 2 times 365.25, which equals 730.5

trips per year. We scale the other responses proportionately to the number of times according to the responses.

This process introduces measurement error into our calculation of annual travel mode use. Furthermore, this imputation may yield implausible estimates of the total number of annual trips taken by each mode. We reduce this measurement error by using a second set of data, available from daily travel diaries. Households provide a single-day travel diary in which they provide information on each trip they took during that day. The information includes the travel mode, the distance, and the purpose of the trip. Since many households take only one or two modes during their travel day, we aggregate these data to the CBSA level to compute an average number of daily trips made by each household. We then scale the imputed annual trips taken by a constant factor so that the new scaled imputed annual trips are consistent with the aggregated daily trip counts. Although this still likely includes measurement error at the household level, the scaling ensures that the total number of annual trips at the CBSA level is consistent with the daily travel diary data.

We use a third source of data to differentiate ridesharing trips from taxi trips. An unfortunate characteristic of the annual trip frequency question is that it does not differentiate between using a ridesharing app and taking a taxi. These trips are aggregated into a single response in the survey. Fortunately, the survey has a separate ridesharing usage question that logs the number of times a ridesharing app was used in the last month by each member of the household. We combine this response with the annual imputed rideshare/taxi response to obtain a separate annual imputed trip count for each mode. To do this, we annualize the monthly ridesharing app use by multiplying this response by 12, then aggregating over individuals to the household level. This serves as the annual imputed rideshare trip count. We then subtract the original annual imputed rideshare/taxi response from this value to obtain residual taxi trips. If this subtraction yields a negative number, we assign a zero for annual taxi trips. For example, suppose two individuals state that they used ridesharing three times in the past month. Then their annual ridesharing trips are 3*2*12 = 72. Furthermore, suppose their annual imputed rideshare/taxi trips are 92. Then their annual imputed taxi trips become 92 - 72 = 20. This household is recorded as having 72 ridesharing trips and 20 taxi trips per year.

This merging yields estimates for annual trip counts for walking, biking, car, rideshare, taxi, bus, and rail for every household in the NHTS.[2] Table 1 presents summary statistics for trip

[2]To investigate the substitution between ridesharing and other travel modes, we focus on intra-city trips with a distance of less than 25 miles. Cross-city trips that may involve long-distance trains, buses, and airplanes are not considered in our analysis.

counts.[3] The data show that a large majority of trips are taken using private car. Vehicle driving is the most popular travel mode, and the average trip count for cars is 2,247.4. The second most popular travel mode is walking, with an average trip count of 296.6. Walking is a typical travel mode for short trips. The third most popular travel mode is biking, and households on average have 27.1 biking trips annually. Bus and rail rank as the fourth and fifth among all travel modes, with average trip counts of 34.2 and 22.3, respectively. Ridesharing and taxi are the least frequent travel modes, since they have a relatively high cost. Ridesharing has a larger trip count than taxi as ridesharing is getting more popular because of its convenience and lower price.

For the purposes of quantifying the effect of ridesharing on VMT, we merge data from the daily travel diaries on average trip distance by mode and CBSA. These data are sample weighted averages across all trips taken, where the weighted averages are computed separately by mode and CBSA.

We collect and merge a few other data sources on greenhouse gas (GHG) emissions. We merge data from the National Transit Database to compute per passenger per mile fuel use intensities and GHG emissions for public bus and train trips. We assume that cars, rideshares, and taxis emit 0.0004 metric tons per mile of GHGs, which is consistent with the 2017 fleet fuel economy average of 22 miles per gallon. We assume that biking and walking do not create emissions. To investigate the substitution of ridesharing with other travel modes, we restrict our sample to the household commuting trips with a distance of less than 25 miles and exclude longer-distance cross-region trips. In Table 1, we show average trip distance and emissions intensities for each of the travel modes. The data show that trip length by car, rideshare, and taxi are 5.7, 6.0, and 6.1 miles, respectively, and are comparable to public transit modes. Travel length by these modes is considerably longer than biking and walking, which are usually for short-distance trips.

3 Empirical Framework

Consider a setting where households decide how to travel. Each household i faces a set of mode options $\mathbb{J}_i$ alternatives indexed as $j = 0, 1, ..., J_i$, where $j = 0$ denotes the outside option. Household i has T_i choice occasions, indexed by $t = 1, 2, ..., T_i$. During choice occasion t, household i chooses a single travel mode. Household i chooses a travel mode that maximizes its utility:

[3] In Appendix Table C.1, we present correlation coefficients among the different modes.

$$u_{ijt} = \delta_{ij} + \epsilon_{ijt} \tag{1}$$

The term δ_{ij} denotes the household-specific utility derived from choosing mode j that is common among all household i choice occasions. Assuming that the error component ϵ_{ijt} is i.i.d. type 1 extreme value and the outside option's utility is normalized to zero, $\delta_{i0} = 0$, a log-share equation can be derived[4]:

$$\delta_{ij} = \ln(s_{ij}) - \ln(s_{i0}) \tag{2}$$

This equation relates household-specific utility from choosing mode j to the difference between the log of the share of mode j, $\ln(s_{ij})$, and the log of the share of the outside option, $\ln(s_{i0})$. The share term s_{ij} is equal to the total number of household i trips made by mode j during a single year divided by the total number of household trips made during a single year. The share term s_{i0} has a similar definition. Given that we observe s_{ij} and s_{i0} in the data, we are able to compute the household-specific utility for each travel mode.

This model has three important features that differentiate it from most other standard discrete choice models. The first is that the utility specification in Equation (1) is equivalent to a random coefficients mixed logit model that allows mode-specific utility to vary randomly across households. This is because the δ terms are indexed by households, allowing each household to have a unique utility value for each mode j. The equivalence of our model to a mixed logit model implies that this specification allows for rich substitution patterns to be estimated. The second feature is that the preference heterogeneity is defined without having to specify parametric distributions for taste parameters. This is partly because we do not specify taste parameters for mode attributes, but instead opt to model utility with a single value for every household-mode pair, yielding an extremely flexible form of household preference heterogeneity. The third feature is that it is simple to estimate the parameters δ_{ij} because these are defined by the log difference equation (2). This contrasts with many other standard discrete choice models that require computationally intensive estimation routines involving the maximization of an objective function.

Predicting trips with the removal of a mode

The predicted mode shares are defined by a household-specific logit probability:

[4] See Leard et al. (2019) for a derivation.

$$s_{ij} = \frac{\delta_{ij}}{\sum_k \delta_{ik}} \tag{3}$$

Predicted mode shares with the removal of mode r are simply the same logit probability with mode r removed from the summation in the denominator:

$$s_{ij|r \notin \mathbb{J}_i} = \frac{\delta_{ij}}{\sum_{k \neq r} \delta_{ik}} \tag{4}$$

Assuming that the total number of choice occasions is not affected by the removal of mode r, we can compute the predicted number of trips made by each mode when mode r is removed as the product of the predicted mode share in Equation (4).

4 Estimation Results

Figure 1 summarizes the substitution of ridesharing by CBSA size; the corresponding numerical values are summarized in Appendix Table C.2. At the national level, 54.6 percent of ridesharing trips replace private car driving or taxi,[5] and 34 percent replace walking. The remaining ridesharing trips replace bus, rail and biking, with 3.79 percent, 4.84 percent, and 2.99 percent, respectively. The results also reveal the spatial heterogeneity of the substitution pattern. In larger and more populated CBSAs, ridesharing replaces more walking and less car driving. In smaller CBSAs with a lower population density where travel distances are usually longer, ridesharing replaces more car driving and less walking.

Figure 2 depicts the substitution patterns in Los Angeles, San Francisco, Seattle, Boston, Washington D.C., New York City, San Diego, Chicago, Houston, and Philadelphia. In Los Angeles, if ridesharing were not available, the majority of ridesharing trips would have been taken by a private car or taxi, whereas in New York and Washington D.C., ridesharing has displaced a significant amount of walking and more public transportation. Cities where ridesharing replaced more walking are likely to experience a significant increase in VMT and a proportional increase in VMT-related externalities, such as congestion and air pollution. And cities where ridesharing replaces mostly private car and taxi use would see a smaller increase in VMT and emissions. In the Appendix, we provide additional figures reflecting the substitution for the major cities of each state.

[5] Because private car driving and taxi rides produce the same emissions effect and taxi trips account for the smallest share among all modes, we combine private car driving and taxi rides during estimation and construct a single mode for cars.

Figure 3 and Appendix Figure C.4 show the substitution patterns based on the income and age groups of the household members. In general, ridesharing replaces more walking and public transportation trips for lower-income households. For higher-income households, most of the ridesharing trips would be taken by a private car or taxi if ridesharing were not available. For older households, ridesharing replaces slightly more car driving and more bus trips, relative to the younger group.

5 The Effect of Ridesharing on VMT and Emissions

Since ridesharing and other travel modes have different trip distances and GHG emissions, removing ridesharing from households' choice sets will affect total VMT and GHG emissions. And because of city-level differences in substitution patterns, ridesharing will have heterogeneous environmental implications in each location. Policymakers may take into account of the heterogeneous environmental consequences when deciding whether to support this travel mode.

For each CBSA, we evaluate two effects of ridesharing: changes in VMT and GHG emissions. The changes are estimated by simulating the counterfactual scenario where ridesharing were removed from household mode choice set and comparing the counterfactual outcomes with the observed data. Tables 2 and 3 summarize the total change and percentage change in VMT and GHG emissions for different cities. At the national average, ridesharing increases total annual VMT in one city by 4,741 miles, 0.08 percent. Ridesharing leads to a small increase in VMT for several reasons. First, ridesharing VMT represent a tiny fraction of total travel demand. Ridesharing during our sample period was well under 1 percent of all VMT (Table 1). The effect of adding ridesharing as a travel mode is limited by this small travel share. Second, we find that a majority of ridesharing trips are replacing private car trips. In our sample, private car trips have a similar travel distance to ridesharing trips. Therefore, households that switch to using ridesharing instead of their private vehicles have nearly a zero effect on total VMT.

On average, total annual GHG emissions in each city increase by 3.1 metric tons with the introduction of ridesharing, representing a 0.14 percent increase. The introduction of ridesharing leads to a modest increase in total GHG emissions in each CBSA, since ridesharing replaces some trips that have a lower emissions rate, such as public transit, biking, and walking. Because of city-level heterogeneity in the substitution pattern and average trip distance of each travel mode, the changes in VMT and GHG emissions are different across cities. As indicated by Table 2, the increases in VMT and emissions are larger in more populous cities because ridesharing replaces more walking in these cities, as shown in Figure 1. At the national level, the average trip distance of ridesharing is close to that of private cars. But in some cities, the average trip distance for private cars is longer than for ridesharing. If ridesharing mainly replaced car trips, we would expect to see a slight decrease in VMT and GHG when ridesharing is introduced in those cities. However, if the emissions reduction due to fewer miles driven is then offset by the increased emissions from households switching from walking, biking and public transit to ridesharing, we would expect to see that ridesharing increases the overall emissions.

6 Explaining the Heterogeneous Effects of Ridesharing

We document that ridesharing has modest effects on VMT and GHG emissions across US cities. But the results also show that the effects are quite different across cities. In cities where public transit is more developed, such as San Francisco and New York City, ridesharing has a larger effect on VMT and GHG emissions. In this section, we explore two channels that could account for the heterogeneous effects of ridesharing on each city's emissions and VMT: a city's drivability and public transit use. Bento et al. (2005) find that the urban spatial structure (city shape and road density) significantly affects VMT, and the supply of public transportation also greatly effects travel demand. The spatial heterogeneity of travel habit and travel demand across cities will then determine the effects of ridesharing on miles driven and commute mode choices. In cities where households rely more on driving and less on public transit, the introduction of ridesharing will mostly replace private vehicle driving, resulting in little change in VMT and on-road emissions. In Figure 4, we plot the effects of ridesharing on VMT and emissions in each city against the percentage of trips made by car. Although the introduction of ridesharing increases VMT and emissions only slightly in most of cities, in cities where more trips are made by driving, ridesharing tends to have a smaller effect on VMT and emissions. This suggests that ridesharing substitutes for part of the private vehicle driving in cities where households mostly rely on driving, resulting in little environmental change. However, in cities where households drive less often, by introducing a new travel mode, ridesharing could increase overall car usage and result in more miles traveled and higher emissions.

Public transportation infrastructure could also affect households' usage of ridesharing. In cities where more households use public transit, the availability of ridesharing might encourage some households to switch from public transit to ridesharing, thus increasing total VMT and emissions. However, this increase in emissions could potentially be offset by the complementary between ridesharing and public transit (Hall et al., 2018).[6] Figure 5 plots the effects of ridesharing on VMT and emissions in each city against the percentage of trips made by public transit (rail and bus). The results show that in cities where more trips are made by public transit, ridesharing increases VMT and emissions with a larger magnitude because it encourages more travelers to switch from public transit to ridesharing.

7 Discussion

With our results come several caveats. First, our estimates are conditional on the assumption that the fuel economy of vehicles that are used for ridesharing is the same as that of the cars used for private driving. If Uber drivers drive vehicles that are less fuel efficient, ridesharing may increase total emissions even if there is no increase in VMT. To examine the emissions effect more accurately, we would need more detailed data on the characteristics of vehicles driven by Uber and non-Uber drivers.

Second, we assume that VMT per trip is exogenous. A more accurate representation of the household decision problem would include a joint decision of mode choice and miles traveled per trip. Joint models of discrete-continuous choice have been developed for studying the joint decision of vehicle and VMT choice (Bento et al., 2009). This could be relevant for measuring the effects of ridesharing, since ridesharing could alter trip length in addition to mode choice.

Third, we estimate the choice model parameters and perform simulations based on the assumption that households have choice sets restricted by using a mode at least once during the prior month. This could bias our results if households were to switch to a mode that they had not used at all. For example, if we observe a household taking a rideshare but never taking the bus, this household could decide to take a bus if the rideshare were not available. We address this concern by reestimating the model and performing simulations with the assumption that households have choice sets restricted by the availability of a mode in their CBSA. For example, if a household that walks, uses a private car, and rideshares but lives in an area where bus, rail, and taxi are also available, then their choice set will include all the modes instead of just walking, car, and rideshare. We report the results in Appendix Section A. We find that our benchmark results are qualitatively unaffected by this assumption.

Fourth, our choice model implies that substitution is proportional to each household's annual

[6] By solving the last-mile problem, ridesharing could induce more households to switch from driving to public transit.

travel mode shares. This result is driven by the assumed structure of our choice model. For some households, removing a mode from their choice set could cause disproportional substitution. One cause of disproportional substitution could be the use of modes for different trip purposes. For example, a household could prefer ridesharing and biking for leisure trips but private car and the bus for work-related trips. Ridesharing, therefore, would be replacing biking trips for this household. In the Appendix, we report simulation results using an alternative model where substitution patterns are estimated based on trip purpose. We find qualitatively similar results to our benchmark model, where ridesharing is primarily replaced by private car trips and walking trips.[7]

Fifth, our results should be interpreted as short-run effects. We are assuming that household decisions about where to live are exogenous to the availability of ridesharing. Some individuals may decide to locate in a high-density area that offers another option besides public transit for traveling to locations that they cannot reach by walking or biking. Modeling long-run adjustments such as the choice of where to live would require exogenous variation in the decision of where to live, and thus it would require developing a joint model of location and mode choice. We leave developing such a model for future work.

8 Conclusion

Ridesharing services have become part of the discussion surrounding the radical transition of the transportation system. Their effects on social welfare critically hinge on interactions with current travel modes. In particular, the types of trips that ridesharing is replacing determine the effects that ridesharing has on traffic and pollution. If ridesharing replaces trips that would have been made by walking or biking, then we expect to increase total VMT and GHG emissions due to the new mode. If ridesharing replaces trips that would have been made by a privately owned vehicle, however, then ridesharing's effect on total VMT and emissions could be close to zero.

We perform an empirical analysis of how households substitute between alternative modes of travel to see how the introduction of ridesharing affects VMT and emissions. To estimate substitution patterns and effects of ridesharing, we estimate a computationally simple discrete choice model using a nationally representative sample of household travel mode choices. One feature of our model is that we estimate preference heterogeneity at the household level using

[7] Another alternative would be to use variation from stated second choices to define substitution patterns (Berry et al., 2004). Unfortunately, the NHTS does not include questions regarding what modes individuals would use if their mode choice were not available.

household data on annual trips taken by each travel mode. With the model parameters estimated, we simulate mode choices in a hypothetical setting where ridesharing is removed from mode choice sets. We compare these simulated choices with observed choices to identify the effects of ridesharing on VMT and emissions.

We find that ridesharing has had small effects on VMT and GHG emissions. The availability of ridesharing has increased national VMT by 0.08 percent and GHG emissions by 0.14 percent. The effects are small for two reasons. First, ridesharing is an expensive travel mode that represents well less than 1 percent of all trips taken. Second, we find that ridesharing mostly replaces private vehicle or taxi trips. Policymakers interested in offsetting the increase in VMT could do so with very modest increases in congestion charges or gasoline taxes.[8]

Furthermore, the effects of ridesharing are relatively small in comparison with the gradual changes in VMT and GHG emissions due to other reasons. For example, Leard et al. (2019) find that national VMT is expected to increase by about 1 percent per year because of changes in household demographics and economic characteristics. Rising household income, in particular, is a significant cause of the expected VMT growth.

The effects of ridesharing, however, vary considerably by city. San Francisco, for example, sees VMT increase by 1.38 percent, but VMT in many smaller cities increases by less than 0.05 percent. We find that this heterogeneity is partly caused by underlying city-specific mode preferences. San Francisco has a relatively high rate of walking, biking, and public transit use. The introduction of ridesharing in this city has encouraged some residents to take a rideshare instead of these alternative travel modes, which effectively increases total city-wide VMT. Therefore, policymakers considering restricting access to ridesharing as a way to reduce traffic congestion should do so at a local, city-by-city level and account for the substitution patterns that we uncover.

[8] For example, an increase in the federal gasoline tax of 0.2 cents per gallon would reduce VMT by about 0.1 percent, assuming an elasticity of VMT with respect to the gasoline tax of -0.1.

Table 1: Summary Statistics of Household Annual Trip Counts and Emissions

						Average distance	GHG emissions	Annual distance		Annual GHG emissions	
Mode	Obs	Mean	Std. Dev.	Min	Max	Miles	Metric tons/mile	Miles	Pct.	Metric tons	Pct.
Walking	120,985	296.6	477.6	0.8	2922.0	0.68	0.0000	192.9	3.53	0.00	0.00
Biking	120,985	27.1	129.8	0.0	2922.0	2.48	0.0000	65.2	1.07	0.00	0.00
Car	120,985	2247.4	1028.0	0.0	2922.0	5.70	0.0004	12825.5	88.75	5.19	92.08
Rideshare	120,985	9.1	52.2	0.0	3282.5	6.00	0.0004	50.6	0.61	0.02	1.05
Taxi	120,985	3.9	34.4	0.0	2922.0	6.10	0.0004	21.0	0.57	0.01	1.09
Bus	120,985	34.2	154.9	0.0	2635.7	6.07	0.0003	201.3	3.27	0.05	4.34
Rail	120,985	22.3	110.1	0.0	1094.5	9.15	0.0001	181.3	2.21	0.02	1.45
Total	120,985	2640.5	962.2	3.2	7236.8	5.05	0.0003	13537.8	100	5.29	100

Note: The table summarizes annual trip counts, average trip distance, GHG emissions per mile, total annual vehicle miles traveled, and total annual GHG emissions for each travel mode for the 2017 National Household Travel Survey sample. To investigate the substitution of ridesharing with other travel modes, the sample is based on commuting trips with a distance less than 25 miles.

Table 2: The Effect of Ridesharing on Total VMT and Emissions, by CBSA Size

	VMT		GHG emissions	
CBSA population	Miles	Percentage	Metric tons	Percentage
National	4,740.75	0.08	3.10	0.14
3 million or more	22,587.97	0.16	15.01	0.28
1 million to 3 million	2,140.68	0.03	1.42	0.05
500k to 1 million	565.48	0.01	0.37	0.02
250k to 500k	645.40	0.03	0.32	0.04

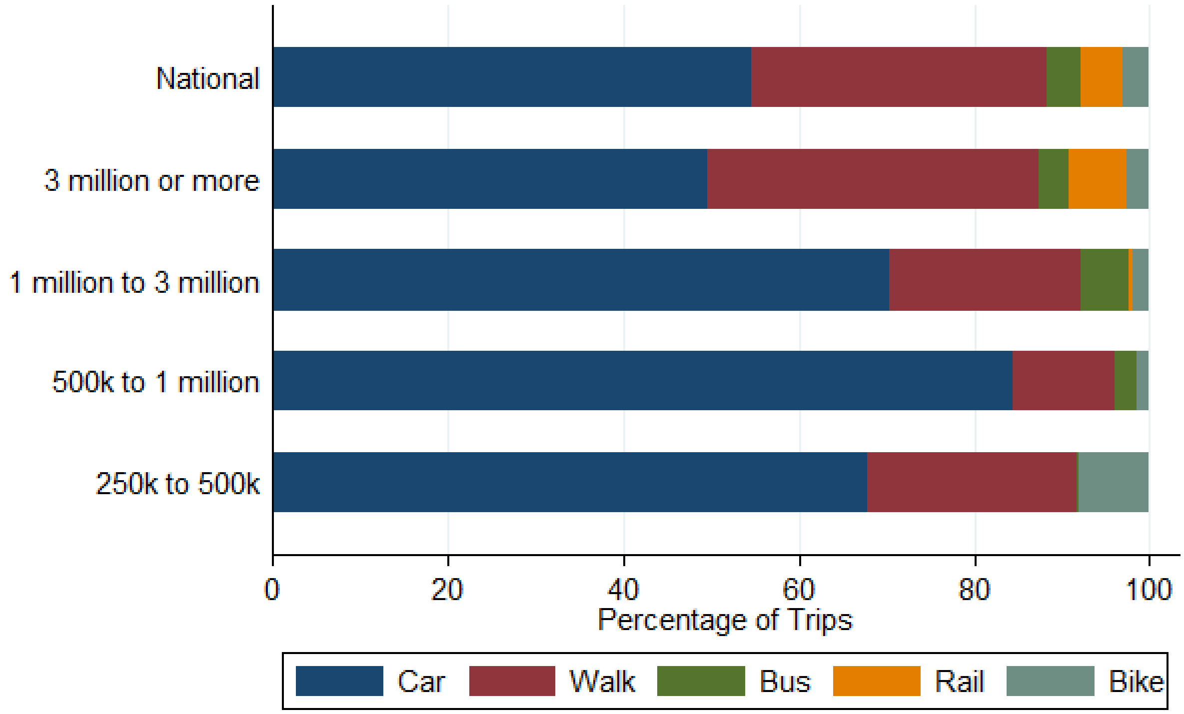
Note: The table summarizes the average change and percentage change in VMT and GHG emissions for each CBSA by CBSA size due to the introduction of ridesharing. We estimate the changes by simulating the counterfactual scenario where ridesharing is removed and comparing the counterfactual outcomes with the observed data.

Table 3: The Effect of Ridesharing on VMT and Emissions for Major Cities

	VMT		GHG emissions	
CBSA	Miles	Percentage	Metric tons	Percentage
Los Angeles	54,754.74	0.18	33.03	0.29
San Francisco	155,149.91	1.38	87.76	2.21
Seattle	5,053.32	0.14	4.71	0.36
Boston	500.31	0.04	1.40	0.33
Washington,DC	7,904.58	0.10	12.29	0.41
New York	55,779.17	0.19	131.78	1.59
San Diego	84,363.60	0.21	40.32	0.26
Chicago	13,044.17	0.19	11.12	0.44
Houston	57,976.93	0.08	28.25	0.10
Philadelphia	-718.23	-0.03	0.75	0.07

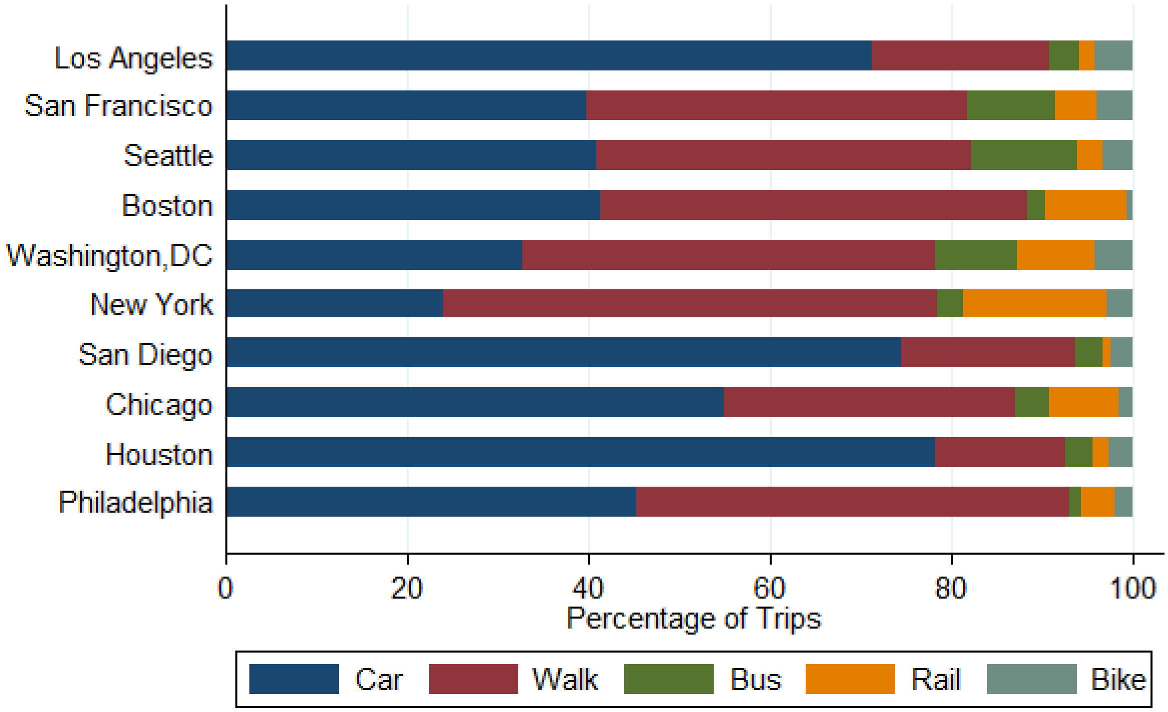
Note: The table summarizes the average change and percentage change in VMT and GHG emissions for each CBSA due to the introduction of ridesharing. We estimate the changes by simulating the counterfactual scenario where ridesharing is removed and comparing the counterfactual outcomes with the observed data.

Figure 1: Rideshare Substitution, by CBSA Size



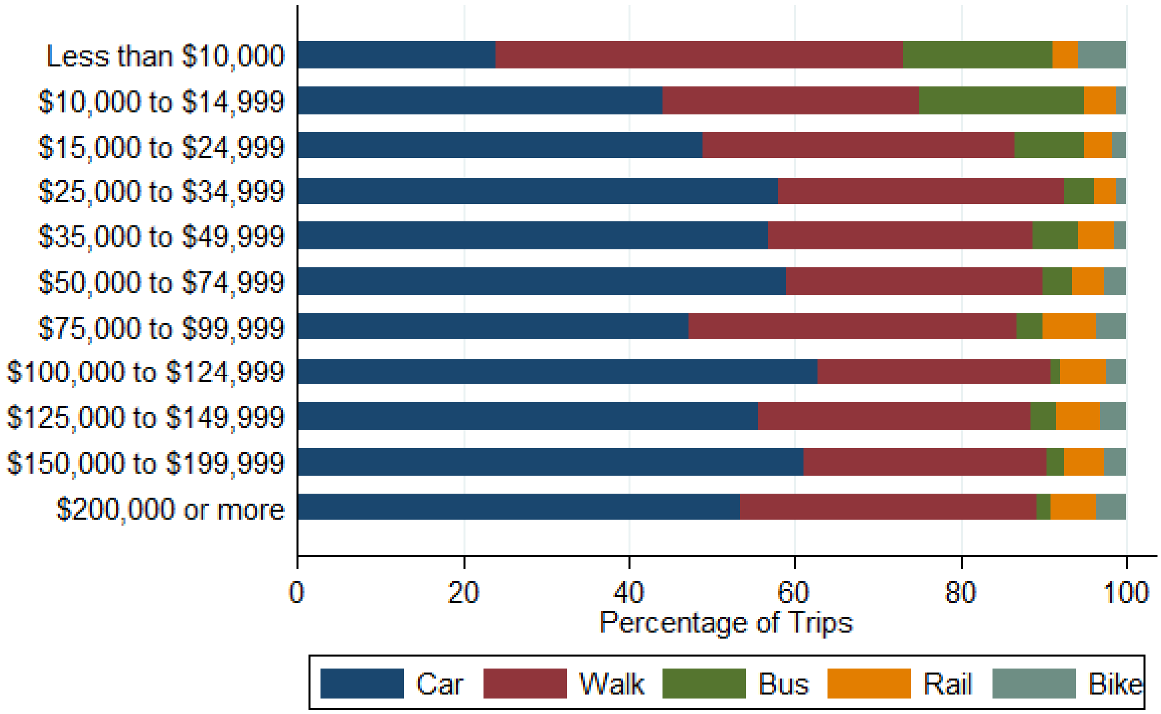
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available in each CBSA. The car option includes both privately owned vehicles and taxis.

Figure 2: Rideshare Substitution for Major Cities



Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis.

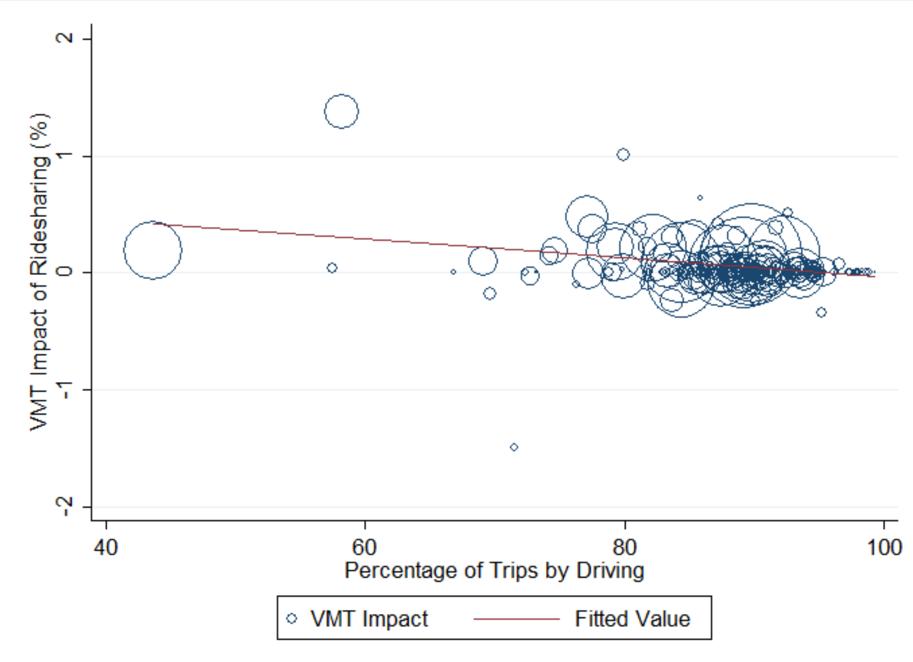
Figure 3: Rideshare Substitution, by Income Group



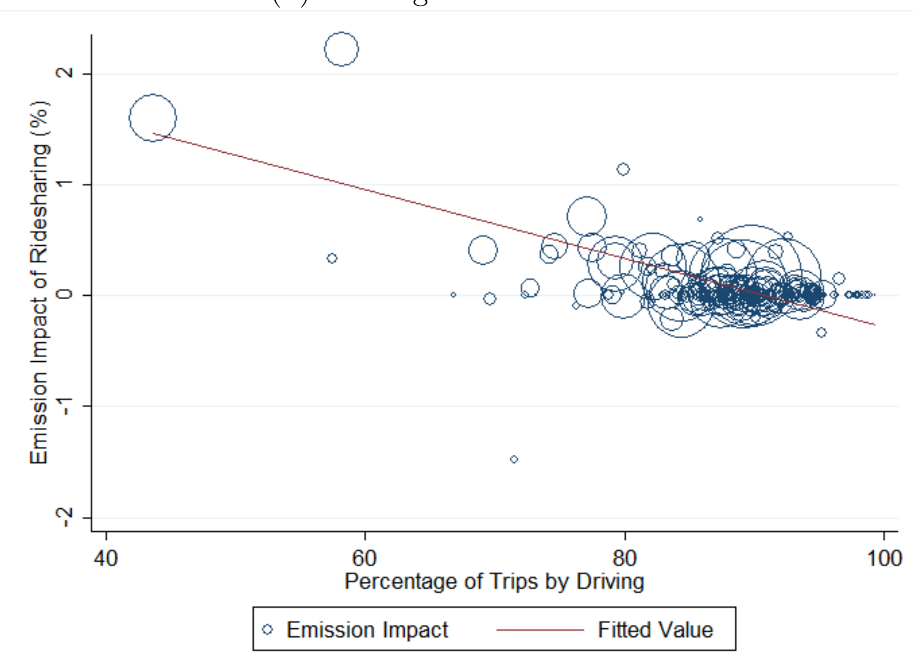
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available for different income groups. The car option includes both privately owned vehicles and taxis.

Figure 4: Heterogenous Effects of Ridesharing Due to Drivability

Panel (a) Heterogenous VMT Effects



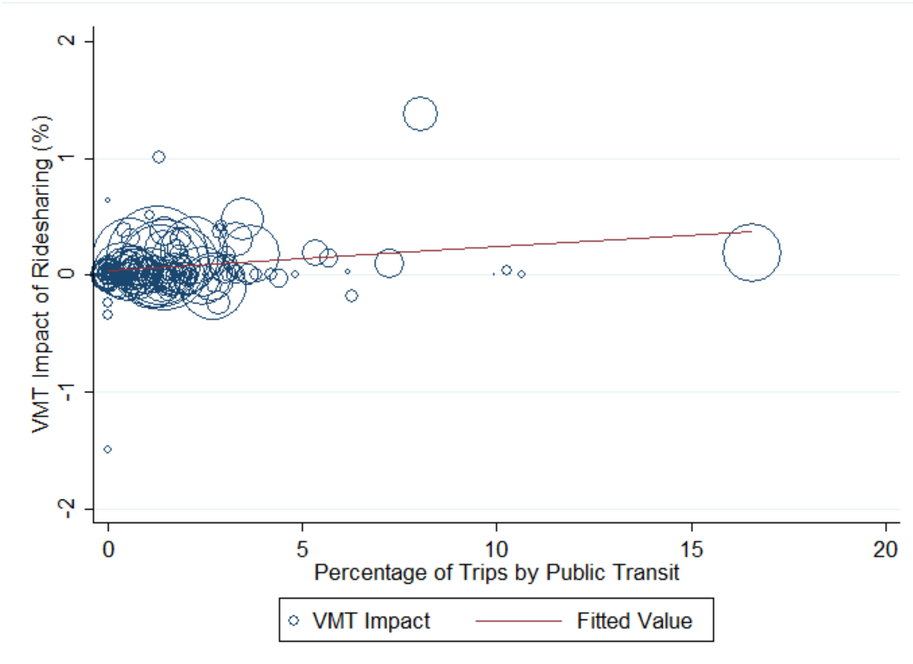
Panel (b) Heterogenous Emission Effects



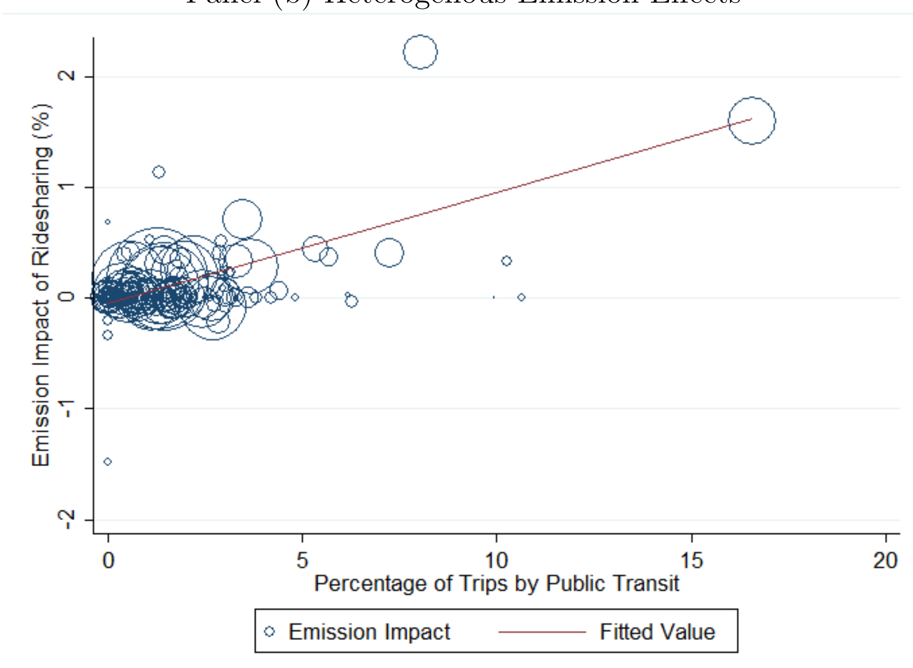
Note: The figure plots the relationship between the heterogeneous effects of ridesharing and the percentage of trips that are made by car in each city. The effects represent the percentage change in VMT and emissions from household transport in each CBSA due to the introduction of ridesharing. The fitted lines are created from weighted regressions where the weights are proportional to VMT and emissions, respectively. The weight of each data point is represented by the size of the circle.

Figure 5: Heterogeneous Effects of Ridesharing Due to Public Transit

Panel (a) Heterogenous VMT Effects



Panel (b) Heterogenous Emission Effects



Note: The figure plots the relationship between the heterogeneous effects of ridesharing and the percentage of trips that are made by public transit (bus and rail) in each city. The effects represent the percentage change in VMT and emissions from household transport in each CBSA due to the introduction of ridesharing. The fitted lines are created from weighted regressions where the weights are proportional to VMT and emissions, respectively. The weight of each data point is represented by the size of the circle.

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Appendices

A Alternative Model with Expanded Choice Sets

In this section, we consider an alternative model specification that relaxes the restricted choice set assumption in our benchmark model. In particular, we estimate an alternative model in which every household has a positive probability of choosing each mode. This alternative allows us to examine whether the restricted choice set assumption in our benchmark model affects the qualitative results. We follow the same notation as in prior sections. Household utility is

$$u_{ijt} = \delta_{gj} + \epsilon_{ijt}. \tag{A.1}$$

Household utility is defined by an average utility for choosing mode j, where the average is taken over household group g. We define household groups by income quintile and CBSA.[9] We choose these characteristics to differentiate households for several reasons. Households of different economic status generally differ in the types of modes they use. For example, lower-income households tend to use public transit more often than the typical household. Furthermore, CBSAs differ greatly in ways that affect the types of modes households take, including the availability of public transit, urban density and lane miles.

Assuming that the error component ϵ_{ijt} is i.i.d. type 1 extreme value and the outside option's utility is normalized to zero, $\delta_{g0} = 0$, a log-share equation can be derived:

$$\delta_{gj} = \ln(s_{gj}) - \ln(s_{g0}). \tag{A.2}$$

This equation relates the household group g share of choosing mode j and the outside mode to the average utility that household g gets from choosing mode j. Given the definition of household groups and the sample size in our data, these shares are strictly positive for all alternatives. Therefore, we are able to compute a mean utility for each group, which implies that households have a positive probability of choosing each mode type that is available in their CBSA.

This alternative model specification is a more restrictive form of household heterogeneity relative to our benchmark model. This is the price for relaxing the assumption of restricted choice sets while maintaining a model that is computationally simple.

We estimate this model with groups defined by income quintiles and CBSAs and perform

[9] For example, households in the bottom income quintile living in the Los Angeles CBSA obtain the same observed utility from choosing mode j.

the same simulations of removing the ridesharing option from the choice set. The substitution patterns with the alternative model are presented in Figures C.5 and C.7, with the corresponding numeric values summarized in Appendix Tables C.6 and C.8. The CBSA-income model predicts that 67.7 percent of ridesharing trips replace private car driving, which is larger than the previous estimate, and 23.09 percent of ridesharing trips replace walking, which is smaller than what the benchmark model estimates. The substitution of ridesharing for public transit and biking are similar to the results of the benchmark model. The spatial heterogeneity revealed by the alternative model is also similar to the benchmark model: in larger and more populous CBSAs, ridesharing replaces more walking and less car driving. Figure C.6 reveals that ridesharing replaces mainly car driving and less walking in Los Angeles, but it replaces more walking and less driving in New York City. The alternative model predicts that a larger fraction of driving but a smaller fraction of walking are replaced by ridesharing in Washington,DC, compared with the benchmark model. In terms of the ridesharing substitution by income group, although the alternative model predict that a larger share of car driving is replaced by ridesharing, the income heterogeneity findings are consistent with the benchmark model. For richer households, ridesharing substitutes for more car driving and less public transit usage, compared with lower-income households. To summarize, the alternative model preserves the qualitative findings from the benchmark model even though it relaxes the restricted choice set assumption. Therefore, our findings of the substitution pattern between ridesharing and other travel modes are not heavily influenced by the restricted choice set assumption in our benchmark model.

B Alternative Model That Accounts for Trip Purpose

Ridesharing trips may have different purposes than a typical household trip. For example, ridesharing may be primarily used for recreational purposes. Other modes like walking may be closer substitutes for ridesharing for certain trip purposes, such as recreation. Therefore the substitution patterns between ridesharing and other modes may depend on which types of modes have the same trip purposes as ridesharing. In this section, we estimate an alternative form of the model to accommodate this possibility. Instead of defining the unit of observation at the household-mode level, we aggregate the trips in the NHTS daily travel diaries to the CBSA-mode-trip purpose level and estimate and simulate the model with this unit as the observation. This alternative specification accounts for trip purpose heterogeneity rather than individual heterogeneity, as in our benchmark model. Appendix Table C.5 reports the frequency of each trip purpose for each travel mode. A plurality of ridesharing trips are made for social and recreational purposes (36.86 percent), which is similar to biking and walking trips, whereas the main purpose for privite car driving is shopping (33.19 percent).

Appendix Figures C.8 and C.9 plot the estimated substitution patterns when ridesharing is removed, by CBSA size and for a group of major cities based on this alternative model, with the corresponding numeric values reported in Appendix Tables C.9 and C.10, respectively. The results show that at the national level, 38.95 percent of the ridesharing trips replace car and taxi trips, and 28.16 percent replace walking. In total, our alternative model predicts that about two-thirds of ridesharing trips would have been taken by car, taxi, or walking. These frequencies are moderately smaller than in our benchmark model. Compared with our benchmark model, this alternative model predicts a larger fraction of ridesharing substitution to bus (12.37 percent) and biking trips (15.89 percent). This is because the substitution pattern now depends more on the similarity in trip purposes, and ridesharing, bus, and biking share more common trip purposes.

This alternative model predicts similar effects on VMT and emissions. Ridesharing is predicted to have a slightly larger increase in total VMT because fewer ridesharing trips replace car and taxi trips relative to our benchmark model simulation. The emissions effects, however, are similar, since the increase in VMT is somewhat offset by fewer walking trips being replaced by ridesharing.

This alternative model does not predict much variation in mode substitution across different regions because there is not much spatial heterogeneity in terms of trip purposes for different travel modes. Since spatial heterogeneity greatly matters for the eventual environmental effects and the individual heterogeneity model partly accounts for the heterogeneity in trip purposes as different households generally have different travel needs, we still consider the benchmark model, which incorporates individual heterogeneity, as our preferred specification and will use it for our analysis that evaluates VMT and emission effects.

C Additional Tables and Figures

Table C.1: Correlation Between Different Travel Modes

	Walking	Biking	Car	Rideshare	Taxi	Bus	Rail
Walking	1	0.18	-0.20	0.10	0.06	0.20	0.23
Biking	0.18	1	-0.14	0.04	0.02	0.06	0.04
Car	-0.20	-0.14	1	-0.05	-0.10	-0.22	-0.17
Rideshare	0.10	0.04	-0.05	1	0.05	0.06	0.13
Taxi	0.06	0.02	-0.10	0.05	1	0.07	0.06
Bus	0.20	0.06	-0.22	0.06	0.07	1	0.27
Rail	0.23	0.04	-0.17	0.13	0.06	0.27	1

Note: The table summarizes the correlation coefficients between different modes used by the 2017 NHTS households.

Table C.2: Rideshare Substitution, by CBSA Size

CBSA population	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
National	54.57	33.82	3.79	4.84	2.99
3 million or more	49.67	37.64	3.54	6.46	2.69
1 million to 3 million	70.37	21.88	5.38	0.49	1.89
500k to 1 million	84.50	11.48	2.46	0	1.56
250k to 500k	67.80	23.84	0.27	0	8.08

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing is not available. The car option includes both privately owned vehicles and taxis.

Table C.3: Rideshare Substitution for Major Cities

CBSA	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
Los Angeles	71.12	19.60	3.28	1.66	4.34
San Francisco	39.65	42.12	9.54	4.64	4.05
Seattle	40.83	41.37	11.55	2.98	3.27
Boston	41.29	46.87	2.00	9.13	0.70
Washington,DC	32.69	45.40	9.01	8.71	4.19
New York	23.82	54.55	2.80	15.94	2.90
San Diego	74.51	19.11	3.04	0.76	2.59
Chicago	54.86	32.14	3.79	7.62	1.59
Houston	78.21	14.33	2.99	1.71	2.76
Philadelphia	45.17	47.73	1.30	3.78	2.04

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis.

Table C.4: Rideshare Substitution for Different Income Groups

Income group	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
Less than $10,000	23.98	49.15	17.90	3.05	5.92
$10,000 to $14,999	43.96	31.08	19.92	3.80	1.24
$15,000 to $24,999	48.76	37.67	8.37	3.52	1.68
$25,000 to $34,999	57.92	34.55	3.65	2.73	1.16
$35,000 to $49,999	56.69	31.93	5.60	4.25	1.52
$50,000 to $74,999	58.85	31.01	3.54	3.96	2.64
$75,000 to $99,999	47.19	39.57	3.18	6.36	3.70
$100,000 to $124,999	62.86	28.04	1.13	5.46	2.51
$125,000 to $149,999	55.50	32.88	3.15	5.41	3.06
$150,000 to $199,999	61.16	29.12	2.34	4.66	2.72
$200,000 or more	53.48	35.59	1.78	5.43	3.72

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both a privately owned vehicles and taxis.

Table C.5: Trip Purposes for Different Travel Modes

Travel mode	Work (%)	Shopping(%)	Social and recreation (%)	Other (%)
Walking	6.18	21.39	32.29	40.04
Biking	21.74	17.39	37.62	23.26
Car	19.77	33.19	15.41	31.64
Rideshare	22.05	18.04	36.87	23.04
Taxi	21.11	35.77	11.64	31.48
Bus	31.93	23.30	12.12	32.64
Rail	54.48	13.01	15.00	17.50

Notes: The summary does not include non-home-based trips because NHTS reports the trip purposes only for home-based trips.

Table C.6: Rideshare Substitution, by CBSA Size (Expanded Choice Set Model)

CBSA population	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
National	67.66	23.09	3.09	4.58	1.58
3 million or more	63.39	25.88	3.21	5.93	1.58
1 million to 3 million	84.48	11.79	2.51	0.19	1.04
500k to 1 million	83.78	13.06	1.95	0	1.22
250k to 500k	71.19	20.92	4.03	0	3.86

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis. The estimates are based on the alternative model as described in Appendix Section A.

Table C.7: Rideshare Substitution for Major Cities (Expanded Choice Set Model)

CBSA	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
Los Angeles	80.79	14.53	2.64	0.83	1.21
San Francisco	60.09	29.10	5.17	2.89	2.75
Seattle	74.69	17.64	4.70	1.10	1.87
Boston	55.96	33.33	1.61	7.77	1.32
Washington,DC	69.89	21.80	3.29	3.88	1.13
New York	45.43	36.97	4.18	11.58	1.83
San Diego	80.98	14.88	2.40	0.46	1.28
Chicago	76.72	17.41	1.61	3.06	1.20
Houston	88.33	8.78	1.28	0.39	1.22
Philadelphia	76.70	19.25	1.70	1.56	0.79

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis. The estimates are based on the alternative model as described in Appendix Section A.

Table C.8: Rideshare Substitution for Different Income Groups (Expanded Choice Set Model)

Income group	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
Less than $10,000	46.30	35.91	12.51	3.00	2.30
$10,000 to $14,999	63.58	25.87	6.77	2.53	1.25
$15,000 to $24,999	69.02	22.50	4.55	2.87	1.06
$25,000 to $34,999	76.97	16.47	2.70	2.07	1.79
$35,000 to $49,999	72.25	18.97	3.79	3.61	1.37
$50,000 to $74,999	72.55	19.64	2.42	3.71	1.69
$75,000 to $99,999	72.12	19.96	2.35	4.29	1.28
$100,000 to $124,999	71.43	20.33	2.33	4.61	1.31
$125,000 to $149,999	69.81	22.13	1.61	5.28	1.17
$150,000 to $199,999	69.18	21.98	1.96	5.47	1.40
$200,000 or more	61.60	28.14	1.35	6.95	1.97

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis. The estimates are based on the alternative model as described in Appendix Section A.

Table C.9: Rideshare Substitution, by CBSA Size (Trip Purpose Model)

CBSA population	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
National	38.95	28.16	12.37	4.63	15.89
3 million or more	42.31	33.06	9.72	0.88	14.03
1 million to 3 million	41.41	29.58	12.49	1.89	14.63
500k to 1 million	37.53	26.69	14.52	5.10	16.17
250k to 500k	34.54	23.12	13.41	10.28	18.65

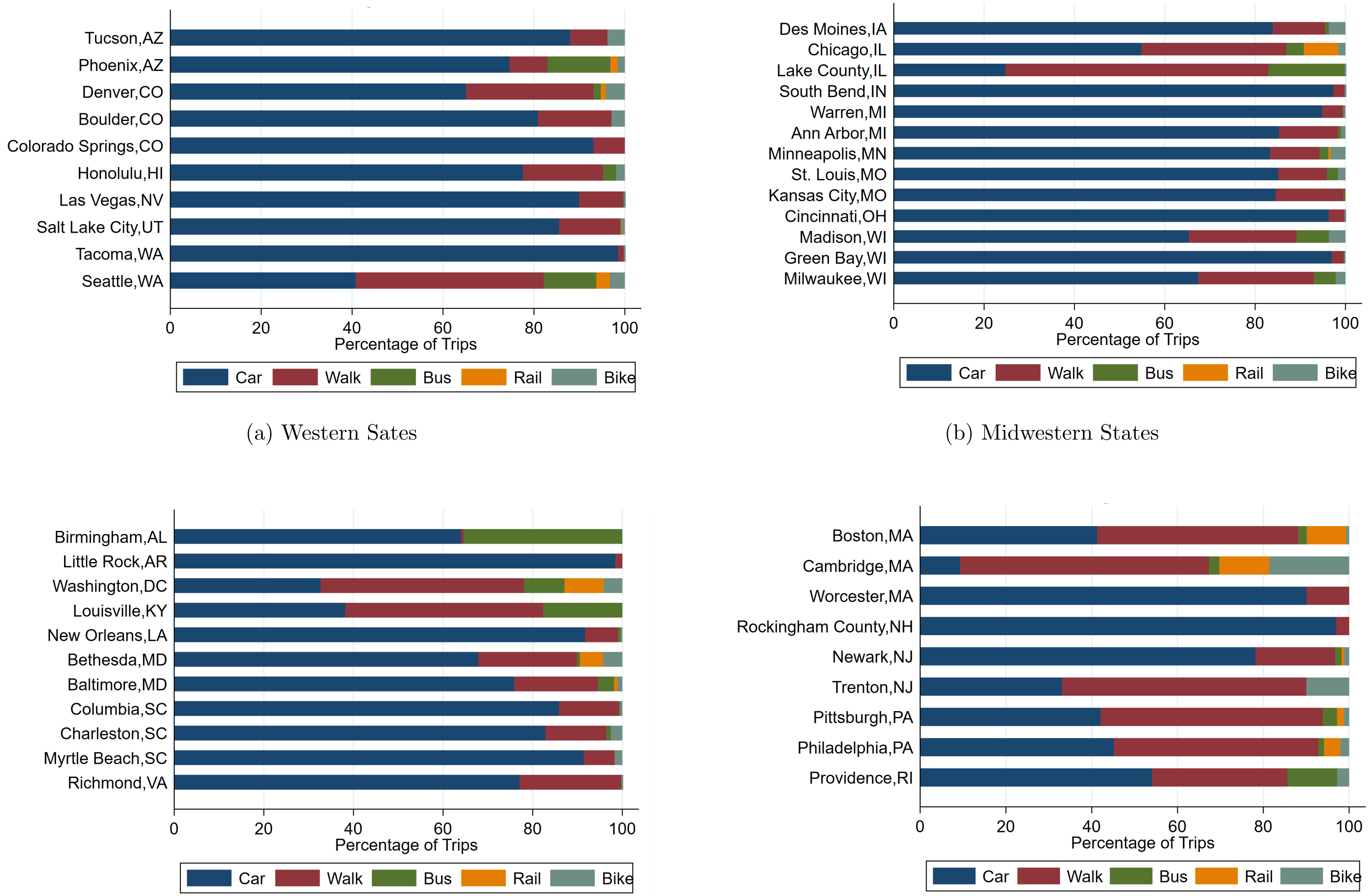
Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes trips both privately owned vehicles and taxis. The estimates are based on an alternative model that accounts for heterogeneity of trip purpose as described in Appendix Section B.

Table C.10: Rideshare Substitution for Major Cities (Trip Purpose Model)

CBSA	Car (%)	Walking (%)	Bus (%)	Rail (%)	Biking (%)
Los Angeles	36.87	19.07	13.56	15.39	15.11
San Francisco	35.88	18.01	15.67	12.75	17.70
Seattle	32.21	20.88	17.24	12.37	17.31
Boston	28.28	23.15	17.18	16.86	14.52
Washington,DC	33.08	21.21	18.71	12.14	14.86
New York	33.05	20.19	14.42	14.63	15.71
San Diego	35.11	19.35	14.81	14.06	16.66
Chicago	33.16	22.82	16.35	12.25	15.43
Houston	29.95	19.99	14.60	17.11	18.34
Philadelphia	29.67	23.93	18.63	10.75	17.02

Note: The table summarizes the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis. The estimates are based on an alternative model that accounts for heterogeneity of trip purpose as described in Appendix Section B.

Figure C.1: Rideshare Substitution, by Region



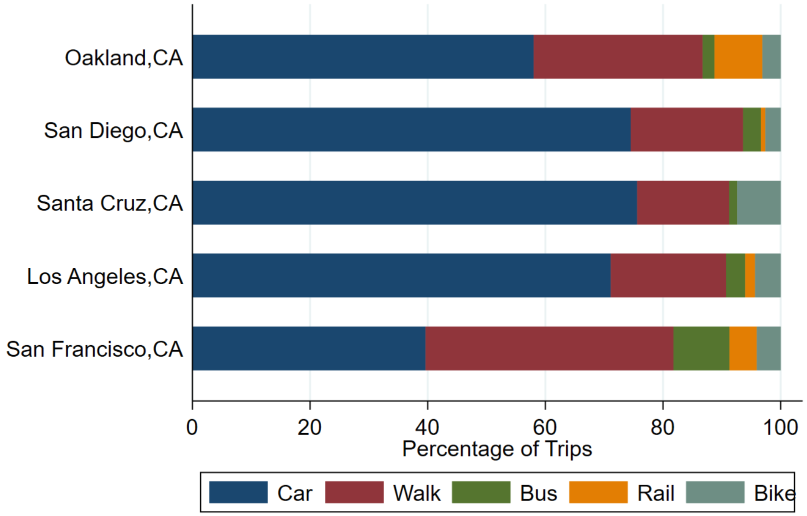
(a) Western Sates

(b) Midwestern States

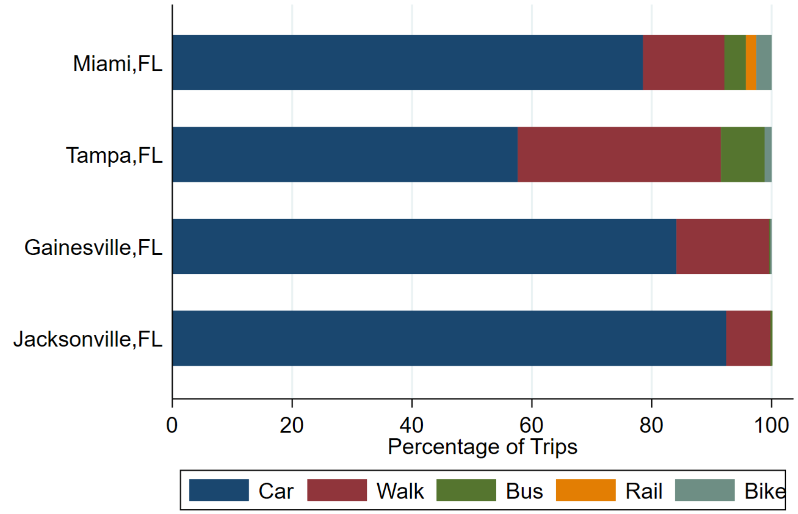
(c) Southern States

(d) Northeastern States

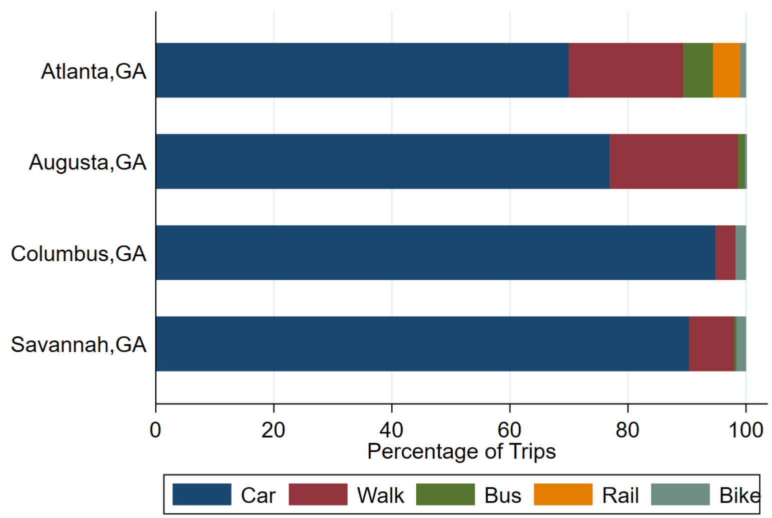
Figure C.2: Rideshare Substitution for CA, FL, and GA



(a) California

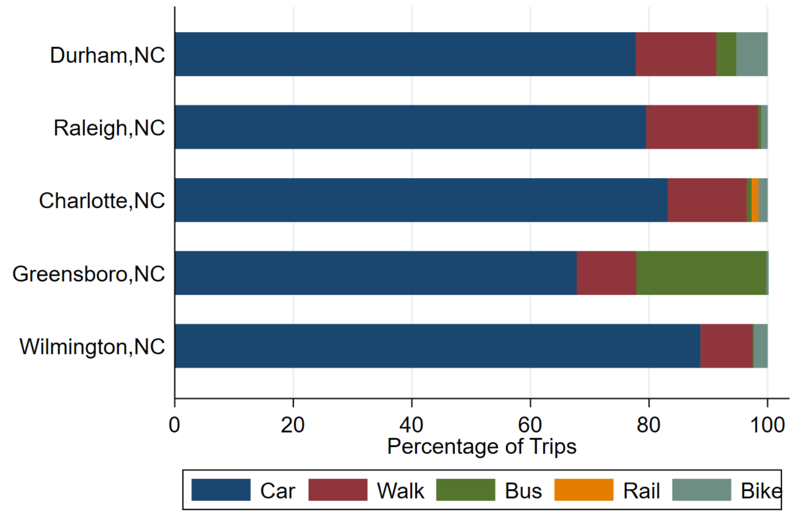


(b) Florida

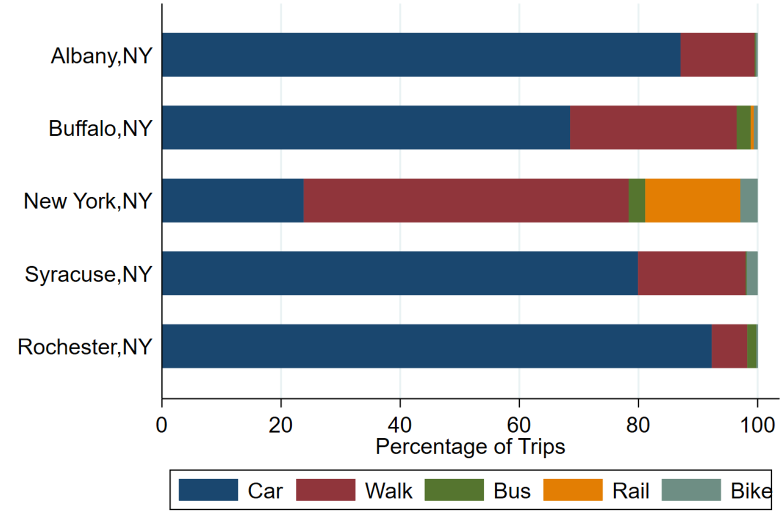


(c) Georgia

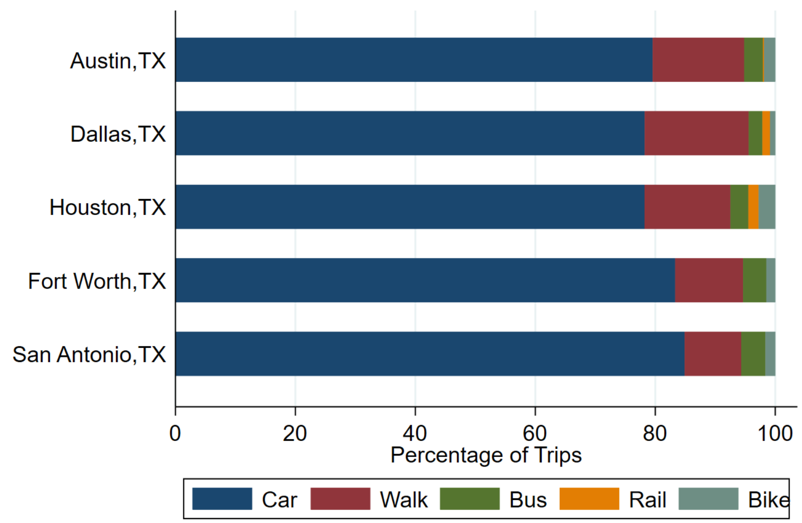
Figure C.3: Rideshare Substitution for NC, NY, and TX



(a) North Carolina

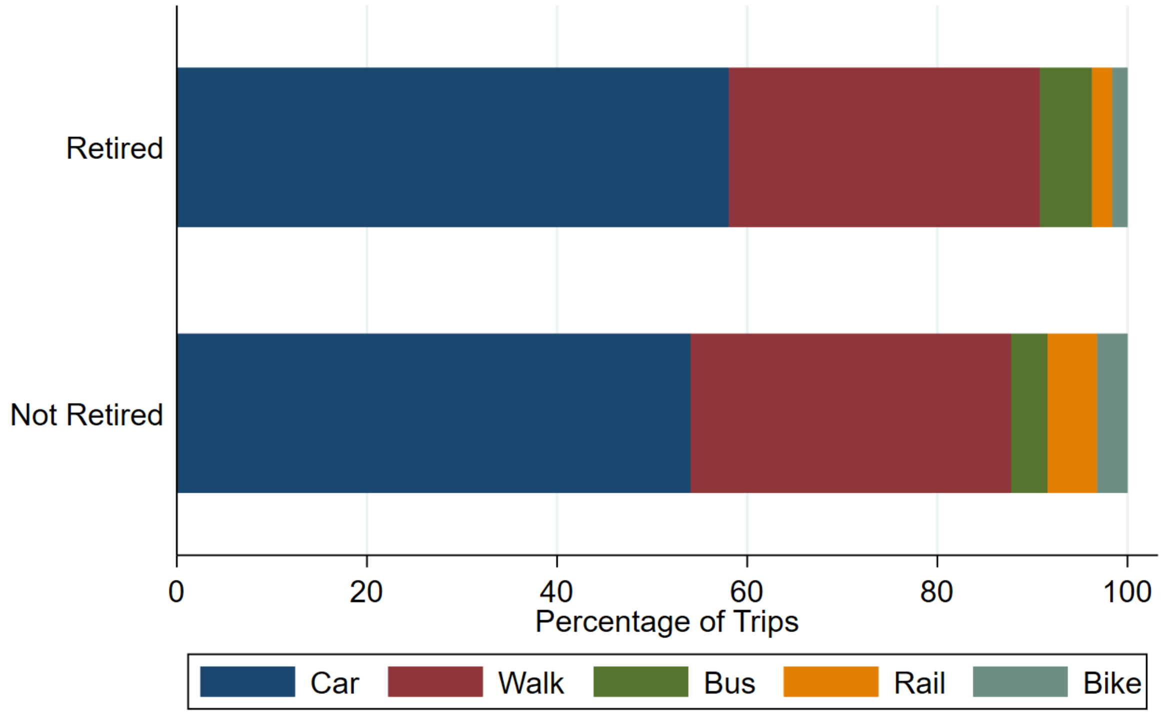


(b) New York



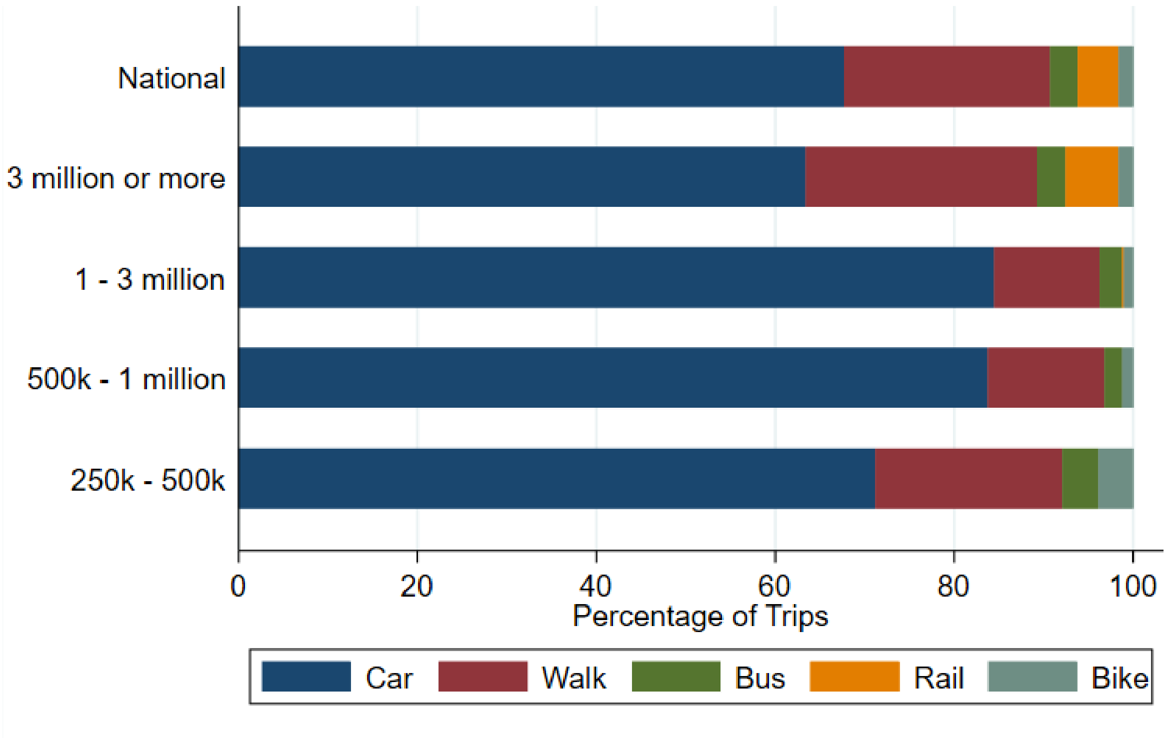
(c) Texas

Figure C.4: Rideshare Substitution, by Age Group



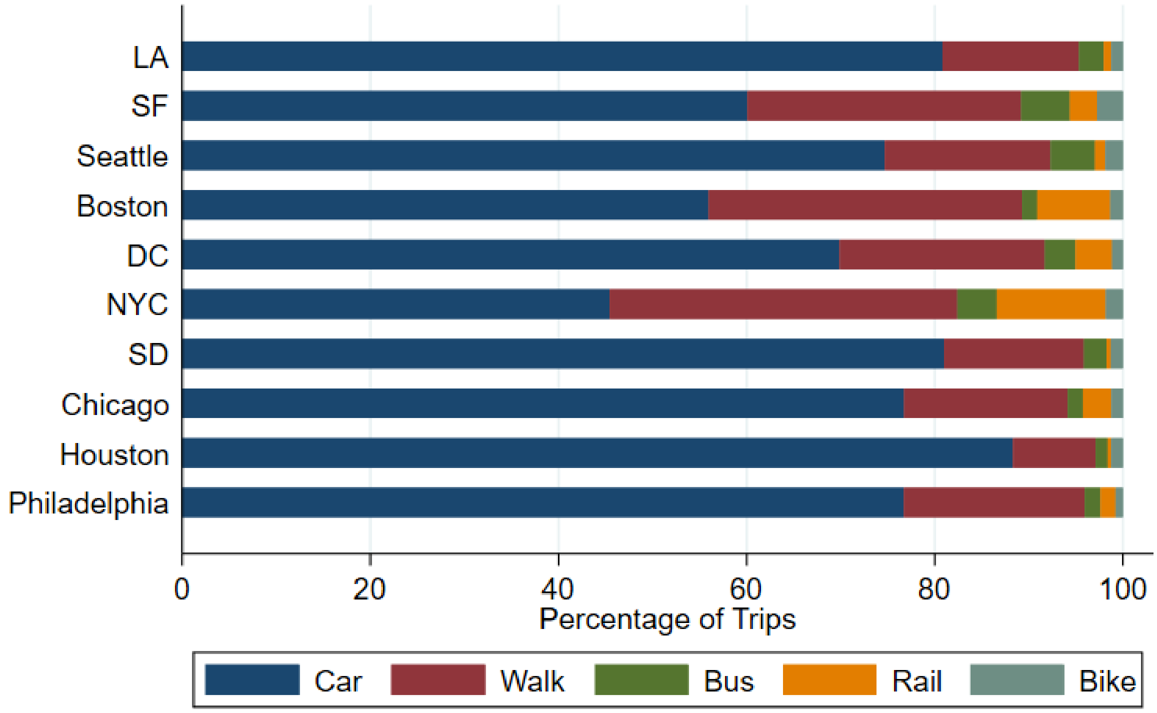
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available for different income groups. The car option includes both privately owned vehicle or taxis.

Figure C.5: Rideshare Substitution, by CBSA Size (Expanded Choice Set Model)



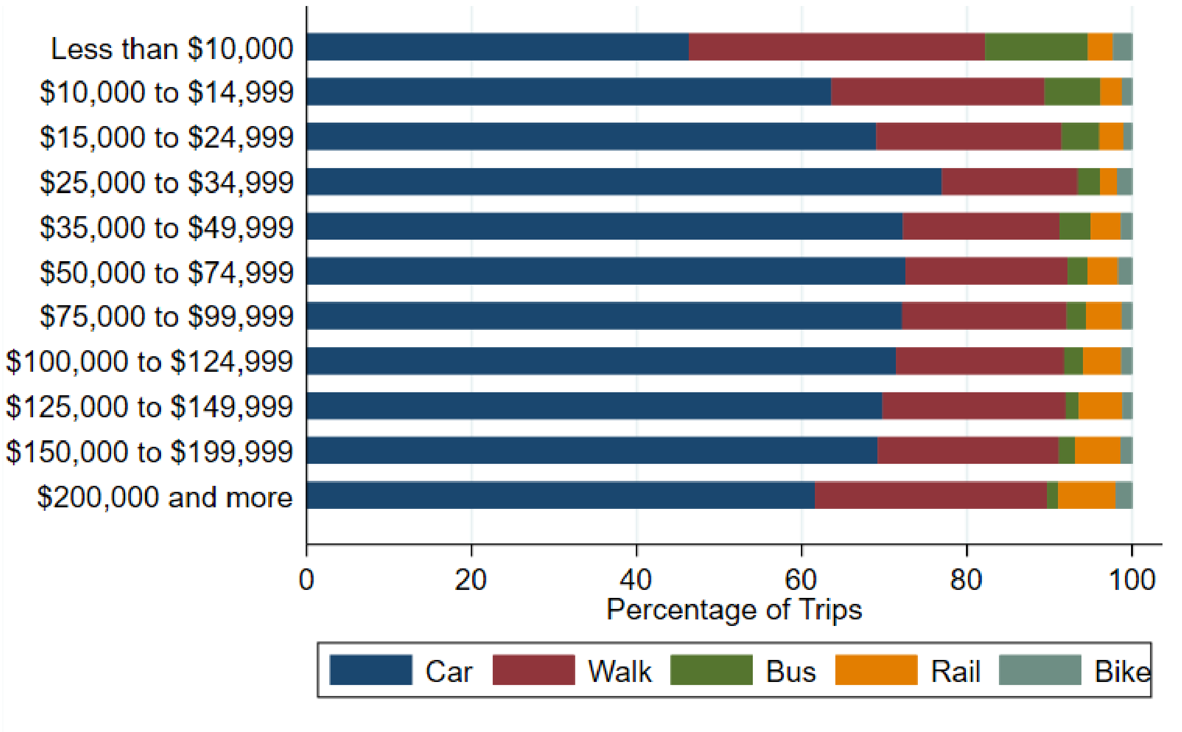
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing is not available in each CBSA. The car option includes both privately owned vehicles and taxis. The estimates are based in the alternative model as described in Appendix Section A.

Figure C.6: Rideshare Substitution for Major Cities (Expanded Choice Set Model)



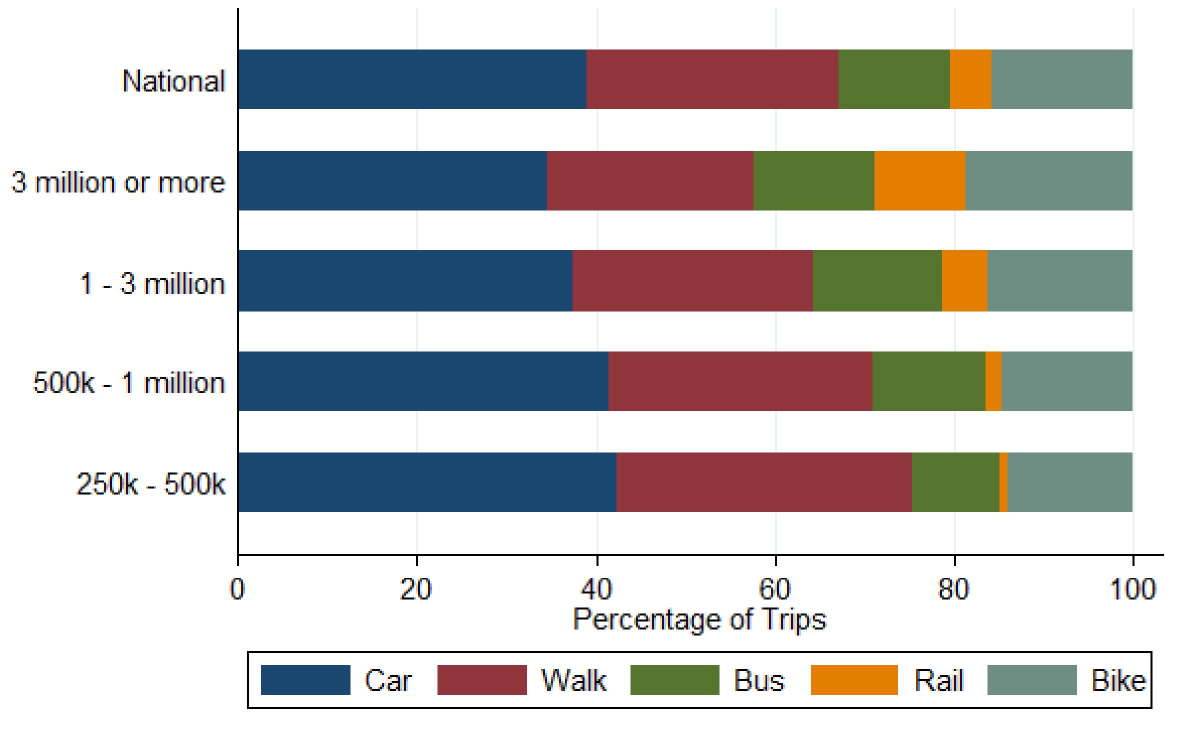
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing is not available. The car option include both privately owned vehicles and taxis. The estimates are based in the alternative model as described in Appendix Section A.

Figure C.7: Rideshare Substitution, by Income Group (Expanded Choice Set Model)



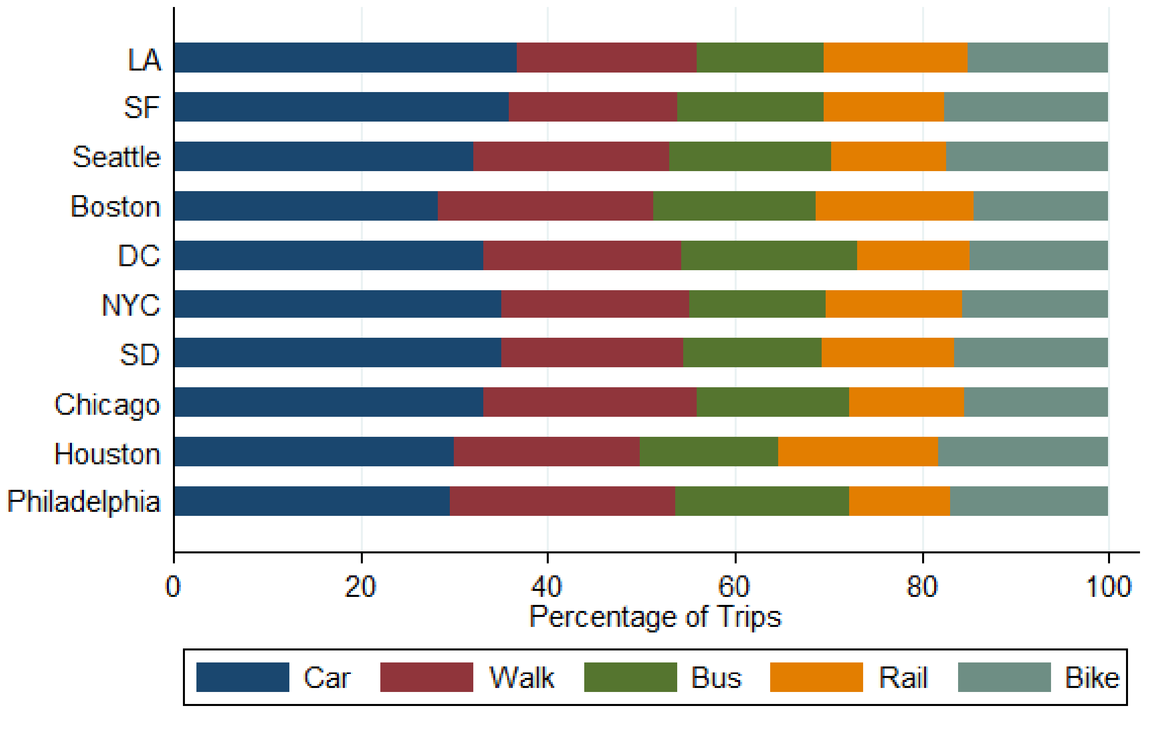
Note: The figure plots the percentage of each mode that travelers would choose if ridesharing is not available for different income groups. The car option includes both privately owned vehicles and taxis. The estimates are based in the alternative model as described in Appendix Section A.

Figure C.8: Rideshare Substitution, by CBSA Size (Trip Purpose Model)



Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available in each CBSA. The car option includes both privately owned vehicles and taxis. The estimates are based on an alternative model that accounts for heterogeneity of trip purpose as described in Appendix Section B.

Figure C.9: Rideshare Substitution for Major Cities (Trip Purpose Model)



Note: The figure plots the percentage of each mode that travelers would choose if ridesharing were not available. The car option includes both privately owned vehicles and taxis. The estimates are based on an alternative model that accounts for heterogeneity of trip purpose as described in Appendix Section B.