

ANALYSIS OF TRAVEL CHOICES AND SCENARIOS FOR SHARING RIDES

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TABLE OF CONTENTS

Executive Summary	1
Chapter 1. Project Overview	5
Project Purpose	5
Approach and Methodology	5
Survey of Transportation Network Company Users.....	5
Analysis of App-Based Carpooling Use	6
Literature Review on Driving/Parking Price and Behavioral Response.....	7
Development of an Analytical Model for City-Level Scenario Assessments	7
Document Organization	8
Chapter 2. Sharing Rides in an Environment of On-Demand Ridehailing.....	9
Overall Context.....	9
Ridehailing Literature	9
Survey Approach and Data Preparation.....	13
Trip Alternative Questions.....	13
Appended Data on Observed Trips.....	14
Sample Cleaning	15
Data Weighting	16
Discrete Choice Model Development.....	16
Passenger Occupancy in Private Rides	19
Limitations of Approach	20
Analysis of Market Segments	21
Frequency of Sharing by User Characteristic	23
Distribution of Shared and Private Trips by Trip Characteristic	23
Distribution of Shared and Private Trips by Built Environment Characteristic	24
Analysis of Price and Travel Time Effects on Choice to Share	29
Effect of Price on Sharing.....	29
Market Segmentations and Price Sensitivity	30
Effect of Time on Sharing.....	35
Relative Effect of Price and Time.....	37
Discussion: Ridesharing and Transportation Network Companies	41

Chapter 3. Encouraging Carpooling Using App-Based Incentive Tools.....	45
Impact of Rewards and Incentives using Data from Metropia™ Driving Up Occupancy Platform.....	47
Impact of Rewards and Incentives using Examples from Hytch™	53
Chapter 4. Shared Ride Use Under Different Scenarios.....	59
Scenario Details	59
Overview of Scenarios.....	59
Use of the Scenarios in the Analytic Model	65
Analytic Model For Scenario Assessments	66
Analytic Model Inputs and Assumptions.....	67
Interpreting Analytic Model Outputs.....	69
Limitations of the Analytic Model.....	72
Scenario Analysis Results.....	72
Scenario 1: Lower Relative Prices for Shared Transportation Network Company Trips.....	74
Scenario 2: Faster Relative Travel Time for Shared Transportation Network Company Trips	74
Combination of Scenarios 1 and 2: Greater Price Differential and Less Time Differential.....	78
Scenario 3: Increase Price Difference of Private Car Trips and All Other Modes	80
Chapter 5. Implications for Cities.....	83
Chapter 6. Potential for Future Research.....	85
References.....	87
Acknowledgements.....	91

LIST OF FIGURES

Figure 1. Graph. Distribution of observed frequency of sharing according to user characteristic. Bars of the same frequency level sum to 100 in each panel (n = 4,365). (Source: Federal Highway Administration)	26
Figure 2. Graph. Distribution of shared and private trips according to trip characteristics (n = 4,365). (Source: Federal Highway Administration)	27
Figure 3. Graph. Distribution of shared and private trips according to the built environment characteristics. Categories on the x-axis represent percentiles (n = 4,365). (Source: Federal Highway Administration)	28
Figure 4. Graph. Share of private transportation network company users that switched to shared travel. Users in dataset that switched from private to shared travel at three levels of price differences offered (with average price differential shown in parentheses). These three alternatives represented shared trips with identical travel times to the observed private trip. (Source: Federal Highway Administration)	30
Figure 5. Graph. Effect of \$1 per mile relative price difference on a user's percent probability of sharing rides. (Source: Federal Highway Administration)	32
Figure 6. Graph. Share of private transportation network company users in dataset that switched from private to shared travel at each level of travel time difference and price difference offered. (Source: Federal Highway Administration)	35
Figure 7. Graph. Effect of 1 minute/mile reduction in relative travel time difference on the percent probability of sharing. (Source: Federal Highway Administration)	36
Figure 8. Graph. Driving Up Occupancy timeframes and user data definition. (Source: Metropia™).....	48
Figure 9. Diagram. Tiered analysis framework. (Source: Metropia™).....	50
Figure 10. Graph. Temporal carpool use. (Source: Metropia™).....	52
Figure 11. Graph. Carpool driver and passenger incentive point trend. (Source: Metropia™).....	53
Figure 12. Diagram. Total miles per user per month compared to average rewards per mile. (Source: Middle Tennessee State University Data Science Institute)	54
Figure 13. Percentage of trips with no rewards and last trips per month. (Source: Middle Tennessee State University Data Science Institute)	55
Figure 14. Graphic. Explanation of modes and decisions affected by scenarios 1 and 2. (Source: Federal Highway Administration)	65
Figure 15. Graphic. Explanation of modes and decisions affected by scenario 3. (Source: Federal Highway Administration)	65
Figure 16. Graphic. Explanation of modes and decisions affected by experimental scenario 4. (Source: Federal Highway Administration)	66
Figure 17. Image. Screenshots, from left to right: “Scenarios” sidebar tab, “Segments” sidebar tab, and “Customize Initial Mode Shares” sidebar tab. (Source: Federal Highway Administration).....	68

Figure 18. Image. Screenshot of slider bars features in “Assumptions” sidebar tab. (Source: Federal Highway Administration)	70
Figure 19. Graph. Sample output of analytic model for illustrative purposes. (Source: Federal Highway Administration).....	71
Figure 20. Graph. Effect of scenarios on vehicle miles traveled (total change and percent change). (Source: Federal Highway Administration).....	73

LIST OF TABLES

Table 1. Summary of findings.	3
Table 2. Alternative options examples. (Source: Federal Highway Administration).....	14
Table 3. Characteristics of cards presented to private and shared transportation network company users in trip alternative analysis. (Source: Federal Highway Administration)	14
Table 4. Share of adjusted survey data at three occupancy levels for private ridehailing trips (n = 3,518). (Source: Federal Highway Administration)	20
Table 5. Exponentiated coefficients of Model 8. (Source: Federal Highway Administration)	31
Table 6. Initial rate of opting in to shared rides for selected market segments. (Source: Federal Highway Administration).....	33
Table 7. Reported reasons why respondents chose a private ride over a shared ride (values do not add to 100 percent because respondents could select more than one reason). (Source: Federal Highway Administration)	38
Table 8. Illustration of effect of price and time differences on overall level of sharing. (Source: Federal Highway Administration)	38
Table 9. Implied value of time based on choice between 11 pairs of shared ride options. (Source: Federal Highway Administration)	40
Table 10. Implied value of time based on choice between nine pairs of shared ride options. (Source: Federal Highway Administration)	41
Table 11. Number of Metropia™ users contacted via the micro-survey, by market. (Source: Metropia™)	48
Table 12. Distribution of carpool users included in the trend analysis. (Source: Metropia™)	51
Table 13. Counts and percentages for no reward and last trip (Source: Middle Tennessee State University Data Science Institute).....	55
Table 14. Average rewards per mile per month for a user (Source: Middle Tennessee State University Data Science Institute).....	56
Table 15. Weekly totals for a Hytch™ rewards partner (Source: Middle Tennessee State University Data Science Institute).....	58
Table 16. Overview of scenarios considered for analysis.....	60
Table 17. Average cost of drive-alone trips in study cities, with and without parking costs. (Sources: City Observatory Price of Parking, Shoup (2005), National Household Travel Survey (2017))	63
Table 18. Sample effect of increasing relative per-trip drive-alone costs on drive-alone mode share according to Trip Reduction Impacts of Mobility Management Strategies elasticity estimate of -0.30. (Source: Federal Highway Administration).....	63
Table 19. Effect of \$1/mile price difference for shared transportation network company trips across three geographies, for all segments, and for trips starting in dense office districts. See scenario 1. (Source: Federal Highway Administration)	76

Table 20. Effect of 15 seconds/mile reduced travel time difference between private and shared transportation network company trips across three geographies, for all segments, and for trips ending in dense office districts. See scenario 2 (affects only shared transportation network company modes). (Source: Federal Highway Administration)	77
Table 21. Effect of both a \$1/mile increased price difference and a 15 seconds/mile reduced travel time difference between private and shared transportation network company trips across three geographies, in all segments (left) and trips ending in dense office districts (right). See scenarios 1 and 2 (affects only transportation network company modes). (Source: Federal Highway Administration)	79
Table 22. Effect of \$1/trip relative increase in the price of private car trips compared to all other modes (affects all modes), in all segments for three different geographies. See scenario 3. (Source: Federal Highway Administration)	81

LIST OF ABBREVIATIONS

DUO	Driving Up Occupancy (a Metropia™, Inc. smartphone application)
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
ITS	Intelligent Transportation Systems
NHTS	National Household Travel Survey
SOV	Single occupancy vehicle
TDM	Transportation/travel demand management
TNC	Transportation network company
USDOT	United States Department of Transportation
VMT	Vehicle miles traveled
VOT	Value of time

EXECUTIVE SUMMARY

Automobile occupancy has important implications for the efficiency of highway operations. Increasing automobile occupancy by sharing rides may help reduce overall vehicle miles traveled (VMT), and thereby alleviate congestion, curtail vehicle emissions, and support economic growth.

Two approaches to facilitate higher automobile occupancy have emerged in practice and from pilot studies. They are:

- ***Shared options in ridehailing applications.*** Ridehailing applications have significantly impacted the transportation landscape by providing an alternative to personal vehicles, and in some cases, an alternative to public transportation. These services, offered by transportation network companies (TNC), such as Uber™, Lyft™, and Via™, are available through mobility apps. These mobility apps allow users to select private rides, such as UberX™ or a standard Lyft™, or shared rides, such as UberPool™, Shared Lyft™, or Via™. The apps provide an upfront estimate on price and time for all options presented, enabling users to make calculated decisions about their travel behavior.
- ***Ridesharing using app-based incentive tools.*** Emerging app-based ridesharing models continue to augment traditional carpooling by providing features that allow dynamic ridematching (with matches created in real-time and through automated mechanisms including through the establishment of trusted networks), incentive programs, occupancy verification and other options that allow for more flexible carpool formation, higher user satisfaction and sustained use of these services.

This study seeks to understand behavior and the impacts of price and time tradeoffs for both the aforementioned models of sharing private rides. By analyzing the tradeoffs users make when presented the option to share a ride, typically with incentives to do so, this study may be able to discern impacts of various choice and incentive structures.

While transportation researchers have analyzed ridehailing behavior before, there is limited research describing the effect of price and time on a rider's choice between private party and shared ridehailing. This Federal Highway Administration (FHWA) study used data on revealed preferences for private party and shared ridehailing trips in 15 American cities, coupled with a large TNC's survey of 4,365 of its users in late 2018. The TNC survey included stated preference questions focused on various alternative options for each participant's most recent trip choice. The TNC survey explored different market segments: for users who took a private TNC ride, would they be willing to choose a less expensive and longer ride, and for users who took a shared TNC ride, what changes would lead them to choose a more expensive and faster ride?

FHWA conducted a separate analysis surrounding users' preferences when choosing one shared TNC option over other shared TNC options. Results yielded significant heterogeneity in cost and time savings tradeoffs among users, meaning that there were substantial differences in user preferences. This suggests that, by offering customers more than one shared product option with time delay and varying price points, and by providing these in combination with vehicle routing

decisions designed to accommodate differing user preferences, TNCs could increase the proportion of shared trips.

Ridehailing is not the only way to share private automobile rides. Some transportation agencies are working with emerging app-based carpooling and navigation services, like Scoop™, Waze™, Metropia™, Agile Mile™, and Hytch™, to pilot incentives for ridesharing in private vehicles. This study uses data from and analyses conducted by two app-based systems (Metropia™ and Hytch™) to understand the impact of incentives on desired behaviors.¹ These should only be considered as examples, since app-based carpooling systems that exist in the marketplace vary significantly in their user interfaces and the incentive structures they offer. Moreover, for both Metropia™ and Hytch™, the study used data that the app developer collected previously and not specifically for the research questions of interest to this effort. An important additional limitation was that travel choice data gathered via surveys prior to app use was not sufficiently specific to enable attribution of the cause(s) of behaviors to the use of these apps.

Based on the data and analysis gathered from the two sharing approaches and literature, the FHWA study developed an analytical model to facilitate the assessment of three scenarios (plus one experimental scenario) to test incentive impacts and the effectiveness of strategies to encourage travel choices that increase vehicle occupancy through sharing TNC rides and carpooling in private vehicles. Two scenarios focused on TNCs by increasing the cost savings of shared trips relative to private trips (cheaper) or by reducing the travel time penalty for shared trips relative to private trips (faster), one that focused on personal vehicles by increasing the price difference between private car trips and carpools, and an experimental scenario of rewarding shared personal vehicle trips through an app. Due to insufficient data regarding the impacts of incentives of interest, the last scenario was deemed experimental in nature. Currently, available data in this experimental area does not lend itself to a robust scenario evaluation. This study explains why such a scenario would be valuable and outlines the future research efforts needed to discern the impact of app-based incentives on carpooling formation.

Analysis of the scenarios reveal that changes to the relative price of private vehicle travel (i.e., driving alone rather than with a passenger) offer the greatest opportunity for reduction in VMT. The reason for this impact is that private vehicle travel accounts for the majority of VMT and person trips in the United States. The study finds, for example, that a \$1 per trip increase for “drive-alone” trips over the price for shared trips would save more than 3.5 billion vehicle miles annually in the 15 markets studied in this report. More modest or more targeted interventions could also reduce VMT by focusing on particular geographies or population segments.

¹ FHWA requested that Metropia™ and Hytch™ each analyze data they had already gathered prior to this study in response to questions developed by FHWA for this study. FHWA describes the results of this analysis in Chapter 3 of this report. FHWA also used the analysis from Metropia™ as inputs in experimental scenario 4, as described in Chapter 4. Because such data were not initially gathered to answer FHWA’s questions, however, FHWA did not consider it adequate for its use in the analytical model it subsequently developed that enables city-level policy assessments, which is described later in this document and is made available to the public as part of this research.

This study does not explore factors (beyond cost and travel time) that, according to other research, sometimes make people averse to sharing a vehicle with strangers, such as safety, privacy, and convenience. Secondly, analyses in this study do not address interactions across all modes. For that reason, this study can estimate how price and time affect a user's choice between a private and shared TNC ride, but it does not estimate how price and time affect a user's choice among TNCs, transit, driving, carpooling, walking, bicycling, or any other modes. Similarly, the study provides no data to consider how TNC characteristics affect a user's decision to take a trip in the first place. Additional multimodal discrete choice analysis is necessary to properly nest these decisions within an integrated mode choice model.

Table 1 organizes findings from this study by research question and directs readers to sections of this paper with related key findings.

Table 1. Summary of findings.

Research Question	Key Findings	Technical Details
For which types of trips are transportation network company (TNC) users most willing to share rides?	Solo trips, weekend trips, trips from work, trips home, and trips to entertainment or personal business were a greater proportion of shared trips.	Chapter 2: Distribution of Shared and Private Trips by Trip Characteristic
How much <i>cheaper</i> would the <i>price</i> of shared TNC rides have to be than private TNC rides to increase the probability for ridesharing by 10 percentage points?	A price difference of \$1.16 per mile would increase the probability of sharing for general trips by 10 percentage points (from roughly 30 percent of trips to roughly 40 percent).	Chapter 2: Effect of Price on Sharing
How much <i>less travel time penalty</i> for shared TNC rides relative to private TNC rides would be required to increase the probability for ridesharing by 10 percentage points?	A travel time difference of 18 seconds per mile would also increase the probability of sharing for general trips by 10 percentage points (again, from roughly 30 percent of trips to 40 percent). This differential might be difficult to obtain from travel time changes and could more easily result from changes in waiting time (e.g., by prioritizing pick-ups for shared TNC rides).	Chapter 2: Effect of Time on Sharing
What types of TNC trips are relatively insensitive to differences in <i>price</i> between shared and private rides?	Trips to or from the airport or other intermodal travel centers were very insensitive to price, likely due to time sensitivity. Similarly, trips paid for by a third party were also insensitive to price differences.	Chapter 2: Market Segmentations and Price Sensitivity
What proportion of TNC users are completely unwilling to consider taking a shared ride?	Almost 35 percent of TNC users would not share a ride for any price savings presented, even without any time penalty.	Chapter 2: Effect of Price on Sharing

Research Question	Key Findings	Technical Details
For which sorts of trips are TNC users most sensitive to differences in <i>travel time</i> between shared and private rides?	Trips to, from, or within dense office districts or areas with competitive transit, or trips to or from the airport or other intermodal travel centers were sensitive to differences in time, and thus were less likely to be shared.	Chapter 2: Relative Effect of Price and Time
What personal characteristics make a TNC user more likely to select ridesharing, based on other research?	Frequent sharers were more likely to be younger, unmarried, female, from zero-car households, and more frequent transit users.	Chapter 2: Ridehailing Versus Ridesharing
Could heterogeneity in user time and cost tradeoffs among shared product offerings enable TNCs to design additional such offerings that could lead to more sharing?	The high degree of heterogeneity in user preferences found in the study suggests that offering customers more than one shared product option with time delay and price points that vary could, if done in combination with vehicle routing decisions, increase the proportion of trips that are shared.	Chapter 2: Relative Effect of Price and Time
What factors limit carpooling adoption?	Convenience and trust issues are the two most critical factors that limit carpooling adoption.	Chapter 3: Overall Context
How effective are carpooling incentives in sustaining desired behavior among users of transportation apps that provide such incentives?	Incentives of only 2 cents per mile on the Hytch™ platform were effective at sustaining desired travel behavior. Monthly average awards of \$7.54 for participants receiving 2 cents per mile appear affordable when compared to other transportation investment options. Both Metropia™ and Hytch™ gradually reduced reward levels over time, with user engagement tending to hold stable or grow despite the reductions (although it plummeted when the elimination of rewards was tested).	Chapter 3: Impact of Rewards and Incentives using Examples from Hytch™ Chapter 3: Impact of Rewards and Incentives using Data from Metropia Driving Up Occupancy Platform

CHAPTER 1. PROJECT OVERVIEW

Governments and road users have a direct interest in ensuring efficient operations and use of highway investments and resources. Updated information regarding factors affecting growth of vehicle miles traveled (VMT) and remedies to curtail such growth—including both those within and those beyond government control and influence—would help guide improvements to highway efficiency.

With the proliferation of shared mobility options, it is becoming more important to extract and understand traveler behavior and decision choices (such as vehicle/mode, vehicle occupancy, service types, and times) and how various travel cost and performance factors can affect those choices. The goal is to grow the capability of service providers and governments to assess how changing the choice set provided to travelers can support shifts toward more efficient road use and travel patterns. It will also support the analysis of alternative future scenarios and their effects on travel choices and aggregate outcomes, such as congestion.

The central question posed in this project is: What influences a user’s decision between riding or driving alone versus a more transportation-system-efficient choice, and what specific financial- and travel-time-related levers can be brought to bear to influence this choice? A complicating factor around the central question is the complex public-private interplay between available “drive-alone” versus “shared-ride” mobility options.

PROJECT PURPOSE

In light of the larger central question, the purpose of this study is to gain a deeper understanding of the factors influencing traveler decisions about driving or taking a transportation network company (TNC) trip alone versus with others. The study focuses on learning about the tradeoffs among desired features of different travel options and trip price, and the potential effects of mode-shifting incentives and disincentives.

APPROACH AND METHODOLOGY

The study developed and/or used three major data source types—TNC surveys, app-based ridesharing data, and studies in the literature about behavioral responses to changes to the price of driving and parking. After general reporting of findings, the study developed, explained, and made available an analytic model that enables users to test their own scenarios nationally or in different U.S. locations. This report highlights a few sample case studies enabled by the assessment analytic model.

Survey of Transportation Network Company Users

In fall 2018, the research team was able to review data gathered by a large TNC, which administered a survey of its riders and provided related administrative data about trips. The TNC survey used a raffle-based incentive and targeted users who had scheduled a ride via the

company's app in the previous 24 hours. The survey targeted users of the company's traditional private ridehailing product and its ridesharing product.

Using the respondents' most recent trip as an anchor, the survey asked users questions about their choice of shared (ridesharing) or private ridehailing products and how that choice might have changed had they been presented with shared and private options at different prices and trip durations. The survey offered respondents a series of choices between their observed trip cost and travel time, and alternatives. Unlike a typical stated preference survey, trip alternative questions asked respondents to make decisions as if these options had been presented for their recent trip, which provided the respondents with realistic context anchored in a recent experience. The survey also asked respondents to provide information about their trip purpose, personal characteristics (e.g., annual income, age, gender), and travel behavior (e.g., car ownership, frequency of transit use) not available from the administrative data acquired.

The TNC administered the survey between November 26 and December 10, 2018, in 15 markets that have access to its ridesharing product: Atlanta, Austin, Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, Nashville, New York City, Philadelphia, Portland (Oregon), San Francisco, Seattle, and Washington, DC. The sample size in each market ranged from 154 (Nashville) to 761 (New York City). The TNC oversampled smaller markets to capture multiple population segments in these markets that could later be weighted to the true market size.

Analysis of App-Based Carpooling Use

While many app-based carpooling solutions are emerging, data on incentives and their impact on carpooling rates are hard to obtain. This study used data and analyses provided by two app developers (Metropia™ and Hytch™) to evaluate the impact of incentives on carpooling behavior. Findings from both apps are not representative of the other app-based carpooling systems in the marketplace. The significant variations in how each app-based carpooling solution interfaces with its users and in the incentive structures prevent the findings from these datasets from being generalizable. More importantly, the data gathered from both apps preceded this study, so the ability to conduct deliberate tests in line with research questions for this study was limited.¹ One important limitation was that travel choice data gathered via surveys prior to app use was not sufficiently specific to allow discernment of the degree of behavior change caused by incentives offered in the apps.

¹ FHWA requested that Metropia™ and Hytch™ each analyze data they had already gathered prior to this study in response to questions developed by FHWA for this study. FHWA describes the results of this analysis in Chapter 3 of this report. FHWA also used the analysis from Metropia™ as inputs in experimental scenario 4, as described in Chapter 4. Because such data were not initially gathered to answer FHWA's questions, however, FHWA did not consider it adequate for its use in the analytical model it subsequently developed that enables city-level policy assessments, which is described later in this document and is made available to the public as part of this research.

Literature Review on Driving/Parking Price and Behavioral Response

A series of studies was reviewed to arrive at an elasticity value to use to estimate the effect on mode share of increasing the relative cost of driving alone over carpooling in a set of metropolitan areas (the same metropolitan areas studied in the TNC survey).^{2,3,4,5} Both the effects of parking and non-parking costs were reviewed. In addition to these studies, the literature review analysis referred to the Trip Reduction Impacts of Mobility Management Strategies (TRIMMS) model from the Center for Urban Transportation Research at the University of South Florida. This provides another method for estimating the impacts of various transportation demand management (TDM) strategies, which itself cited Hymel, Small, and Van Dender, and Concas and Nayak for their demand elasticity values for non-parking and parking costs, respectively.⁶ Considering all these studies and reviews together, this paper proposes a benchmark travel price elasticity of -0.30 for drive-alone trips. This assumed elasticity affects all travel costs, which this paper calculates for each of the metropolitan areas included in the TNC survey using sources such as the American Automobile Association and City Observatory's *Price of Parking* tool.

Development of an Analytical Model for City-Level Scenario Assessments

The study formulated various scenarios seeking to understand the potential use of higher-occupancy modes. The scenarios were informed by research findings on the use of shared rides in the context of TNCs, app tools providing carpooling incentives, and price changes for personal vehicle travel. To evaluate the effect of these scenarios on ridesharing behavior, an analytic model was created to provide an understanding of how changes in trip cost and travel time affect mode choice for various market segmentations in different cities.

The analytic model was constructed in R (statistical open-source software) and R Shiny (a package for interactive web-based applications in R). The analytic model code, user instructions to run the model, and an example of model outputs are available at [Intelligent Transportation System \(ITS\) CodeHub](#),⁷ the U.S. Department of Transportation's (USDOT) portal for open-source ITS code.

² Shoup, D. (2005). *Planning Advisory Services Report Number 532: Parking Cash-out*, American Planning Association, Chicago, IL.

³ Concas, S. and Nayak, N. (2012). "A Meta-analysis of Parking Pricing Elasticity." Presented at the Transportation Research Board Annual Meeting.

⁴ Farber, M. and Weld, E. (2013). *Econometric Analysis of Public Parking Price Elasticity in Eugene, Oregon*, Thesis, University of Oregon, Eugene, OR.

⁵ Litman, T. (2013). *Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior*, Victoria Transport Policy Institute.

⁶ Hymel, K.M., Small, K.A., and Van Dender, K. (2010). "Induced Demand and Rebound Effects in Road Transport." *Transportation Research Part B: Methodological*, 44, pp.1220–1241.

⁷ The direct link to the project information on ITS CodeHub is <https://doi.org/10.21949/1520429>

Readers can download the code from the ITS CodeHub and run the analytic model to further explore the findings of the research in this report. Readers can conduct tests of a preferred policy scenario at a particular price point for one of the fifteen cities included in the model.

DOCUMENT ORGANIZATION

The rest of the document is organized as follows:

- Chapter 2 provides an overview of research findings related to sharing rides in an environment of on-demand ridehailing.
- Chapter 3 provides an overview of research findings related to sharing rides encouraged by app tools providing carpooling incentives.
- Chapter 4 describes various scenarios for time and cost differentials and their associated impacts on the likelihood of sharing rides.
- Chapter 5 describes the implications to cities based on the findings of this project.
- Chapter 6 identifies potential areas for future research beyond the scope of this study.

CHAPTER 2. SHARING RIDES IN AN ENVIRONMENT OF ON-DEMAND RIDEHAILING

OVERALL CONTEXT

Over the past decade, transportation network companies (TNC) like Uber™ and Lyft™ have replaced, supplemented, and disrupted traditional modes of transportation with their on-demand ridehailing services. In 2014, these TNCs introduced dynamic *ridesharing* products such as UberPool™ and Lyft Shared™ (formerly known as Lyft Line™).

While most TNCs primarily offer private ridehailing service in which a driver is paired with a single rider (or party of riders), many companies have also offered ridesharing services that pair multiple riders (or parties) on shared, overlapping trips with the same driver. While the terms “ridehailing” and “ridesharing” are often used interchangeably, this research holds that the terms have distinct meanings and this document uses them accordingly. Ridehailing refers to all TNC services. Ridesharing applies only to hailed rides where riders elect a product that may pair them with one or more other travelers en route. Ridesharing refers to all trips during which a user’s product choice indicates a willingness to share, even if they are not paired with another party. This report refers to the balance of ridehailing trips for which users do not opt into a potential multi-party trip as private ridehailing.

Increasing ridesharing relative to private ridehailing is of interest to policymakers to promote more efficient use of the transportation network. It is critical to understand which riders are adopting these services and in what contexts. While transportation researchers have analyzed ridehailing behavior in general, the literature describing ridesharing trips and users or the effect of trip cost and travel time on a rider’s choice between a shared or private TNC trip is much more limited. To strengthen the understanding of this specific segment, the research reported on for this study provides (1) a descriptive analysis of ridesharing trips and users in 15 American cities, and (2) a scenario-based analysis of the effect of differences in relative trip price and travel time between private and shared TNC trips on vehicle miles traveled (VMT) in an urban and metropolitan context. The survey data described in this chapter informs a broader study of shared ride scenarios, presented in chapter 3. As described more fully in the approach section, this research differs from other survey efforts, as this directly involved a major TNC which provided administrative detail and reached ridehailing service users within one to two days of a recent trip. Because of this survey targeting and additional data, detailed context and personalized questions were possible.

Ridehailing Literature

There is a growing body of literature on TNC use and users in American transportation markets. This literature can be divided into two categories: those that describe ridehailing users broadly and those that characterize ridesharing users more specifically.

Ridehailing Users

Most ridehailing literature does not distinguish between private and shared products. Typically, this product detail is not available in the data sources (usually surveys) utilized by researchers, either because the data were collected for another purpose unconcerned with this distinction or these newer products were not offered at the time of collection.

The 2017 National Household Travel Survey (NHTS)—the first to ask respondents about TNC use—is one important source used by scholars to characterize ridehailing users. Using this data, Schaller found that most TNC users are located in nine large, densely populated metropolitan areas and predominantly affluent, well-educated, and young.¹ Conway, Salon, and King used the same data to identify correlations between higher ridehailing use and greater transit/nonmotorized travel, higher residential density, and lower vehicle ownership.² One important limitation of using the NHTS to study ridehailing use is that trip locations are sampled at the metropolitan level (i.e., core-based statistical area), so it is not possible to distinguish trips that occur in the urban core versus more suburban locations. Geographic coverage areas for Lyft and Uber are typically defined broadly and are treated as such in this study (e.g., the Chicago TNC market is not just the City of Chicago, but several surrounding counties as well). TNC trips are more prevalent in city centers than in outlying areas of a metropolitan region, meaning that decisions made at the city-level to encourage more shared trips will impact a larger proportion of vehicles in a city than is implied by the results reported here.

Beyond the 2017 NHTS, other studies have used online, in-vehicle, or on-street intercept surveys to characterize TNC users according to age, income, education, vehicle ownership, trip purpose, and gender. Henao found a correlation between ridehailing and certain trip types, namely social and airport trips (among TNC users who are also frequent drivers) and work and school trips (among TNC users who are not frequent drivers).³ Rayle et al. and Schaller found that non-car owners are overrepresented among TNC users.^{4, 5}

Studies in the U.S. show TNC users are younger, better educated, higher-income individuals than the average American. Clewlow and Mishra found younger, college-educated, affluent Americans have adopted ridehailing more quickly than older, less educated, lower income populations.⁶ Young and Farber’s examination of household travel survey data characterized ridehailing as a “wealthy younger generation phenomenon.”⁷ Kooti et al. described the average

¹ Schaller, B. (2018). *The New Automobility: Lyft, Uber, and the Future of American Cities*.

² Conway, M.W., Salon, D., and King, D.A. (2018). “Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the U.S. National Household Travel Survey.”

³ Henao, A. (2017). *Impacts of Ridesourcing—Lyft and Uber—on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior*.

⁴ Rayle, L., Dai, D., Chan, N., Cervero, R., and Shaheen, S. (2016). “Just a Better Taxi? A Survey-Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco.”

⁵ Schaller, B. (2018).

⁶ Clewlow, R.R. and Mishra, G.S. (2017). *Disruptive Transportation: The Adoption, Utilization and Impacts of Ride-Hailing in the United States*.

⁷ Young and Farber (2019).

active TNC user as “an individual in his or her mid-20s with an above-average income.”⁸ The authors found older riders use ridehailing services less frequently but take longer rides; higher-income riders take more rides and are more likely to use more expensive ridehailing products.

Studies differ in their assessment of whether ridehailing users are predominantly male or female. In a meta-analysis, Moody and Zhao provide a complete summary of travel survey studies focused on the sociodemographics of ridehailing patrons in the U.S. and Singapore.⁹ Their extensive literature review considers the impact of age, income, education, gender, and car ownership on the number of times a month individuals use ridehailing services. The authors confirm use is generally higher among younger, more educated, and more affluent individuals.

Beyond descriptive research, studies have estimated predictive models with similar parameters and implications. Dias et al. used household travel surveys from metropolitan Seattle to create a model estimating adoption and frequency of ridehailing and carsharing use.¹⁰ Alemi et al. surveyed over 2,000 ridehailing users in California about their use of TNCs to create a model of ridehailing use.¹¹ The model developed by Dias et al. found higher vehicle ownership and greater residential density to be correlated with ridehailing/carpooling use, while Alemi et al. found that increased land use diversity, and centrality are associated with higher adoption of these services. Alemi et al. found that use of other newer transportation services (bikesharing, carsharing) and technology (online shopping, social media) were predictors of TNC use. Both papers found adoption was positively correlated with income, education, and employment status and negatively correlated with age and presence of children.

Ridehailing Versus Ridesharing

Despite the growing body of ridehailing literature relying on travel surveys and mode choice models, very few studies distinguish between types of ridehailing service. This report identifies four noteworthy exceptions.

Amirkiaee and Evangelopoulos considered users’ motives in ridesharing (i.e., cost, time, anxiety, trust, and reciprocity), but did not report demographics of respondents.¹² Additionally, their research analyzed respondents’ intention to use ridesharing, but did not collect data on actual observed trips.

⁸ Kooti, F., Grbovic, M., Aiello, L.M., Djuric, N., Radosavljevic, V., and Lerman, K. (2017, April). “*Analyzing Uber’s Ride-sharing Economy.*”

⁹ Moody, J. and Zhao, J. (2019). “Adoption of Private and Shared Ridehailing in Singapore and the U.S.”

¹⁰ Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendayala, R.M., and Bhat, C.R. (2017). “*A Behavioral Choice Model of the Use of Car-sharing and Ride-sourcing Services.*”

¹¹ Alemi, F., Circella, G., Handy, S., and Mokhtarian, P. (2017). “What Influences Travelers to Use Uber? Exploring the Factors Affecting the Adoption of On-Demand Ride Services.”

¹² Amirkiaee, S.Y. and Evangelopoulos, N. (2018). “*Why Do People Rideshare? An Experimental Study.*”

Sanriera et al. analyzed a survey of TNC users that asked about recent use of UberPool™ and Lyft Line™.¹³ They found that younger, unmarried, non-car-owning individuals were more likely to have used ridesharing options; income and gender did not have a significant effect on ridesharing opt-in; and the majority of ridesharing trips were for leisure, rather than commuting or airport access. Respondents' most common motivations for ridesharing were cost savings and speed and comfort compared to transit and walking. The top deterrents to sharing were lack of privacy, uncertainty about travel time, and fear of being paired with an unpleasant passenger.

Moody, Middleton, and Zhao found TNC users who are younger and employed are more likely to have used ridesharing (they analyzed the same survey data as Sanriera et al.).¹⁴ All other sociodemographic characteristics were not significantly predictive. For the subset of respondents who had used a ridesharing service, students, respondents with graduate degrees, and those who were unmarried reported the highest percentage of their ridehailing trips being shared.

Liu et al. created a mode choice model that incorporated ridehailing and ridesharing alongside traditional modes by collecting stated preference data in New York City.¹⁵ The model estimates the effects of travel time, trip cost, and other factors on mode choice, but does not incorporate other characteristics of the traveler or trip. This is the only mode choice survey analysis that included both shared and private TNC trips in the United States at the time of this writing.

Two recent studies have considered the role of pricing and travel time in the choice between private and shared TNC trips. First, Alonso-González et al. used a stated preference experiment to analyze individual willingness to share by comparing preferences towards individual and pooled rides in the Netherlands.¹⁶ Considering price, time, and privacy, the study found that up to 85 percent of users were willing to share rides with one to two extra passengers in cases without a time penalty and with a 3-euro price difference between private and shared rides. However, the study also identified a class of travelers—29 percent of their sample—that resist sharing, have a high value of time (VOT), and strongly prefer individual rides. Second, Hou et al. used the anonymized TNC trip, vehicle, and driver data from the City of Chicago to estimate customers' willingness to share.¹⁷ Controlling for factors like trip purpose, population density, distance, and travel time, the authors found that the price difference between private and shared trips had a relatively small effect on willingness to share; a 10 percent increase in the difference leads to 0.82 percent increase in sharing.

The goal of this research is to add to this limited literature on shared ridehailing choices in the United States by reporting on new surveys linked to actual TNC trips, both shared and private.

¹³ Sanriera, J.M., Álvarez, G.E., Blynn, K., Alesbury, A., Scully, T., and Zhao, J. (2017). *"To Share or Not to Share: Investigating the Social Aspects of Dynamic Ridesharing."*

¹⁴ Moody, J., Middleton, S., and Zhao, J. (2019). *"Rider-to-Rider Discriminatory Attitudes and Ridesharing Behavior."*

¹⁵ Liu, Y., Bansal, P., Daziano, R., and Samaranayake, S. (2018). *"A Framework to Integrate Mode Choice in the Design of Mobility-on-Demand Systems."*

¹⁶ Alonso-González, M., Cats, O., Van Oort, N., Hoogendoorn-Lanser, S., and Hoogendoorn, S. (2019). *"Willingness to Share Rides in On-demand Services for Different Market Segments."*

¹⁷ Hou, Y., Garikapati, V., Weigl, D., Henao, A., Moniot, M., and Sperling, J. (2020). *"Factors Influencing Willingness to Share in Ride-Hailing Trips."*

SURVEY APPROACH AND DATA PREPARATION

The TNC's survey of its users collected several types of data, including preferences for trip alternatives and data on observed trips (which the TNC appended to the survey results). The survey also asked respondents to provide information about their trip purpose, personal characteristics (e.g., annual income, age, gender), and travel behavior (e.g., car ownership, frequency of transit use) that were used in the discrete choice modeling and market segment analysis described later in this chapter.

Trip Alternative Questions

The data collection process combined data on observed trips and stated preference responses to trip choice questions. Survey respondents were divided into two branches: those who used private ridehailing for their most recent ride and those who used ridesharing. In each branch, respondents reviewed combinations of shared ride prices and travel times relative to a private ridehailing trip. For recent private trip takers, the comparison trip was their observed trip. For shared trip takers, the comparison trip approximated the private trip they were offered when they selected a shared ride, based on price differentials and travel times. Prices of hypothetical trips ranged from 15 to 150 percent of the observed trip and travel times ranged from 70 percent to 155 percent of the observed trip. Ridesharing times were presented as a range, reflecting how shared trips are displayed in the smartphone app.

The survey presented respondents with combinations of price, time, and mode (private or shared), referred to collectively as a "card." Each question asked users to select one card from a trio of cards, as shown in table 2 and table 3. For private TNC users, each set of options compared the observed trip cost and time to various levels of price differentials and time penalties for hypothetical shared trips. The price differentials were intended to represent a typical shared discount (35 percent of the observed private price) and two higher discounts (50 percent and 75 percent).¹⁸ The various time penalties also include a typical time penalty alongside higher and lower options.

For shared TNC users, each set of options compared the approximated private trip cost and travel time to various levels of cost and time that were either more or less attractive than the observed shared ride. The comparison levels were set to represent the typical case (a private TNC trip at 150 percent the price of a shared ride with travel time 70 percent as long), and the objective of the survey was to understand at what level of service these known users would stop choosing the shared product. Table 2 shows examples of how the cards were presented as choice questions. Private TNC users were asked 13 questions and shared ride users 16 questions.

Table 3 displays the price and time levels presented for shared and private TNC users. For shared TNCs, alternative times were presented as a range as is typical within the app. Card 1 served as the comparison private trip for most choice sets. Time penalty caps were enforced to ensure the shared TNC times presented were realistic.

¹⁸ Hou et al. found that median shared rides in Chicago cost approximately 66 percent the cost of a private ride.

Table 2. Alternative options examples. (Source: Federal Highway Administration)

Variable	Example 1: Private Transportation Network Company (TNC) Users			Example 2: Shared TNC Users		
	Option 1 (Observed)	Option 2	Option 3	Option 1 (Observed)	Option 2	Option 3
Price	\$25	\$16	\$13	\$16	\$22	\$24
Time	30 min	35-39 min	44-47 min	39 min	32-34 min	27 min
Mode	Private	Shared TNC	Shared TNC	Shared TNC	Shared TNC	Private

Table 3. Characteristics of cards presented to private and shared transportation network company users in trip alternative analysis. (Source: Federal Highway Administration)

Private Transportation Network Company (TNC) Users				Shared TNC Users			
Card	Price Relative to Observed	Time Relative to Observed	Mode	Card	Price Relative to Observed	Time Relative to Observed	Mode
1	100%	100%	Private	1	150%	70%	Private
2	65%	100%	Shared	2	100%	100%	Shared
3	50%	100%	Shared	3	100%	81-91%	Shared
4	15%	100%	Shared	4	100%	91-102%	Shared
5	65%	115-130%	Shared	5	120%	100%	Shared
6	50%	115-130%	Shared	6	120%	81-91%	Shared
7	15%	115-130%	Shared	7	120%	91-102%	Shared
8	65%	125-150%	Shared	8	135%	100%	Shared
9	50%	125-150%	Shared	9	135%	81-91%	Shared
10	15%	125-150%	Shared	10	135%	91-102%	Shared
11	65%	145-165%	Shared	11	120%	70%	Private
12	50%	145-165%	Shared				
13	15%	145-165%	Shared				

Appended Data on Observed Trips

In addition to the TNC users' anonymized survey responses, the TNC provided the research team with the following data on respondent behavior for each survey response:

- The frequency which the respondent opted into the shared ride option between July and November 2018 relative to all users in the market.
- The frequency which the respondent used the TNC's services between July and November 2018 relative to all users in the market.
- The length of the user's most recent trip relative to all trips in the market.

- The share of a user's TNC trips for which the user opts in to shared rides, classified according to three levels: frequent (greater than 50 percent of trips), sometimes (10 to 50 percent), and rarely (less than 10 percent).
- The price charged for the user's most recent trip.
- The travel time of the user's most recent trip.

The first three items were provided as the quantile in which the data fell for the distribution of that measure in each of the 15 markets. The TNC partner appended the following variables from the Environmental Protection Agency's (EPA's) Smart Location Database to describe the built environment surrounding the pick-up and drop-off locations of each survey response:

- Gross residential density (housing units/acre) on unprotected land.
- Gross retail and entertainment employment density (jobs/acre) on unprotected land.
- Gross office and industrial employment density (jobs/acre) on unprotected land.

The TNC did not attach the exact value for these variables to each survey response, but rather categorized quantiles for each variable: less than 50 percent, 50 to 80 percent, 80 to 90 percent, 90 to 95 percent, and greater than 95 percent. These quantiles refer to the relative density of locations within a given market, rather than relative density at a national level.

Sample Cleaning

The complete dataset included 5,373 unique survey responses. To ensure validity and applicability of the data collected for the research questions, the research team, in conducting its analysis, removed invalid or inapplicable responses and weighted the remaining responses to the surveyed population. The following filters were used to limit records used for further analysis:

- Trip distance and price must be greater than 0 (to eliminate trips that were not completed).
- The group size reported by the trip's driver must be 1 or 2 passengers (shared options are available only to groups of 1 or 2 passengers, so data about larger traveler parties were not applicable to this study).
- The respondent must have taken at least one trip with the TNC in the respective survey market between July and November 2018 or must have indicated that he/she was a visitor (otherwise no data were available to weight based on frequency of opting in to sharing and the data were unusable).

This filter resulted in the removal of 625 responses, for a sample size of 4,748. In addition to the filters above, responses were tested for logical consistency in preferences between the ridehailing options presented. The checks identified users who chose an option that was strictly inferior to another in terms of both travel time (i.e., slower) and cost (i.e., more expensive). To ensure users completed the survey with attention and thoughtfulness, responses failing two or more checks were removed.

Screening responses with these filters resulted in removing an additional 383 responses (for a total of 1,008) and produced a final dataset of 4,365 responses. While this process resulted in the removal of a high number of screened responses (approximately 18.8 percent), this level is similar to other online surveys of TNC users.¹⁹

Data Weighting

To produce generalizable findings, survey samples must match the characteristics of the population surveyed. For this reason, the research team applied data weighting techniques to the survey sample to make it more representative of the population of TNC users across the markets studied. The team weighted responses in a two-step process: *within* TNC markets and *between* TNC markets.

Within each of the 15 markets studied, responses were weighted to match five characteristics: users' sharing opt-in rate, users' number of TNC trips taken, trip distance, trip day of the week, and trip time of day. This approach required the appended quantile information described above as well as data on the share of trips within each market by day of the week and time of day and appended day-of-week and time-of-day information for the survey anchor trip. The team applied an iterative proportional fitting model to the survey data distributions to calculate weights that matched distributions of these five characteristics in the survey responses to the population distributions of each market as closely as possible. The team trimmed weights to prevent the outsized influence of specific responses. After weighting within each market, the team used data from the TNC on the number of active users within each market to weight responses between markets.

Weighted data on respondents and their trips was then used to conduct the market segmentation analysis described in the following section. Before turning to that analysis and results, a final data preparation step for the choice analysis warrants description.

Discrete Choice Model Development

In the discrete choice analysis, the unit of analysis is not the observed trip, but each choice of a private or shared TNC ride presented in the trip alternative portion of the survey. Because each respondent answered many triplet questions and each question represented two preferences (the selected card over two unselected cards), the 4,365 valid responses produced 110,320 choice observations.

Because of the structure of the choice question triplets, each observation represented one of three choice types: private over shared, shared over private, or one shared option over another. The last choice type was discarded from analysis (although later revisited) because it did not represent the choice between sharing and not sharing, but rather preferences for time and cost in shared TNC rides (additionally, some shared options were strictly preferable to others in terms of both time

¹⁹ Moody, J., Middleton, S., and Zhao, J. (2019). "*Rider-to-Rider Discriminatory Attitudes and Ridesharing Behavior.*"

and cost). The result was 79,667 usable observations. These choice observations were associated with the full data for each respondent and weighted appropriately.

The research team used the dataset of 79,667 choice observations to build several discrete choice models. In each model, the dependent variable is the binary shared–private product choice. The mode used for the observed trip on which the choice survey was based was not used as a dependent or predictor variable in these models.

As a first step in the discrete choice analysis, the research team created a series of univariate models that estimated correlations between trip and user characteristics (i.e., predictor variables) and the choice of mode (private or shared) for each observation. These univariate models considered the following predictor variables:

- Shared TNC cost savings per trip
- Shared TNC travel time penalties per trip
- Shared TNC cost savings per mile
- Shared TNC travel time penalties per mile
- Level of shared TNC cost savings (see table 1)
- Level of shared TNC travel time penalty (see table 1)
- Trip distance
- Group size
- Availability of express option
- Day of week
- Time of day
- Trip purpose
- Origin type
- Destination type
- Market (i.e., city)
- Visitor status
- Whether trip was paid for by an employer
- Land use characteristics of origin
- Land use characteristics of destination
- Annual income
- Age
- Gender
- Car ownership
- Transit use
- Bicycle use
- Household size and composition

Trip distance, cost savings, and travel time penalties were treated as continuous variables. Cost savings and travel time penalties (per trip and per mile) are particularly important predictor variables in this project. These variables were calculated as the cost and time difference between the preferred and the rejected travel alternative (in all cases, one alternative was a private TNC trip and the other a shared TNC trip). Because travel times were presented as a range for shared TNC trips, the travel time penalties were calculated based on the midpoint of the range presented. Although the uncertainty implied in the range may have affected each respondent's decision, the design of the survey did not allow for consideration of this uncertainty, so midpoints were used for the analysis instead. It is possible, though, that users focused on the longest time presented for each trip option, in which case using that time instead of the midpoint would make sense, but we lack evidence of this and thus chose to use the midpoint values.

The team treated all other predictor variables as discrete variables or multiple binary variables in the various univariate logit models. Annual income, for example, was classified according to five levels (e.g., less than \$50,000, \$50,000 to \$75,000, etc.). Household composition, on the other hand, was classified as a set of binary examples (e.g., one child, no children, many children).

Because the dependent variable in each of these models is a binary outcome variable (whether a user selected the shared option for the hypothetical choice), the team used logistic regression for the discrete choice models of the logit form. Logit models estimate the log-odds of an outcome as a linear combination of predictor variables that can have positive or negative effects on the probability of sharing. The logit model is specified by a set of coefficients and the ability to calculate standard errors and associated p -values for each predictor variable. These values can indicate whether the variable has a significant effect on the dependent variable. The coefficients describe the change in the log-odds outcome for a one unit increase in the predictor variable. Using exponentiated coefficients, it is possible to observe the impact of each of the above predictor variables on the probability of sharing.

The research team tested various combinations of predictor variables in a series of multivariate models. Initial models were constructed based on predictor variables shown to have significant effects in the univariate models and refined in order to identify the combinations of variables that best predict choice, measured using the Akaike information criterion, a measure of logit model fit. The team explored nine logit models in depth as listed below:

- Model 1: Shared TNC cost savings and travel time penalties.
- Model 2: Shared TNC cost savings per mile and travel time penalties per mile.
- Model 3: Shared TNC cost savings and travel time penalties and market/city indicators.
- Model 4: Shared TNC cost savings and travel time penalties and market/city characteristics (e.g., population density, employment density).
- Model 5: All categorical variables found significant in univariate discrete choice models.
- Model 6: All categorical variables found significant in model 5.
- Model 7: Shared TNC cost savings and travel time penalties and all variables in model 5.
- Model 8: Shared TNC cost savings per mile and time penalties per mile and all variables in model 5.
- Model 9: Shared TNC percent of observed cost and time (categories from table 3) and all variables in model 5.

Furthermore, the research team divided the data into subsets in various ways to calculate these effects according to population segments of interest from a policy perspective. For each segment, the models above were estimated for the specific population of interest.

These segments include:

- Annual income (less than \$50,000, greater than \$50,000).
- Relative office and industrial employment density for the market at the origin and destination (less than 90th percentile of the metropolitan area, greater than 90th percentile).
- Regional centrality index by transit, relative to automobile centrality at the origin and destination (less than 90th percentile of the metropolitan area, greater than 90th percentile).²⁰
- Trips to and from airports or other intermodal hubs.

Calculating coefficients for each of these segments allowed the research team to observe how population-level characteristics affect willingness to use a shared TNC and to identify the market segments where an intervention (for example, via a targeted incentive) would have the greatest effect.

Passenger Occupancy in Private Rides

While this chapter describes differences between private (i.e., ridehailing) and shared (i.e., ridesharing) rides, it is worth noting that private rides often have a passenger occupancy of greater than 1. Some ridehailing vehicles, for example, have the capacity for up to 6 passengers in one private party. Shared ride parties, meanwhile, are restricted to either a single passenger (most common) or a single passenger and 1 companion (which typically requires payment of a small additional fee that reduces the price difference between private and shared rides).

The survey data gathered by the TNC allowed for analysis of passenger occupancy in private rides. Doing so requires a slightly different dataset than the one used in the rest of the analysis described in this chapter. Specifically, the data were re-filtered to include only private trips and to include party sizes greater than two riders (which had been previously omitted to account for the fact that such parties are not eligible for ridesharing). This re-filtering produced a new dataset with 3,518 observations.

In the survey, respondents described their party size as “On my own,” “1 other person,” or “2 or more other people.” Table 4 summarizes party size according to these three levels. Because the level “2 or more other people” includes parties of 3 or more, it is not possible to calculate average occupancy precisely. However, knowing that all users traveling with “2 or more other people” represents party sizes of at least three, then the average occupancy of a private ride (not including the driver of course) is *at least* 1.462. If, as is more likely, it is assumed that parties greater than 2 have an average occupancy of 3.1, then the average occupancy increases to 1.475.

²⁰ This value is the ratio of the EPA’s Smart Location Database’s Regional Transit Centrality Index (D5dei) to the Regional Automobile Centrality Index (D5cei). Both D5dei and D5cei represent a Census Block Group’s modal destination score relative to the maximum score for the core-based statistical area.

Table 4. Share of adjusted survey data at three occupancy levels for private ridehailing trips (n = 3,518). (Source: Federal Highway Administration)

Party Size	Share of Observed Trips (Weighted)
“On my own”	64.2%
“1 other person”	21.5%
“2 or more other people”	13.0%

This estimate is compatible with findings from other research. Henao and Marshall found, for example, an average occupancy of 1.37 using data collected from 416 ridehailing rides (private and shared).²¹ While this estimate is somewhat lower than the occupancy presented above, Henao and Marshall include shared rides in their survey, which counterintuitively lowers the average occupancy per party-trip by restricting party size to 2.

This average occupancy makes even private ridehailing rides more favorable from an occupancy perspective than personal vehicle trips, but it is also worth noting that these estimates do not account for the miles that a driver spends without a passenger between rides (i.e., deadheading miles). Balding et al. estimate the share of TNC VMT without a passenger to be 42 percent. Using this estimate, factoring the miles in which the passenger occupancy of a TNC vehicle is zero into occupancy results, leads to an effective occupancy for private ridehailing trips of approximately 0.855 (assuming that parties greater than 2 have an average occupancy of 3.1).²² For comparison, Henao and Marshall used an estimate of 40.8 percent deadheading miles, which reduced their average vehicle occupancy from approximately 1.4 to approximately 0.8.²³

Limitations of Approach

Using our broad sample of 4,365 ridehailing users living in areas where on-demand ridehailing is available, this research shows (1) which market segments in our weighted sample opted in to shared and private modes more or less frequently, and (2) how differences in price and travel time may affect ridesharing behavior. Before presenting these findings in greater detail, several limitations to the methodological approach warrant attention.

First, the data presented here are only a snapshot in time of a TNC user base that is growing and changing rapidly, with a 37 percent increase from 2016 to 2017 in passengers transported.²⁴ As this user base evolves and TNCs alter their services, this analysis will need to be updated to reflect the point-in-time reality of travel behavior. Longitudinal/panel research would support an understanding of how sharing behavior changes over time.

²¹ Henao, A. and Marshall, W.E. (2018). “The Impact of Ride-Hailing on Vehicle Miles Traveled.”

²² Balding, M., Whinery, T., Leshner, E., and Womeldorff, E. (2019). “*Estimated TNC Share of VMT in Six US Metropolitan Regions (Revision 1)*.”

²³ Henao, A. and Marshall, W.E. (2018).

²⁴ Young and Farber (2019).

Second, regarding the scenario evaluation and the supporting discrete choice analysis, results are limited by trip alternative questions asked in the TNC's survey. That is, this study does not have data to evaluate the effects of price and time differences that exceed those presented in Table 3 (i.e., maximum shared/private TNC price differential of 75 percent). It is not possible, for example, to analyze the effects of free shared TNC trips on the rate at which people choose to use shared TNCs. Also, because cards were generated based on set levels of discount relative to the observed trip, data are not granular enough to truly calculate non-linear effects that might exist even within the range tested.

Third, the survey results do not address interactions across all modes. For that reason, this study can estimate how price and time affect a user's choice between a private and shared TNC ride, but it cannot estimate how price and time affect a user's choice between TNCs, transit, driving, carpooling, walking, bicycling, or any other mode. This research provides previously unavailable detail on shared versus private TNC rides but does not analyze how changes to shared or private rides might affect, for example, transit use. Similarly, the study has no data to consider how TNC characteristics affect a user's decision to take a trip in the first place. Naturally, TNC users face many travel decisions beyond whether to share a TNC ride. Nonetheless, the results presented below focus narrowly on this one decision by assuming, for the sake of analysis, that travelers make decisions between personal cars, TNCs, transit, and active transportation before making decisions about shared versus private for-hire vehicles. If price and time differentials change between private and shared ridehailing in such a way that average ridehailing trip costs and travel times do not change significantly, it is likely that the overall TNC mode share will not change significantly either.

Finally, although this anchored stated preference approach provides unique insights into choices to share, caution is still recommended when relying on reported preferences (even though "anchored") rather than observational or experimental data. There is no guarantee that respondents' reported choices would have matched their real-world choices had each of the options been available; the TNC's survey did not fully replicate customers' in-app decision-making process. Furthermore, the survey relied on respondents' memories of the observed trip and some customers may have forgotten any number of factors that influenced their actual decision, such as weather, peer pressure, or the urgency of their trip, despite the trip having taken place only within the previous 24 to 48 hours.

With these limitations in mind, the results presented in the following two sections seek to shed light on how travelers chose to take shared or private TNC trips.

ANALYSIS OF MARKET SEGMENTS

The weighted survey data supported the division of respondents into market segments with different propensities to choose ridesharing products. Dividing up market segments allows identification of segments with greater opportunity for mode shift. The research team sought to (1) identify, using personal characteristics, meaningful segments of people who share or show a willingness to share at different frequencies across their total trips, and (2) identify, using trip and built environment characteristics, meaningful segments of trips that are shared or where there is a willingness to share at different frequencies.

The research team selected the following segments for their policy relevance and observed impact on behavior:

- Personal characteristics:
 - Age: under 25 years old, 25 to 45 years old, over 45 years old.
 - Annual income: less than \$50,000; \$50,000 to \$99,999; \$100,000 to \$149,999; greater than \$150,000.
 - Weekly transit use: 0 days, 1 to 2 days, 3 or more days.
 - Household car ownership: 0 cars, 1 car, 2 or more cars.
 - Gender: male, female, or prefer not to respond.
- Trip characteristics:
 - Whether the rider or the rider's employer paid for the observed trip.
 - Size of the traveling party: 1 or 2.
 - Day of the week: weekdays (Monday through Friday) and weekends (Saturday and Sunday).
 - Time of trip start: morning (6:00 to 9:59 a.m.), midday (10:00 a.m. to 2:59 p.m.), late afternoon and evening (3:00 to 7:59 p.m.), and night (8:00 p.m. to 5:59 a.m.).
 - Trip distance: short (less than 5 miles), medium (5 to 15 miles), or long distance (greater than 15 miles).
 - Origin: home, work, personal business, entertainment, or airport/train/bus.
 - Destination: same categories as origin.
- Built environment characteristics for the beginning and end of each trip (city specific):
 - Relative residential density.
 - Relative retail/entertainment density.
 - Relative office/industrial employment density.

Regarding the origin and destination sub-bullets under "Trip characteristics" above, data were derived from questions asking respondents to describe their origin and destination according to one of the following types: "Your home or current residence"; "A workplace, worksite, professional meeting, or school"; "An entertainment, recreation, or social venue"; "Another location for personal business"; or "An airport, inter-city bus terminal, or train station."

The research team divided respondent data into the respective segments. For each segment, the team summed the weights for respondents at each opt-in level (for personal characteristics) or for private/shared trips (for trip characteristics and built environment characteristics). These sums were divided by the total of respondents in each category. The resulting shares are plotted as histograms in the following sections. The research team used the Pearson's Chi-squared test for the absolute counts of the segmented populations to test whether the distributions of each

population (users who frequently, sometimes, or rarely share; shared and private trips) were statistically different. All segments listed above were significant at the 95 percent confidence level except for trip distance.

Frequency of Sharing by User Characteristic

The administrative data for this research contains three levels of long-term sharing behavior among users: rarely (less than 10 percent of trips), sometimes (10 to 50 percent of trips), or frequent (greater than 50 percent of trips). These frequency levels are based on all trips that a user took through the ridehailing app between July and November 2018. Those who rarely share account for 30 percent of the weighted data; those who sometimes share, 45 percent; and those who frequently share, 25 percent. The research addresses five dimensions through which statistically significant and interesting differences in sharing can be identified: gender, vehicle ownership, transit use, annual income, and age.

Figure 1 summarizes the respondents' frequency of opting in to ridesharing according to these five user characteristics. Females, representing 58.5 percent of the weighted survey responses, represent about 66 percent of users that choose shared products more than 50 percent of the time, making them far more likely to be "frequent" or "sometimes" sharers than the men in the sample.

Frequent sharers are most likely to be from zero-car households than from households with one vehicle or multiple vehicles. Respondents who share less than 10 percent of the time are most likely to have two or more vehicles. Riders who share more often also tend to use transit more. Over half of riders who frequently share also use transit more than three times a week. For riders that rarely share, over 50 percent of them responded that they use transit zero times per week.

A significantly larger proportion of frequently-sharing respondents comes from households with under \$50,000 of annual income. Sometimes- and rarely-sharing respondents are much more likely to have annual incomes over \$100,000 per year. Users with annual income between \$50,000 and \$100,000 are more equally divided among those who rarely share, those who sometimes share, and those who frequently share.

Riders who share frequently in the sample tend to be younger. The majority of all users, including from all three sharing groups, are 25 to 45 years old. The proportion of frequent sharers under 25 is nearly twice the proportion of rarely sharing users under 25.

Distribution of Shared and Private Trips by Trip Characteristic

Just as respondents' characteristics affect respondents' willingness to share across trips, details of their surveyed trip were expected to influence their choice for the specific trip surveyed. Shared trips accounted for 28 percent of the weighted sample, while private trips accounted for 72 percent. While many trip characteristics were found to be statistically significant, trip distance was not found to have a significant effect. Figure 2 summarizes the distribution of observed trips according to the product used: shared or private.

The weighted sample demonstrated a greater proportion of shared trips in several market segments. Examples include solo trips, weekend trips, trips from work, trips home, and trips to entertainment or personal business.

Conversely, the study observed a greater proportion of private trips in several market segments. Examples include trips by parties of 2, weekday trips, morning trips, short distance trips (less than 5 miles), trips to work, and trips to or from intermodal travel nodes (i.e., airports, train stations, and bus terminals). The study also observed less sharing for trips paid for by an employer and found that respondents taking employer-paid trips are much less price sensitive than those who pay for their own travel.

Distribution of Shared and Private Trips by Built Environment Characteristic

Three built environment characteristics measure different forms of density: residential, office/industrial employment, and retail/entertainment employment. As noted previously, these density measures were calculated individually for the 15 markets, so that the 10th percentile zone in New York is much denser than the 10th percentile zone in Nashville or Portland. These density measures were studied for both trip origins and destinations to understand if there were specific markets, such as trips to work, for which sharing was more common. Of the six distributions, four are statistically significant; end-of-trip residential density and beginning-of-trip retail/entertainment density are not. Like figure 2, figure 3 summarizes the distribution of observed trips according to the product used and the built environment of trip origins and destinations.

The densest areas (90th to 100th percentile of the metropolitan area) account for disproportionately large shares of trip origins and destinations across all three measures, for shared and private trips. The skewing is especially high toward employment with around 45 percent of all trips coming from the densest 10 percent of retail/entertainment and office/industrial zones. About 30 percent of trips end or start in the densest 10 percent of zones by residential population. These findings support the conclusion that TNC use is greatest in the densest parts of metropolitan areas, but many trips connect dense employment areas to less dense residential areas (likely outside urban cores).

In the weighted sample, a greater proportion of shared trips is observed for trips starting or ending in the least dense office/industrial and retail/entertainment employment areas (0 to 50th percentile). This finding may be correlated to trip length; longer trips are more likely to be shared and trips traveling through less dense areas are likely to be longer. It could also be related to the types of employment and travelers in these areas if they are lower-income jobs or less expensive retail and entertainment establishments. These interactions could be studied further in future work.

In the weighted sample, a greater proportion of private trips started in the least dense residential areas (0 to 50th percentile) and the densest residential areas (95th to 100th percentile) than in the intermediate density categories. These differences are statistically much greater than random, showing that there are multiple factors of sharing propensity at work for residential travel, and probably other area types as well. Differences in built environment characteristics capture a

variety of factors, such as supply and demand factors related to trip density that could affect the efficiency and pricing of sharing as well as interactions with the type of travelers and purposes associated with traveling to these areas. These area density quantiles provide initial insights into how place type may affect sharing and opportunities to increase sharing, but additional work would be necessary to understand in greater detail what really leads to higher use of sharing and to untangle the different factors at play.

Percentage of Total Riders by Category (Rarely, Sometimes, Frequently Opt in to Sharing)

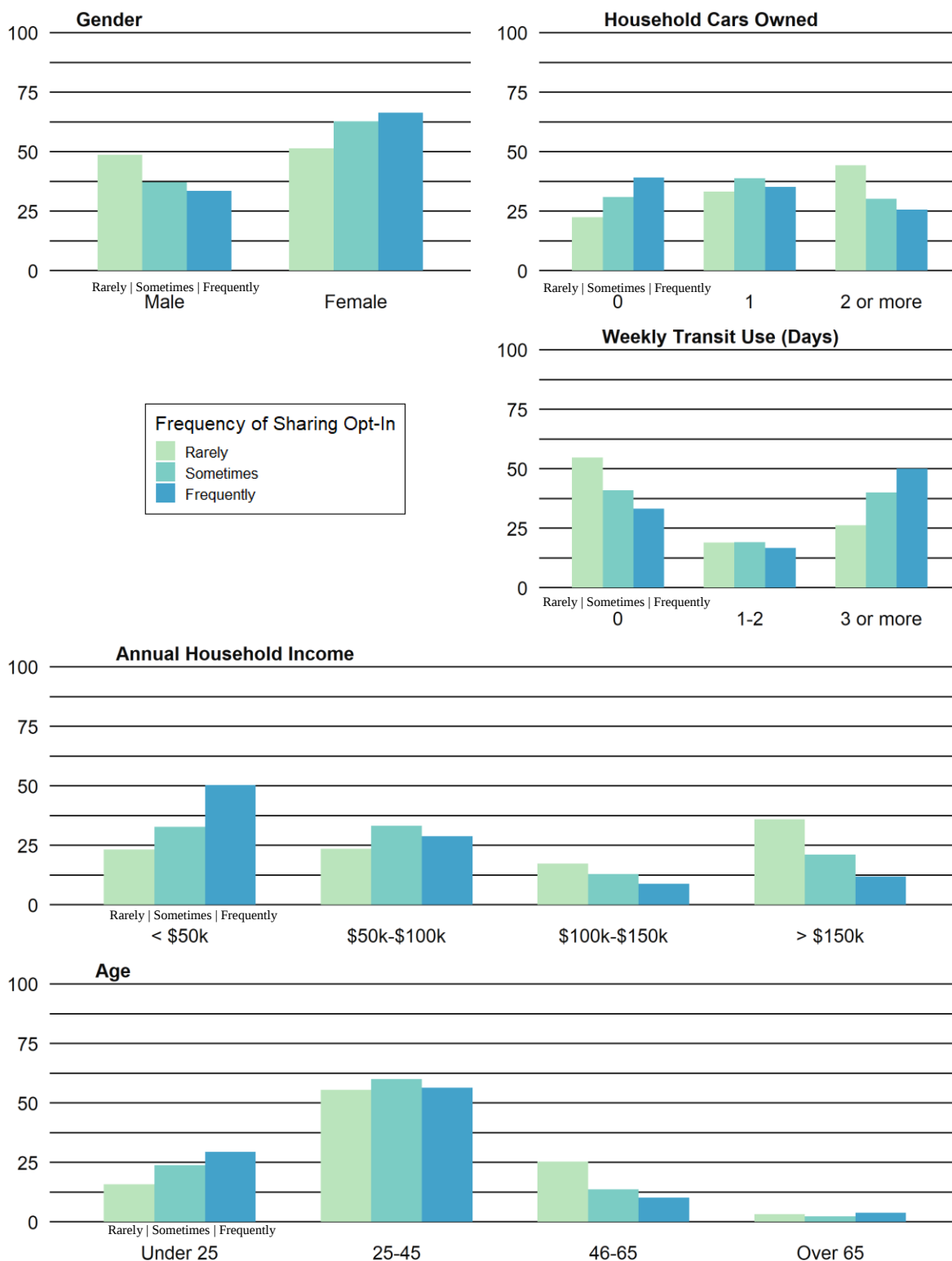


Figure 1. Graph. Distribution of observed frequency of sharing according to user characteristic. Bars of the same frequency level sum to 100 in each panel (n = 4,365). (Source: Federal Highway Administration)

Percentage of Riders by Category (Shared Trips and Private Trips)

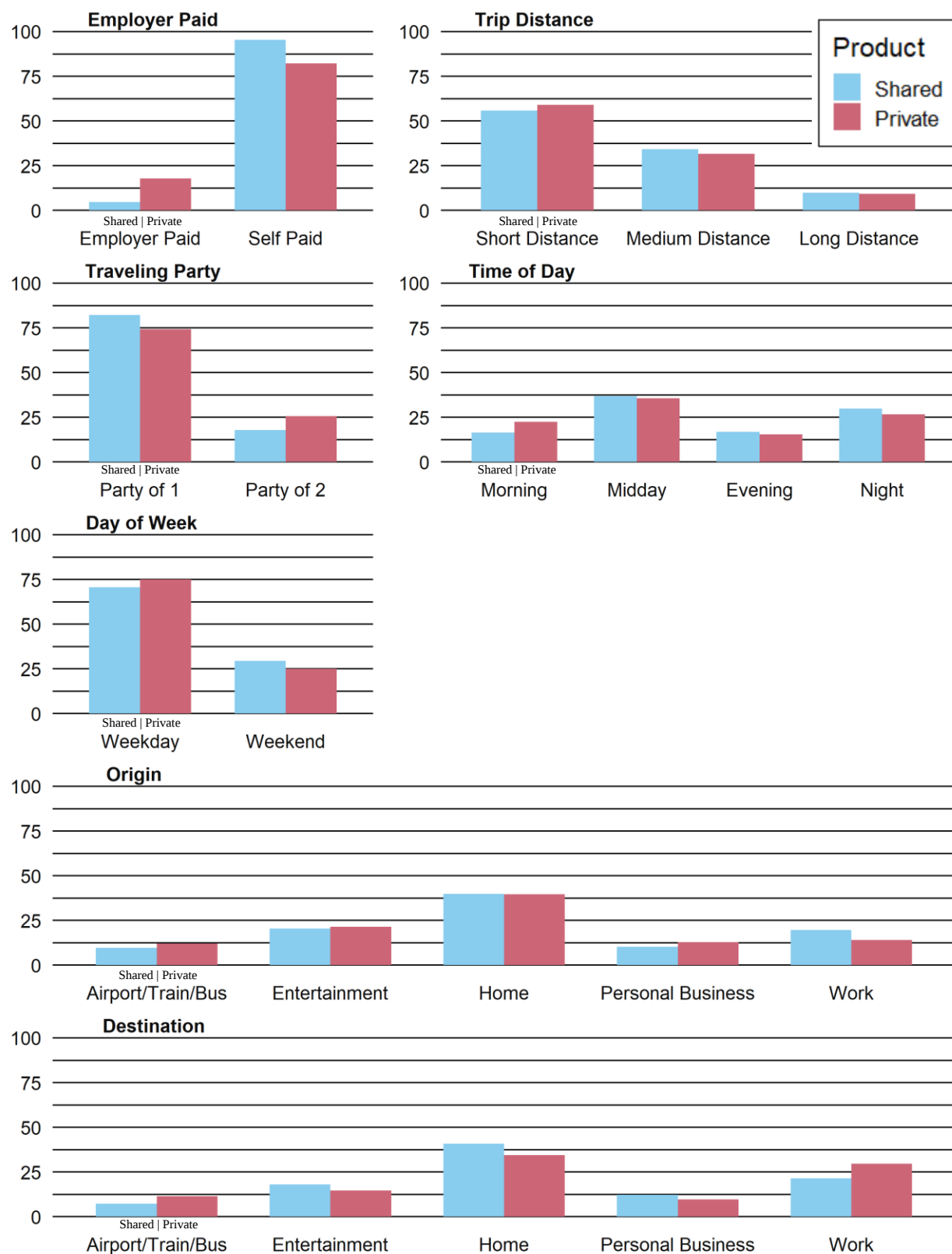


Figure 2. Graph. Distribution of shared and private trips according to trip characteristics (n = 4,365). (Source: Federal Highway Administration)

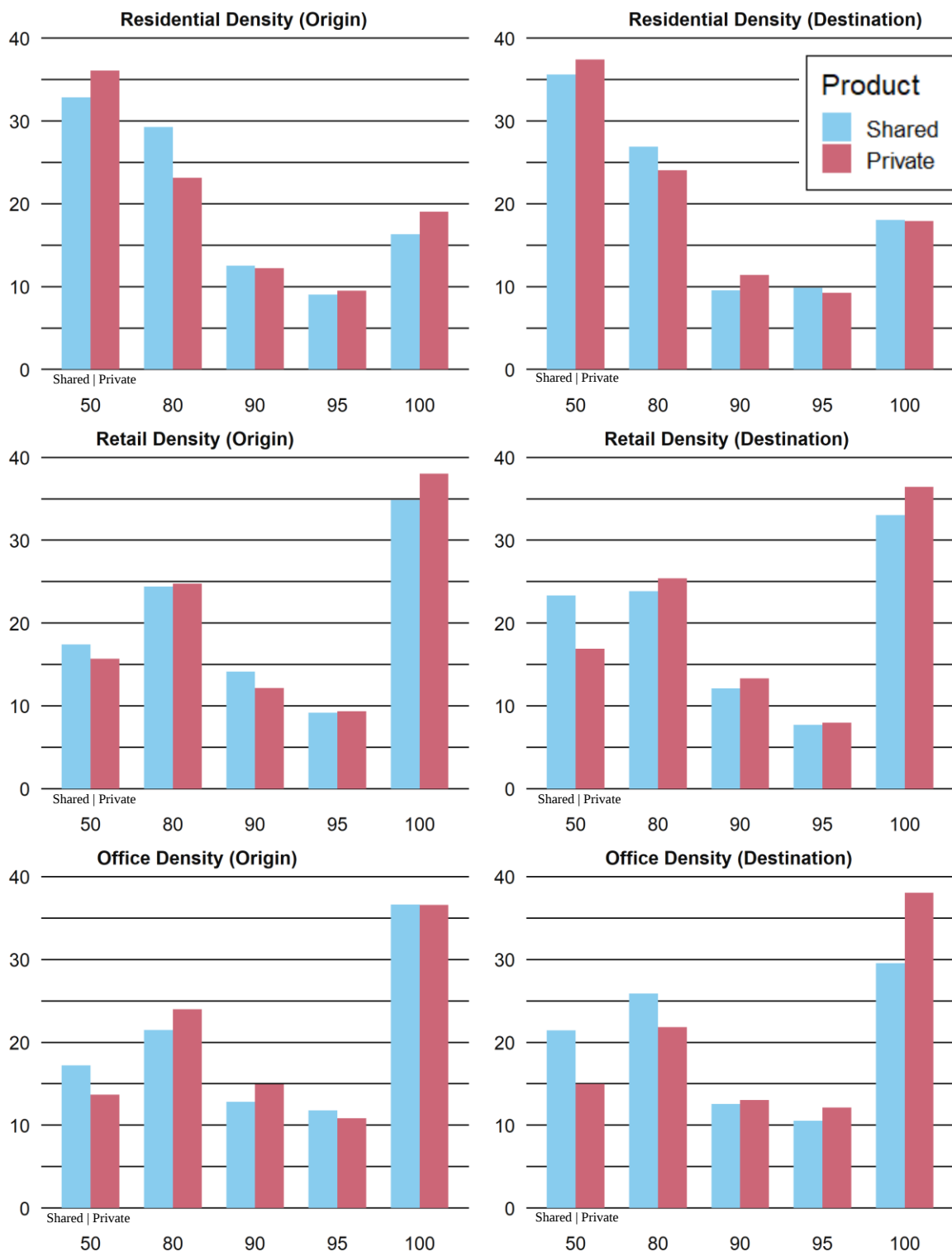


Figure 3. Graph. Distribution of shared and private trips according to the built environment characteristics. Categories on the x-axis represent percentiles (n = 4,365). (Source: Federal Highway Administration)

ANALYSIS OF PRICE AND TRAVEL TIME EFFECTS ON CHOICE TO SHARE

The discrete choice models developed as described in the Survey Approach and Data Preparation section enabled the research team to evaluate how shared product use would change in scenarios where respondents experienced different price and travel time options for shared trips relative to private trips. The scenarios studied were changes in (1) the dollar per mile relative cost differences between shared and private TNC trips, and (2) the minute per mile travel time relative differences between shared and private TNC trips.

To evaluate the effect of these relative differences (by population segment), the research team extracted coefficients from the discrete choice models to estimate the impacts of a change in price or travel time on the probability of sharing. Exponentiating the coefficients results in an estimate of the effect of an additional dollar of cost or minute of travel time on the probability that a user selects a shared TNC product over a private TNC product for a specific trip. The analysis used coefficients from model 8 for cost and travel time savings per mile. When analyzing market segments, coefficients corresponding to the market segment were removed from the model because the segment variables had uniform values.

The discrete choice modeling approach can be used to explore changes in mode choice that might occur as a result of changes in the relative travel time and price of TNCs. These changes are not intended to represent specific policy mechanisms since there might be any number of ways for relative cost and travel time scenarios to come about, especially considering local context factors for travel. As such, these results do not test the impact of specific policies, but rather model the mode choice implications that could result from potential policy outcomes, particularly relative price difference increases between private-party and shared TNC trips.

Effect of Price on Sharing

The effect of price can be understood in two manners based on survey data and based on administrative data, both provided by the TNC. The first is by describing the responses riders reported or were observed to choices presented directly (i.e., descriptive analysis), and the second is by using the discrete choice models to ask how TNC users *would* respond to options generalized from the choice sets presented if they were made available.

Relying on descriptive analysis, figure 4 shows the share of private TNC users that switched from private to shared TNC trips at each of the three levels of price differences offered in the study. These three alternatives represent shared trips with identical travel times to the observed private trip. The figure shows that holding travel time “constant” (i.e., shared and private alternatives have the same estimated travel time), higher discounts for shared rides correspond to greater shares of the population willing to use sharing, indicating some amount of price sensitivity. This relationship presents a roughly linear pattern; increasing the price differential from 35 percent to 50 percent (an average \$2.24 additional discount) increases the user’s willingness to share by 7.5 percent, while increasing the price differential from 50 percent to 75 percent (an average \$3.44 additional discount) increases the user’s willing to share by 11.0 percent. The increase in sharing per dollar price differential between these tiers is quite similar: 3.3 and 3.2 percentage points per dollar. Figure 4 also shows that over 30 percent of

users rejected a shared trip that cost 75 percent less than the observed private trip, even when the presented travel time is identical, reflecting the fact that unwillingness to share is not only related to price and time.

Figure 4 presents this summary for all TNC users (solid orange) and for TNC users with reported annual income under \$50,000 (dotted orange) and over \$100,000 (striped orange). These segments were chosen in order to represent a more and less price-sensitive group, respectively, of the TNC user population. As expected, a greater share of lower-income users chose the shared option at each of the three price differentials. The opposite is true for higher-income users.

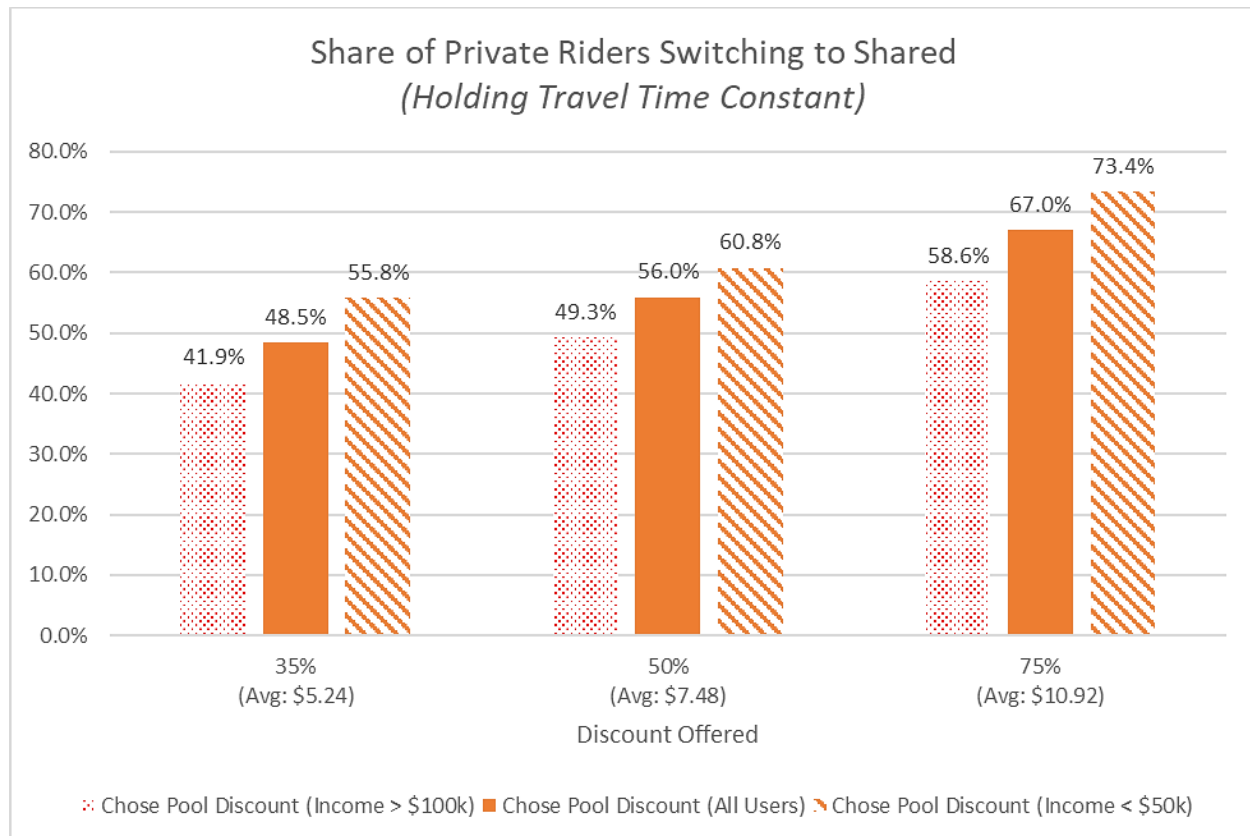


Figure 4. Graph. Share of private transportation network company users that switched to shared travel. Users in dataset that switched from private to shared travel at three levels of price differences offered (with average price differential shown in parentheses). These three alternatives represented shared trips with identical travel times to the observed private trip. (Source: Federal Highway Administration)

Market Segmentations and Price Sensitivity

As noted in the Survey Approach and Data Preparation section, the research team broke down the data into various subsets for its analysis to calculate price and time effects according to population segments of interest from a policy perspective. Segments are relevant to policy discussions if it is possible to design a policy that would affect only that segment through a realistic mechanism such as geographic cordons or an income verification procedure. These

segments included annual income (less than \$50,000 and greater than \$50,000), relative office and industrial employment density for the market at the origin and destination, regional centrality index by transit at the origin and destination, and trips to and from airports or other intermodal hubs.

Table 5 presents exponentiated coefficients of model 8 for the market segments analyzed below (as well as control variables representing market segments not analyzed in depth). Table 6 presents the initial sharing rates for these same segments. The dependent variable in this model is the probability that a respondent opted into the shared ride option (regardless of whether the resulting ride was actually shared). All variables presented in table 5 were significant with p-values less than 0.05, except where noted. These coefficients differ slightly in the segmented models as those models are derived from different (segmented) populations with different characteristics. Coefficients greater than 1 indicate that a unit change in that variable (most are binary, indicating a true or false case) would increase the probability of sharing. Coefficients less than 1 indicate the opposite. The coefficients in table 5 indicate, for example, that the model predicts that users with annual incomes under \$50,000 are 49.7 percent more likely to select a shared ride, “all else equal” (and the initial sharing rate confirms that lower-income users did indeed select a shared ride more frequently in the observed data). However, table 6 shows that the initial sharing rate for users with annual incomes under \$50,000 is not exactly 1.497 multiplied by 29.9 percent because “all else” is not equal; the users in this category also have different trip purposes, origins, destinations, trip lengths, and other trip characteristics that distinguish them from the average user. Like riders with annual income under \$50,000, the model also found that riders whose origin was a relatively dense office district were more likely to share. The opposite was true for trips ending in dense office districts and trips starting in competitive transit districts.

Table 5. Exponentiated coefficients of Model 8. (Source: Federal Highway Administration)

Variable Type	Variable	Coefficient
Market Segment (see Figure 5 and Figure 7)	Annual Income: Under \$50,000	1.497
	Annual Income: Over \$100,000	0.667
	Dense Office District (Begin Only)	1.111
	Dense Office District (End Only)	0.953
	Competitive Transit (Begin Only)	0.859
	Competitive Transit (End Only)	<i>Not Significant</i>
	To/From Airport	0.949
Price and Time	Shared Cost Savings (\$/mile)	1.086
	Shared Time Penalty (min/mile)	0.666
Control Variables	Age: Under 25 years old	1.470
	Age: Over 65 years old	0.759
	Transit Use: 1 or more days/week	1.316
	Household Car Ownership: Owns car	1.031
	Gender: Male	0.924
	Visitor	1.138

Variable Type	Variable	Coefficient
	Employer Paid for Trip	0.464
	Size of Traveling Party: 1	1.208
	Trip Start Time: Morning	0.812
	Trip Start Time: Evening	0.934
	Trip Distance (miles)	1.009
	Home-based Work	1.211
	Home-based Social	1.071

Table 5 shows that Model 8 also presents price and time differences between shared and private rides as a linear explanatory variable for sharing. As noted in the descriptive analysis in the previous section, increasing price differentials for shared rides correlates to a roughly linear increase in users' probability of sharing. Applying the market segmentations from table 5 to the discrete choice model, figure 5 presents the coefficient of this price difference for various population segments. The segments presented are not exclusive of one another, so that a trip could be made by a rider with annual income below \$50,000, starting in a dense office district and ending in a transit competitive area. The two triplets of location segments are exclusive within their characteristics (as shown by use of three bars of the same color).



Figure 5. Graph. Effect of \$1 per mile relative price difference on a user's percent probability of sharing rides. (Source: Federal Highway Administration)

The values in figure 5 can be interpreted as the effect of an incremental increase in the price differential between shared and private TNC trips on an individual's probability of opting into the sharing option. Figure 5 presents this effect on a per-mile basis to normalize price and time considerations by trip length. For example, a \$4/trip discount on a \$6, 1-mile ride would likely have a much greater influence than a \$4/trip discount on a \$25, 10-mile ride.

Table 6. Initial rate of opting in to shared rides for selected market segments. (Source: Federal Highway Administration)

Market Segment	Initial Sharing Rate
Annual income Under \$50,000	39.0%
Annual income Over \$100,000	24.4%
Dense Office District (Begin Only)	30.4%
Dense Office District (End Only)	25.7%
Competitive Transit (Begin Only)	30.8%
Competitive Transit (End Only)	28.7%
To/From Airport	23.5%
All Trips	29.9%

The research finds that the overall effect of a \$1/mile per trip greater price difference is an 8.6 percentage point increase in the probability of sharing. This indicates that, for all users, an additional \$1/mile price difference increase the probability of sharing from 29.9 percent (see initial sharing rates in Table 6) to 38.5 percent. The effect of increasing price differences is even greater for the following segments:

- Riders with annual income under \$50,000.
- Trips that begin in dense office districts.²⁵
- Trips that end in areas with competitive transit.²⁶

This finding is related to the coefficients observed in table 5 in which these three segments are correlated with higher probabilities of sharing. This finding suggests that for each of these segments, riders are more price sensitive and therefore choose lower cost options more often when they are made available. Both past research and economic theory are consistent with lower- income travelers exhibiting higher price sensitivity.

One explanation for differential responses to price differences at different locations is that time sensitivity differs for various trip purposes. For instance, trips to employment districts are likely more time-sensitive because employees need to arrive at the office at a fixed time, but leaving offices, workers enjoy a more flexible schedule and are less concerned about travel time. Considering trips that start in dense office districts, there is considerable overlap with trips originating at work; more than half of all trips with a work origin also begin in the densest office districts. This overlap explains why riders originating in dense office districts appear less price

²⁵ Defined as relative office and industrial employment density for the market at the origin and/or destination (greater than 90th percentile of the metropolitan area).

²⁶ Defined according to the EPA's Smart Location Database's regional centrality index by transit, relative to automobile centrality at the origin and destination (less than 90th percentile of the metropolitan area). The EPA defines regional centrality as proportional accessibility to regional destinations by auto and transit, respectively. Kevin Ramsey and Alexander Bell, *EPA Smart Location Database Version 2.0 User Guide*. March 14, 2014. https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf.

sensitive (i.e., more willing to accept a discount to share). The effect of each additional \$1/mile price difference is similar in trips starting at work (a 19.8 percentage point increase in the probability of sharing) and trips starting in dense office districts (a 22.4 percentage point increase; see figure 5).

The higher sharing propensity for trips ending in areas with competitive transit is harder to explain, but the greater effect of price for these trips may be related to statistically significant correlations with weekly transit use (i.e., this group includes riders who use transit more frequently each week), trip length (i.e., these trips are longer), or time of day (i.e., this group includes more late-night weekend trips). Each of those segments also demonstrates greater willingness to respond to a given price for shared rides, indicating that trips ending in areas with competitive transit are taken by riders who are less time sensitive, more price sensitive, and/or more open to sharing.

Conversely, the effect of greater price differences is much less than average for these other segments:

- Riders with annual income over \$100,000.
- Trips to or from the airport or other intermodal travel centers.
- Trips with both their beginning and ending points in areas with competitive transit.
- Trips with both their beginning and ending points in dense office districts.

For trips to long-distance terminals, time sensitivity is very high as riders need to catch a plane or train. Because of this, riders are less likely to choose lower cost and slower or less time-certain shared rides. Additionally, airport/train station trips are highly correlated with employer reimbursement, lowering price sensitivity (employers paid for 10.2 percent of non-airport trips versus 34.5 percent of airport trips).

For the location-based price insensitive segments, these are very short trips on average. Trips that start and end in transit competitive areas, for example, are 3.2 miles long on average, compared to 7.4 miles for trips that don't fall into this category. Trips that begin and end in dense office districts are 5.4 miles long on average, compared to 7.0 miles for trips that don't fall into this category. The effect of each additional \$1/mile price difference is much higher for longer trips. For example, for trips over 5 miles, each \$1/mile price difference results in a 16.5 percentage point increase in the probability of sharing, compared to 8.6 percentage points for all trips.

Because a large share of these trips stays within the region's core (the most transit-competitive portion of most cities) or other business districts, even steep per-mile discounts are not very meaningful in convincing respondents to choose a shared trip. Furthermore, the private trip cost might already be low enough that price sensitivity does not play a major role. On short trips, the schedule risk of sharing could be perceived to be a higher share of total travel time, despite the survey offering the same percentage-based time penalties.

Effect of Time on Sharing

As with price, the effect of time can be analyzed in two manners: by describing the responses riders reported or that were observed to choices presented directly and by using the discrete choice models to ask how TNC users *would* respond to a different set of choices if they were made available.

The descriptive analysis is shown in figure 6, which reports the share of private TNC users in the dataset that chose a shared option at each of the four levels of travel time differences and price differences offered. The rightmost column matches the values from Figure 4, while the other columns add new information. Within each price differential level, lowering travel time penalties has a similar effect on increasing willingness to share. Additionally, the willingness to share increases with increasing discount, as also shown in Figure 4.

Over 30 percent of users rejected a shared trip with no time penalty that is 75 percent less expensive than the observed private trip. Once even the lowest tested amount of travel time uncertainty is introduced, this number rises to more than 50 percent of respondents being unwilling to share at a 75 percent discount. This value is even higher at lower levels of discount.

The values in figure 6 may be even lower than expected at lower levels of discount and higher travel time differences, because this analysis includes only users who used a private TNC product for the survey anchor trip. Compared with the population of all TNC users, these users share less in general; 33.1 percent of shared TNC anchor trip users fell within the top quintile for opting in to shared TNC trips in their city, with just 21.3 percent of observed private TNC anchor trip users falling into that group of frequent sharers.

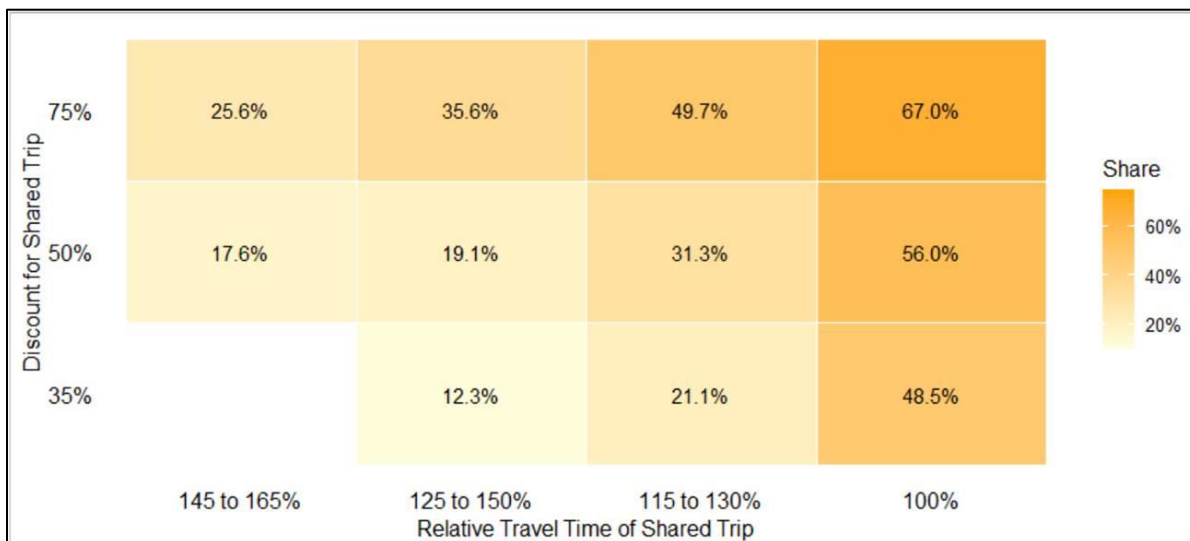


Figure 6. Graph. Share of private transportation network company users in dataset that switched from private to shared travel at each level of travel time difference and price difference offered. (Source: Federal Highway Administration)

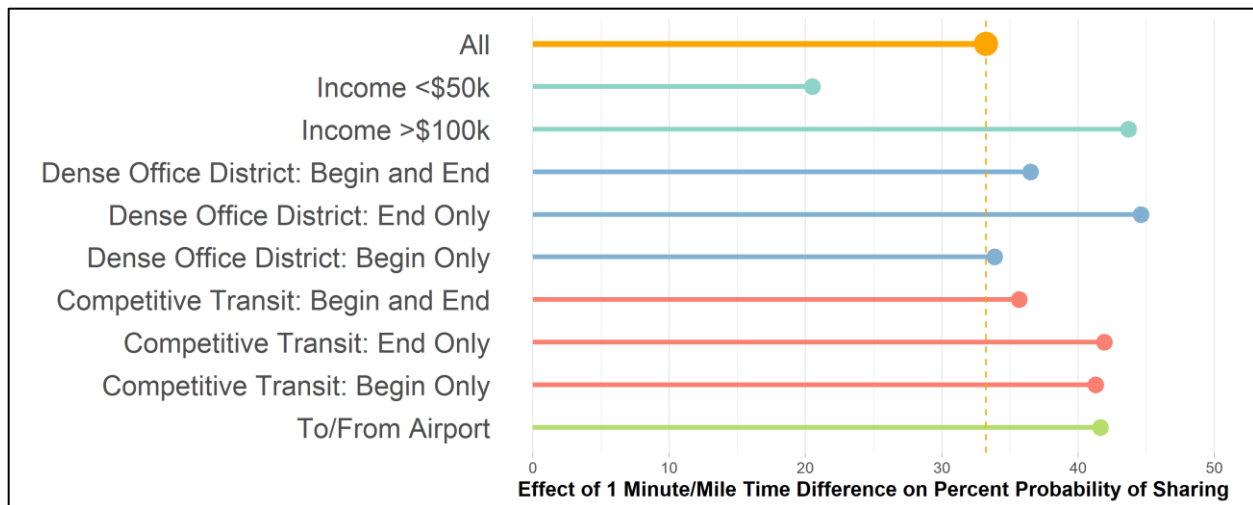


Figure 7. Graph. Effect of 1 minute/mile reduction in relative travel time difference on the percent probability of sharing. (Source: Federal Highway Administration)

Using the linear results of the discrete choice model, figure 7 presents the effect of an incremental decrease in the travel time differential between shared and private TNC trips on an individual's probability of opting in to the sharing option for various population segments. As with price, this effect is presented on a per-mile basis to normalize for differences in trip length.

According to figure 7, the overall effect of reducing the travel time penalty for shared rides by 1 minute per mile is a 33.25 percentage point increase in probability of sharing. That is, travel time savings of 1 minute per mile increase the probability of sharing for all users from 29.9 percent to 63.2 percent (see initial sharing rates in Table 6). Although it is difficult to compare the relative effects of time and money, it is obvious the effect of a 1-minute savings per mile greatly exceeds that of a one dollar per mile savings for all segments (discussed in greater detail in the following section on Relative Effect of Price and Time).

In a dense urban environment, a minute-per-mile travel time improvement may be difficult to achieve. For instance, if average speeds were 15 miles per hour (including stoplights, etc.), each mile would take 4 minutes to travel. Improving this speed by a minute-per-mile would raise average speeds 33 percent to 20 miles per hour. In a less urban context, average speeds of 30 miles per hour would need to be increased to 60 miles per hour to achieve the 1-minute-per-mile improvement—an impossibility under almost any plausible scenario. As such, travel time differentials would be more likely to come from changes in waiting time or matching time for shared versus private rides.

Although the overall effect of a 1 minute-per-mile decrease in the shared ride travel time penalty is quite large, the effect of decreasing travel time penalties is even greater for the following segments:

- Trips by riders with annual incomes over \$100,000.
- Trips to, from, or within dense office districts.

- Trips to, from, or within areas with competitive transit.
- Trips to or from the airport or other intermodal travel centers.

Of the segments chosen for reporting in figure 5 and figure 7, only the lower-income segment exhibits lower effects of reducing time differentials between shared and private products than the average response. The lower effect shows that this segment is less time sensitive than the average survey respondent, although they would still be 20 percentage points more likely to share if the time difference was reduced 1 minute per mile.

The other segments place a higher than average value on travel time. If the travel time difference between shared and private trips was reduced by 1 minute per mile, these findings suggest these groups would be willing to change products at a rate even higher than by 33 percentage points.

Relative Effect of Price and Time

The tables and figures presented point to the finding that, in general, riders appear to place a very high value on their travel time (and presumably on travel time reliability although it was not tested directly through the choice questions). This finding is not surprising in light of the survey responses summarized in table 7, which showed that the risk of delay is the most common deterrent to using the shared TNC option. Nearly half of all private TNC users surveyed indicated that they chose a private ride because of the risk that a shared ride would take longer, while only a quarter of private TNC users indicated that they were motivated by price. Other literature has also shown time to be a more powerful motivator than price in sharing rides; a recent study of Waze™ users by Cohen et al. found that saving commute time was more effective than compensation in encouraging affinity to carpool.²⁷

A simple example helps illustrate the relative effect of price and time changes, as shown in table 8. According to figure 5, a \$1/mile per trip price difference corresponds to an 8.6 percentage point increase in the probability of sharing. A price difference of \$1.16 per mile would increase the probability of sharing for general trips by 10 percentage points (from roughly 30 percent of trips to roughly 40 percent).²⁸ With an average price per mile of \$3.30, this additional price difference represents a 35.1 percent reduction in the price of shared rides.

²⁷ Cohen, M., Fiszer, M., Ratzon, A., and Sasson, R. (2019). *Incentivizing Commuters to Carpool: A Large Field Experiment with Waze*.

²⁸ The actual portion of observed trips that were shared was 29.9 percent, but 30 percent is used here for the simplicity of illustrating the concept.

Table 7. Reported reasons why respondents chose a private ride over a shared ride (values do not add to 100 percent because respondents could select more than one reason). (Source: Federal Highway Administration)

Reasons I chose a private ride over a shared ride	Percent
There was a chance that it was going to take a lot longer and that uncertainty is too risky	49.5%
The shared option was too much slower than the private option	29.2%
The discount was not big enough	24.6%
I prefer not to share my trip with a stranger	21.7%
I didn't see the shared option in the app	6.5%
I don't understand what the shared option is	0.0%

Considering travel time, figure 7 shows that the overall effect of reducing the travel time penalty for shared rides 1 minute per mile is a 33.25 percentage point increase in probability of sharing. A travel time difference of 0.30 minutes (18 seconds) per mile would also increase the probability of sharing for general trips by 10 percentage points (again, from roughly 30 percent of trips to 40 percent). With an average trip speed of 23.8 mph (or 151 seconds per mile), this represents an 11.9 percent reduction in relative travel time for shared rides.

Table 8. Illustration of effect of price and time differences on overall level of sharing. (Source: Federal Highway Administration)

Factor	Price	Time
Unit of change	Dollar/mile	Minute/mile
Unit effect on sharing	8.6%	33.3%
Initial level of sharing	30%	30%
Desired level of sharing	+10% (to 40%)	+10% (to 40%)
Required change to increase sharing	\$1.16/mile	18 s/mile
Initial price and travel speed	\$3.30/mile	151 s/mile (23.8 mph)
Percent change to price and travel speed	35.10%	11.90%

According to this example, the findings of the discrete choice model imply a relative effectiveness of changes in travel time and price differences. Specifically, comparing the change necessary to increase sharing by 10 percentage points is either a \$1.16 per mile price differential or 18 seconds per mile time differential increase. Comparing these values results in a ratio of \$3.86 per minute, which is equivalent to \$231.97 per hour. This number is not equivalent to a value-of-time measure, but rather a simple comparison of the changes in price and travel time necessary to produce equivalent changes in sharing.

This measure has several limitations, particularly the complicating factor of the lived experience of sharing a ride with a stranger possibly detracting from user satisfaction, separate from the time penalty. By comparing the effect of price differential and travel time penalties, this ratio represents the amount that respondents were willing to pay to reach their destinations more quickly (and privately). Because all price and time differentials were presented relative to the

private trip as part of a shared product option, the desire for privacy (which might also have a per-mile value) is not separable from the desire for faster arrival. Because shared choices were presented with fixed uncertainty bands at the different travel time penalty levels, the effect of uncertainty and delay can also not be separated in the TNC's choice survey. These limitations are discussed more in the earlier subsection, Limitations of Approach.

To place this value (\$231.97) in context, it is also useful to consider an otherwise unused element of the dataset collected: the choice of one *shared* ride option over other *shared* ride options, particularly in the case where riders preferred a shared ride with a longer travel time and a lower price to a shared ride with a faster travel time and a higher price. This data holds mode constant, as all choices are between different *shared* options. Thus, it is possible to compare the savings a user accepted (i.e., the rejected higher cost minus the preferred lower cost, or \$3.26 on average) by the delay that they also accepted (i.e., the preferred longer travel time minus the rejected slower travel time, or 3.16 minutes on average), or vice versa. The resulting ratio represents a ceiling on the user's willingness to pay to avoid additional travel time in a shared ride because a user with a higher willingness to pay would have chosen the faster, higher cost ride. A user with a lower willingness to pay would still have selected the cheaper, longer ride. In the choice data, this ratio amounts to a ceiling of \$83.37 per hour—the average minimum discount needed for users to switch to a shared ride. Like the value \$231.97, this estimate also has its limitations because no discounts smaller than 35 percent were tested in the study, meaning that users may have a lower willingness to pay than the study observed. It is also possible to analyze this data by considering each of the “pairwise” choices between different shared ride options presented to survey respondents.²⁹ Considering the average trip cost and average travel time, it is possible to calculate the implied value of time for each of these pairwise choices. Depending on which of the two options the respondent selected, this value of time is either a floor or a ceiling (i.e., one choice may offer the user the chance to pay \$14 per hour to save time; if a user rejects that offer, then the user's value of time is below that threshold and vice versa).

Considering value-of-time ceilings, table 9 and table 10 show the percentage of respondents that accepted the lower-cost, longer-travel option in each pairwise choice (for respondents whose last trips were private and shared, respectively). According to Table 9, a small share of respondents (18.9 percent) have low values of time (below a ceiling of \$14.24), and a large share have ceilings below \$139.19 (70.1 percent). Implied values of time are generally lower in Table 10, with more than half of respondents implying a value of time under \$10.62 and 91.8 percent implying a value of time under \$57.82. These findings are consistent with the expectation that customers whose last TNC trip was private would on average have a higher VOT.

Because this choice data controls for mode (i.e., private or shared TNC), it enables further exploration of consumer preferences among shared options. Exploration of this data could help guide service offerings and encourage more customers to make a shared ride choice (e.g., offering service standard guarantees that limit delay as a higher-priced shared-ride product option, where those paying more for their shared rides are promised a more direct trip).

²⁹ Respondents whose last trip was private were presented with 11 different choices. Respondents whose last trip was shared were presented with nine different choices.

However, this dataset carries three major limitations. First, different alternatives were presented to users whose last trip was private versus shared, so the results are not precisely comparable between these two types of respondents. Second, over multiple survey questions, users were presented shared options reflecting different time and price tradeoffs, and user preferences were not always consistent. That is, sometimes respondents accepted a time delay implying a lower value of time than rejected when presented a different choice set. Third, survey questions were typically presented as a triplet that included one private trip option and two shared trip options. As a result, the stated preference of one shared trip option over another only applies to cases where a respondent chose one of the shared options (over both one other shared option and one private option). Respondents who chose a private trip in every triplet of questions, for example, would not be represented in this data at all, which would skew downward the average implied value of time.

Table 9. Implied value of time based on choice between 11 pairs of shared ride options.
(Source: Federal Highway Administration)

Pair	Discount (Accepted)	Discount (Rejected)	Travel Time Penalty (Accepted)	Travel Time Penalty (Rejected)	Average Value of Time (VOT) Ceiling (Implied)	Percent of Responses
1	50.0%	35%	55.0%	0.0%	\$14.24	18.9%
2	75%	50%	55.0%	0.0%	\$23.73	22.9%
3	50%	35%	22.5%	0.0%	\$34.80	36.6%
4	75%	50%	55.0%	22.5%	\$40.15	40.0%
5	50%	35%	55.0%	37.5%	\$44.74	55.7%
6	50%	35%	37.5%	22.5%	\$52.20	53.2%
7	75%	50%	22.5%	0.0%	\$58.00	47.2%
8	75%	50%	55.0%	37.5%	\$74.57	59.1%
9	75%	50%	37.5%	22.5%	\$86.99	59.3%
10	75%	35%	22.5%	0.0%	\$92.79	58.6%
11	75%	35%	37.5%	22.5%	\$139.19	70.1%

Table 10. Implied value of time based on choice between nine pairs of shared ride options.
(Source: Federal Highway Administration)

Pair	Cost Mark-Up (Accepted)	Cost Mark-up (Rejected)	Time Penalty (Accepted)	Time Penalty (Rejected)	Average Value of Time (VOT) Ceiling (Implied)	Percent of Responses
1	20%	35%	35%	0.0%	\$10.62	55.7%
2	0%	20%	35%	0.0%	\$14.16	57.3%
3	20%	35%	20%	0.0%	\$18.58	92.3%
4	20%	35%	35%	20.0%	\$24.78	73.2%
5	0%	20%	20%	0.0%	\$24.78	69.0%
6	0%	35%	35%	0.0%	\$24.78	80.7%
7	0%	20%	35%	20.0%	\$33.04	80.0%
8	0%	35%	20%	0.0%	\$43.36	87.7%
9	0%	35%	35%	20.0%	\$57.82	91.8%

DISCUSSION: RIDESHARING AND TRANSPORTATION NETWORK COMPANIES

TNC trips continue to grow as a share of U.S. travel, with other emerging mobility paradigms suggesting more on-demand ridehailing in the future. The occupancy of on-demand vehicles will thus come to have an increasing impact on our streets. A shared-ride future could alleviate congestion, reduce VMT, lead to better air quality, and improve travel times for all road users.³⁰ A future with primarily private ridehailing, by contrast, may result in far more VMT growth than one with a larger role for sharing. For that reason, it is critical to understand who is currently choosing shared TNC services and where demographic and trip characteristics may encourage greater sharing.

Using this broad sample of 4,365 ridehailing users living in areas where dynamic ridesharing is available, the analysis in this chapter demonstrates which market segments in the weighted sample selected shared and private modes more or less frequently. Multiple studies have found TNC users in general are younger, better educated, higher income, urban, and non-car owning. This chapter also finds that many of these characteristics are associated with higher rates of sharing among TNC users. For example, younger individuals are more likely to use ridehailing and, among ridehailing users, are also more likely to share.³¹ The opposite is true for annual income; higher-income individuals use ridehailing more, but among ridehailing users, those with lower incomes are more likely to share. The TNC's survey results confirm the conclusions of narrower ridehailing studies that younger riders who do not own cars appear to share with greater frequency. However, where Sarriera et al. found no relationship between income or gender and sharing, the TNC survey finds more sharing among lower-income riders and women.³²

³⁰ Schaller, B. (2018).

³¹ Hou, Y. et al (2020)

³² Sarriera, J.M. et al (2017).

This research goes beyond existing literature in determining the sharing behavior of other population segments and trip types. Notably, the TNC survey finds more sharing among passengers who use transit more frequently and for weekend trips, trips from work, trips to home, and “going out” trips (i.e., trips to entertainment or for personal business). Conversely the TNC survey finds less sharing among two-person rider parties and for employer-paid trips, morning trips, shorter trips, trips to work, and trips connecting to long-distance modes.

These findings are compatible with other research findings and common expectations on travel behavior and preferences. Higher-income travelers, for example, have a corresponding higher value of time, and thus would be expected to prefer a private mode with faster travel times, even if it is more expensive. Riders traveling to the airport or to work in the morning are also less price sensitive, likely because their arrival time is important. On the other side of the issue, the data demonstrate that riders who use transit more frequently also share more frequently, possibly at least partially because they are both more price sensitive and more comfortable sharing public space with strangers. Riders without access to a vehicle—a trait correlated with transit use—also share more frequently, likely because they have lower income or because they are frequent TNC users in general and are looking to save money.

Beyond descriptive analysis of sharing rates by type of trip and user, the results presented in this chapter explore the impact of changing the relative modal characteristics of private and shared TNC trips, particularly price and travel time. This study finds that an increase in the relative price difference of \$1 per mile increases an individual’s probability of sharing by over 8 percentage points. A decrease in the relative travel time of 1 minute per mile has a much larger effect. On the scale of an entire metropolitan area, such a shift could have a noticeable impact on travel behavior and VMT. With an average trip length of 5.6 miles, an additional discount of over \$5 per trip or a travel time savings of over 5 minutes represents a significant change in TNC operations and thus may seem hard to come by.

One valuable aspect of these findings is that they also provide planners and policymakers with the ability to identify which types of TNC trips and TNC users are likely to be more influenced by price- and time-based changes in ridesharing characteristics. While the market segmentation results show what trip types are already likely to be shared (e.g., social trips and weekend trips), the TNC scenario results shows what trip types could be converted to shared trips with the least change in modal characteristics. For example, while riders *to* airports and other intermodal centers are relatively price insensitive, riders traveling *from* these centers may be more influenced by price-based incentives, even though these trips are currently more likely to be private rides, creating a unique opportunity for incentivizing sharing. (In the case of airports, though, the combination of passengers arriving in private TNCs and returning in shared TNCs might just lead to many TNCs—except the shared ones—returning empty after airport drop-offs.)

The TNC’s survey results also show that a sizeable portion of private TNC trips (approximately 35 percent, as shown in Figure 6) will be difficult or even impossible to convert to shared rides through a price-based incentive. That is, for some trips, even a 75 percent discount—the greatest offered in the survey—is not enough to convince some riders to switch from a private to a shared ride, even when they are told the travel time would match the private option. This study’s cross-

tabulations show that these riders are more likely to be older, higher-income, and infrequent transit users. Price incentives also appear to be less effective for shorter trips, likely because such trips are already low-cost relative to longer trips and the overall levels of discount in dollar terms are small even if the per mile rates are not. For these price-insensitive trips and users, travel time-based policies, such as enforced delays for private TNC pick-ups or dedicated travel lanes for shared TNCs, are likely to be more effective in encouraging sharing.

This research offers important opportunities and challenges to planners and policymakers seeking to increase the occupancy of vehicles on the road and thereby optimize the use of the existing transportation network. To that end, chapter 4 uses the results from this chapter to estimate the effect of a wide range of scenarios on the use of shared rides.

Through the use of smartphone applications, stated preference surveys anchored off of real trips can likely provide more accurate results than typical stated preference surveys because they incorporate the genuine context of trips. Taking advantage of that strength, the discrete choice modeling approach used in this study explored changes in mode choice that might occur as a result of changes in the relative price of TNCs. However, despite the strength of the stated preference methodology, we note several limitations to this work and suggest possible avenues for future research.

First, our data are only a snapshot in time of a TNC user base that was growing rapidly during the study period, with a 37 percent increase from 2016 to 2017 in passengers transported. As this user base changes and TNCs alter their services, our descriptive analysis will need to be updated to reflect the point-in-time reality of travel behavior.

Further longitudinal/panel research would support an understanding of how sharing behavior changes over time. Second, the study does not attempt to explain *why* TNC users do or do not share in response to price, time or any number of other factors. We do not assert any causal relationships between market segments and observed sharing behavior. Although it is beyond the scope of this study to draw conclusions as to whether these characteristics explicitly cause sharing, this research points the way for further experimentation with price- and time-based ridesharing incentives in controlled environments.

CHAPTER 3. ENCOURAGING CARPOOLING USING APP-BASED INCENTIVE TOOLS

With the proliferation of shared mobility options, it is important to understand traveler behavior and decision choices (among vehicle/mode, vehicle occupancy, service types, and times) and how various travel cost and travel performance factors can affect those choices. Research and experience show that carpooling represents an important opportunity to enhance the efficiency of urban transportation systems and reduce congestion. Carpooling and vanpooling have been part of metropolitan planning organizations and departments of transportation travel demand management (TDM) programs for decades. Various agencies are further supporting these programs by offering incentives for travelers to carpool and rideshare.

Some transportation agencies are working with emerging app-based carpooling and navigation services, like Scoop™, Waze™, Metropia™, Agile Mile™, and Hytch™, to pilot incentives for ridesharing in private vehicles. For example, Contra Costa Transportation Authority piloted a partnership with Scoop™ to test cash-based carpool incentives through the Scoop™ app from January 2017 to June 2018.¹ The agency tested a \$2 incentive per passenger-ride (deducted from the mileage fee the rider was to pay the driver, minus \$1 going to Scoop) coupled with a \$2 per trip driver incentive and found that the two sides of the incentive were equally important; when the driver incentive was removed, shared trips decreased by 20 percent as carpool matching became unreliable. Similarly, King County Metro Transit recently partnered with Scoop™ and the University of Washington in a 5-month pilot that tested a \$2 incentive for riders and drivers for each carpool trip via Scoop's™ application (which also facilitates distance-based payment from the passenger to the driver). Shen, Wang, and Gifford summarized the results of the pilot, finding that the Scoop™ incentive reduced single-occupancy vehicle (SOV) commute trips, with an estimated decrease of nearly 1,000,000 vehicle miles traveled (VMT), effectively resulting in a VMT reduction at a cost of \$0.40 per mile.² These pilots, and others described below, have shown that incentives may be effective in converting SOV trips to carpool trips and point the way toward a precise study of the effect of incentive levels on sharing in the app-based carpooling context.

Beyond incentive size, many studies have been conducted to identify factors that limit carpooling adoption. Generally, these factors may be divided into four main categories: (1) convenience, (2) trust issues, (3) lack of awareness, and (4) lack of incentive, with the first two recognized as the most critical. Emphasizing trust issues as an example in their paper covering different ways of carpooling, Kurth and Hood noted that if someone is interested in carpooling using a work connection, it would be advantageous not only because the poolers have similar work schedules, but also because the work organization establishes a basic trust level between participants.³

¹ Direct correspondence between Allen Greenberg (FHWA) and Corinne Dutra-Roberts and Peter Engel (Contra Costa Transportation Authority) regarding Carpool Ridematch Platform Pilot. February 9, 2019.

² Shen, Q., Wang, Y., and Gifford, C. (2020). *“Building Partnership Between Transit Agency and Shared Mobility Company: Incentivizing App-Based Carpooling in the Seattle Region.”*

³ Kurth, S.B. and Hood, T.C. (1977). *“Car-pooling Programs: Solution to a Problem?”*

Gardener and Abraham mention that drivers dislike delegating control and value their solitary personal space.⁴ Therefore, they conclude that privacy issues and the fear of riding with strangers are limitations to carpooling success. In another study, the availability of potential carpooling partners and their relationships were dominant elements in affecting this fear.⁵ This was significant enough that Correia and Viegas mark the psychological barrier of riding with strangers as one of two main problems limiting the future of carpooling.⁶

Overcoming psychological barriers is a critical step in adopting carpooling. Drive-alone users may, if motivated, potentially become carpool users and carpool users may alternate between driver and passenger roles based on their travel needs, daily activities, car availability, the perception of transportation costs, conditions, etc.

The central question is: what influences a user's choice between riding (or driving) alone versus carpooling, and what specific financial levers can be pulled to influence this choice? To provide an answer, it is helpful to better understand: (1) the user socio-demographics, temporal and spatial activity characteristics, and the transportation conditions influencing the mobility option decision, (2) what triggers and motivates individuals to transition from one mobility option to another, and (3) the factors that could sustain the behavior change over the long-term.

Making mobility options available, while essential to behavior change, does not mean that travelers will change their behavior immediately or at all. What is missing is actively presenting the mobility options to commuters and engaging them through appropriate means (e.g., gamification and incentives) in order to trigger the desired behavior changes. As such, engagement becomes the second framework behavior tenet with the goal to better understand how it positively affects traveler choices.

While many app-based carpooling solutions are emerging, data on incentives and their impact on sharing rates are hard to obtain. For the purpose of this study, data previously gathered by two companies (Metropia™ and Hytch™) were analyzed by these companies to answer questions FHWA subsequently posed to them. These reported results should be considered examples, as findings from both models are not representative of the other app-based carpooling systems in the marketplace due to significant variations in how each app-based carpooling solution interfaces with its users. More importantly, the data gathered from both apps preceded this study, so the ability to conduct deliberate tests in line with research questions for this study was limited, but the research team considered looking at retrospective data to be meaningful. One important limitation was that travel choice data prior to app use was in general not gathered, thereby making it hard to attribute behavior change to specific app use.

The two app-based systems used in the study, Metropia™ and Hytch™, are described in the following pages.

⁴ Gardner, B. and Abraham, C. (2007) *"What Drives Car Use? A Grounded Theory Analysis of Commuters' Reasons for Driving."*

⁵ Levin, I.P. (1982). *"Measuring Tradeoffs in Carpool Driving Arrangement Preference."*

⁶ Correia, G. and Viegas, J.M. (2011). *"Carpooling and Carpool Clubs: Clarifying Concepts and Assessing Value Enhancement Possibilities Through a Stated Preference Web Survey in Lisbon, Portugal."*

Metropia's™ app includes a complete suite of available mode options and services include driver navigation, dynamic “social carpool” pairing, transit, ride hailing, micro-transit, biking, and walking. For the purpose of the study, only the choice making surrounding carpooling was included. Within the app, Metropia's™ Driving Up Occupancy (DUO) is the module that enables carpooling rewards. DUO is a dynamic tool that tracks drivers and passengers, who are both DUO users, once they are inside a vehicle. DUO leverages the existing types of social relationships in the user's daily life (e.g., working for the same company, being a member of the same recreational/sports team, living in the same household, etc.) to alleviate the trust concerns and psychological barriers of riding with strangers. The impact of incentives on Metropia's™ users was analyzed using app data combined with Metropia's™ micro-survey tool. In addition to identifying variables affecting the magnitude and trend of carpool use, a time-series analysis is presented to better understand how incentive changes over time affect the carpool use trend (i.e., can carpool behavior be sustained if incentives are reduced over time?). This is directly related to the sustainability of monetary resources offered by the incentive provider (typically a public agency or employer).

The Hytch™ platform enables users to simultaneously take advantage of multiple sources of reward funding from different entities. These rewards may be affiliate-based, open to all travelers in a geo-fenced area, or available to travelers attending a large event, depending on the goals of each funding entity. Typical rewarding entities are major employers and local governments seeking to reduce employee parking costs or curtail congestion. The app verifies, measures, and rewards the user for travel decisions that are pre-specified as reward eligible (e.g., nonmotorized travel, carpooling, vanpooling, or taking transit). Like the Metropia™ app, reward sponsors could, if they desire, vary reward amounts to test impacts on travel choices and continued engagement with the Hytch™ app.

IMPACT OF REWARDS AND INCENTIVES USING DATA FROM METROPIA DRIVING UP OCCUPANCY PLATFORM

Metropia's™ DUO 1.0 version, data from which Metropia analyzed for this study, allows a drive-alone user to earn points based on the selected departure time, while for each successfully paired carpool (DUO) trip the driver earns his/her driving points plus a bonus of half of the points each passenger earns (while not taking the points away from the passenger).⁷ Beyond passively collecting data, Metropia's™ platform includes a micro-survey tool which allows questions to be asked directly to the users, using real-time applications, to understand behavior and travel patterns better and to obtain pertinent user characteristics, producing response rates significantly higher than traditional surveys. Metropia™ users included in the study were able to select one of three mobility options (drive alone, carpool driver, and carpool passenger) and earn points for each trip. Roughly 60 points are awarded for each trip between the driver and the passenger. These points can be translated into dollars on a conversion rate of 1,200 points to \$5.

⁷ Since the study, DUO has been updated and additional information on the current DUO 2.0 version can be found at www.metropia.com.

Metropia's™ DUO service was initiated in Austin and El Paso, Texas, and Tucson, Arizona, in January 2016, and the micro-survey feature became available July 1, 2017. Since then, the micro-survey tool has been used on various occasions to acquire user information to support the platform's behavior engine and to validate backend predictive algorithms. From July 1, 2017, through September 30, 2017, Metropia™ conducted its first wave of micro-surveys to better understand user socio-demographic characteristics.

According to Metropia™, it sought to create a rewards platform to encourage and sustain desired behaviors that reduce congestion, including shifting driving out of the heaviest peak periods and encouraging carpooling. Metropia's™ effort preceded the most recent inquiry of the Federal Highway Administration (FHWA) into app-based carpooling incentives, and, as a result, did not test many questions related to the impacts of incentive changes on behavior modification.

Metropia's™ analysis relied on data collected responses from the micro-survey along with the participants' mobility option choices (drive alone or carpool) from January 2016 through December 2017 coupled with passively tracked trip data. Figure 8 illustrates the pertinent timeframes, while table 11 summarizes the number of micro-survey participants by the market.

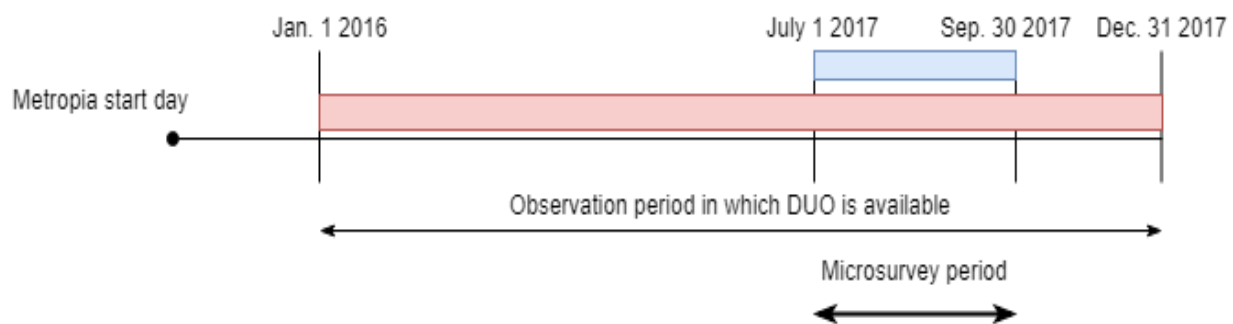


Figure 8. Graph. Driving Up Occupancy timeframes and user data definition.
(Source: Metropia™)

Table 11. Number of Metropia™ users contacted via the micro-survey, by market. (Source: Metropia™)

Market	Number of Users	Percent
Tucson	380	30%
El Paso	566	45%
Austin	314	25%
Total	1,260	100%

Out of the 1,260 users, 644 had a completeness rate of all the survey questions of greater than 40 percent. Metropia™ imputed missing data, where possible, in conducting analysis for this study.⁸ The basic concept behind imputing data is that the number of users participating in the survey and the number of questions administered in the survey form a matrix that is generally sparse (i.e., not all users respond to all questions). The Multivariate Imputation by Chained Equations (MICE) process⁹ was utilized by Metropia™ in this study to complete the sparse matrix, and the micro-survey data were used as explanatory variables. After Metropia™ completed the imputation process, data pertaining to the travel behavior (mobility option and reward points), trip characteristics (travel time and distance), and day of the week (weekday versus weekend) were attached by Metropia™ to its 644 users, resulting in a dataset of 16,897 observations (9,224 for weekday and 7,673 for weekend) based on an average of 14.3 and 11.9 months of activity for each user on weekday and weekend, respectively.

Based on the mobility option selected, Metropia™ mapped each user to one of the following four roles for each trip and computed the proportion of each role for over an observation period:

1. Drive alone: always a driver; never in a carpool.
2. Carpool passenger only: always a passenger; never been a driver.
3. Carpool driver only: always a carpool driver.
4. Carpool both: has been a carpool driver and passenger.

Metropia's™ data support both cross-sectional and longitudinal analysis and thus a three-tiered framework was developed, as illustrated in figure 9.

⁸ Based on Metropia's™ experience and preliminary data analysis, the imputation process for users with lower than 40 percent completeness rate would not have provided enough variables for imputation.

⁹ Zellner, A. (1962). *"An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias."*

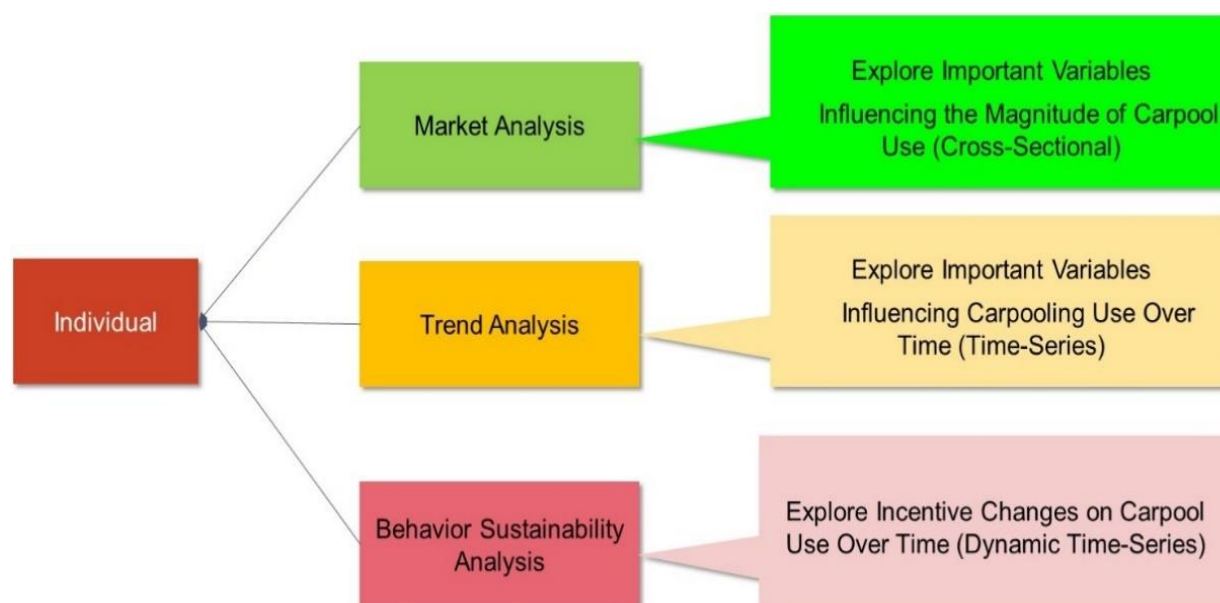


Figure 9. Diagram. Tiered analysis framework. (Source: Metropia™)

Metropia's™ dataset allowed a breakdown of results by a host of demographic and trip characteristics. As the focus of the analysis here is on the broader impacts of the type of strategy that Metropia™ deployed, some detail available from Metropia™ was less relevant to the findings focused on in this document.¹⁰ One area of interest, though, was whether those with growing usage over time were demographically different and/or exhibited other behaviors different from those showing declining participation. This was of interest as those with growing usage are more likely going to be long-term participants in app-based carpooling than those with declining usage.

For the period between January 2016 and December 2017, over 85 percent of the users had used Metropia's™ platform in the last 6 to 15 months. The time-series data associated with the trend analysis reflected monthly carpool utilization for those users who had used the platform for at least 6 months. Carpool use in the Metropia™ app varies by time of day (peak versus non-peak), day of the week (weekday versus weekend), activity type, and user socio-demographic characteristics. Furthermore, segmenting by commute purpose (i.e., travel primarily associated with work or school); the user's familiarity with a specific market; age; education level; and years of driving appeared to have significant explanatory value in attempting to understand the differences (behavior) in carpool-passenger and drive-alone modes.

Metropia™ stated that its primary goal was to create and deploy a behavioral engine that establishes and maintains a new mobility habit for users, while being financially sustainable for partnering agencies. Table 12 summarizes the distribution of the selected users by three markets.

¹⁰ For broader analysis, see Papayannoulis, V., Arian, A., Chiu, Y.C., and Hsieh, C.W. (2020). "Social Carpool Behavior Analysis: Using Data from Incentive-Based Demand Management Platform."

Table 12. Distribution of carpool users included in the trend analysis. (Source: Metropia™)

Market	Number of Users	Percent
Tucson	206	45%
El Paso	134	30%
Austin	113	25%
Total	453	100%

For these markets, Metropia™ divided carpool users into groups that exhibited an increasing trend, decreasing trend, or no trend in utilization, based on the Mann-Kendall test.^{11,12} The Mann-Kendall trend test is a non-parametric test to detect significant trends in time series and requires that trend to be monotonic, meaning that for an increasing trend observation, observation y needs to be higher than observation $y - 1$. Based on the Mann-Kendall test of the 453 users, 308 users or 68 percent had no trend, 93 users or 21 percent had an increasing trend, and 52 users or 11 percent had a decreasing trend. Of the 145 users who had a trend, 24 percent were from Austin, 44 percent from Tucson, and 32 percent from El Paso. Figure 10 illustrates the temporal carpool use for these users, providing the following observations:

- Increased carpool use over time among more than 50 percent of the users for whom a trend has been identified.
- Carpool use is higher for the decreasing trend initially, indicating that some users potentially are interested in the reward points only and jump on the opportunity, but later their interest diminishes as the reward points decrease.
- Carpooling has a slower start among users with an increasing trend, potentially indicating that it takes some time for the users to fully appreciate carpool as a mobility option. As they get more comfortable, carpool use increases.
- Growth of the increasing trend becomes flat after 9 months, potentially indicating that carpool has reached an equilibrium state for users.

¹¹ Mann, H.B. (1945). “Nonparametric Tests Against Trend.”

¹² Kendall, M.G. (1975). *Rank Correlation Methods* (4th Edition).

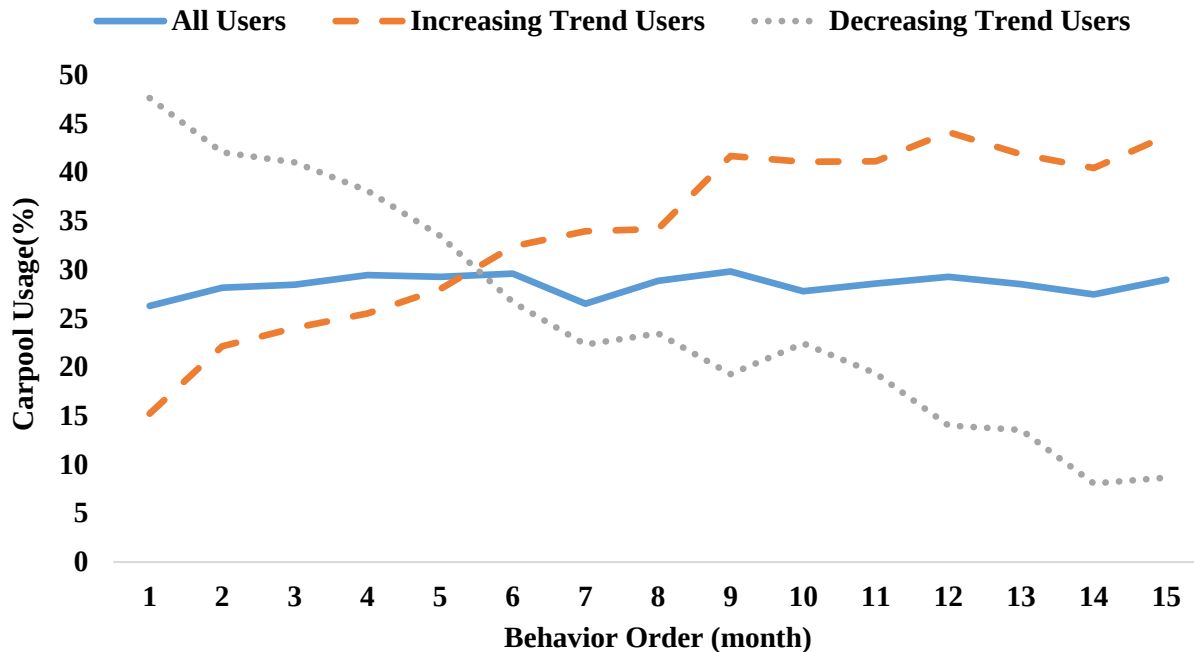


Figure 10. Graph. Temporal carpool use. (Source: Metropia™)

Metropia™ undertook a time-series analysis to better understand how incentive changes over time affect the carpool use trend (i.e., can carpool behavior be sustained if incentives are reduced over time?). This is an important aspect of the overall policy framework, since it is directly related to the ability of the public agency to support a desired change in travel behavior in a cost-effective manner. It is also tied to the underlying principle of using incentives as a mechanism to break an old habit and support a new habit that can be maintained over time with an affordable cost structure.

Figure 11 illustrates how DUO reward points changed over time for both carpool drivers and passengers, indicating that reward points were reduced about 14.5 percent for drivers and 3.3 percent for passengers during the analysis period for this study. User carpooling levels tended to stay the same or increase, rather than decrease, despite declining rewards, suggesting that Metropia™ has created an award structure that is associated with users sustaining desired behaviors.

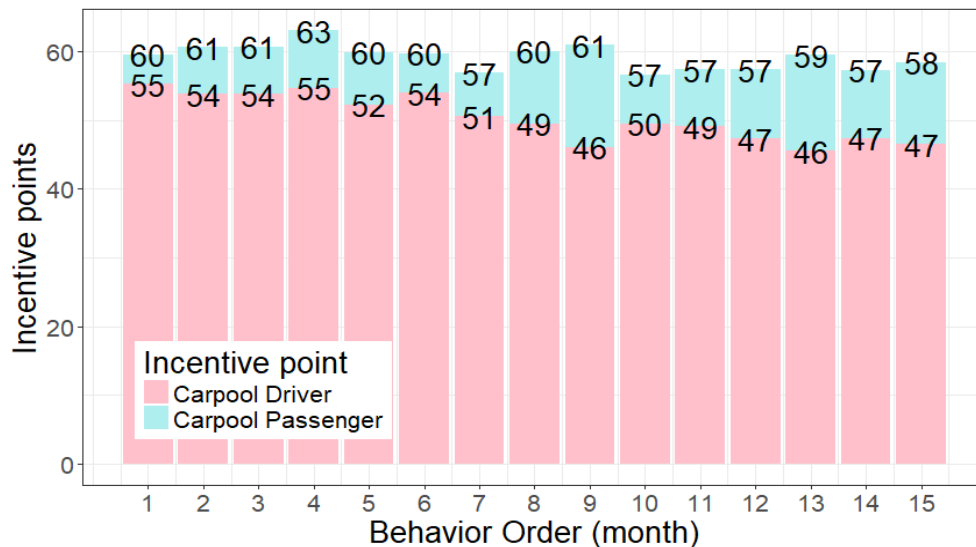


Figure 11. Graph. Carpool driver and passenger incentive point trend.
(Source: Metropia™)

IMPACT OF REWARDS AND INCENTIVES USING EXAMPLES FROM HYTCH™¹³

Hytch™ provided a range of examples about partner reward structures. Since such partnership arrangements provide the financing that may lead to behavior change, understanding these arrangements and the motivations of partners to enter into them offers insights on the potential to expand app adoption and usage. First, the City of South Bend, Indiana, is using Hytch™ to pay 50 cents per mile to the general community to take qualified people to specific work locations by carpool. Second, an anonymous Fortune 100 partner company is deploying Hytch™ to pay for sharing rides by carpool or vanpool to or from a specific pilot site in San Diego. Third, the City of Spring Hill, Tennessee, contracted to deploy Hytch’s™ “corridor rule” to reward citizens when they take longer, but less congested routes within a targeted corridor. Finally, the teledentistry company SmileDirectClub™ contracted with Hytch™ to pay employees and their co-travelers when they carpool to and from specific parking locations with limited parking supply. Their rewards also apply to employees using public transit and other modes.

One feature of Hytch Rewards™ is that the company has arranged to offset carbon emissions from all recorded trips even when monetary rewards to users are not provided. Hytch™ records carpooling trips but does not match carpoolers. Instead, carpools are arranged by individuals, reward partner organizations, or another firm that provides such matching.

In 2018 and 2019, Hytch™ provided rewards to 10,889 individual users, for their over 12 million miles of travel rewarded. During this period, the total average user reward was \$23.62, amounting to about 2 cents per rewarded mile.

¹³FHWA requested that Hytch™ analyze data it had already gathered prior to this study in response to questions developed by FHWA for this study. Related findings are described here as an example of the kinds of analysis that may be possible from data from travel incentive apps.

Over time, Hytch™ reward levels have tended to decrease gradually, largely since reward partners typically seek to find the most cost-effective means to achieve their goals. As can be seen in figure 12, reductions in the number of rewarded miles (which would be contrary to the goals of the reward partners) were not seen until per-mile reward amounts declined to below 2 cents.

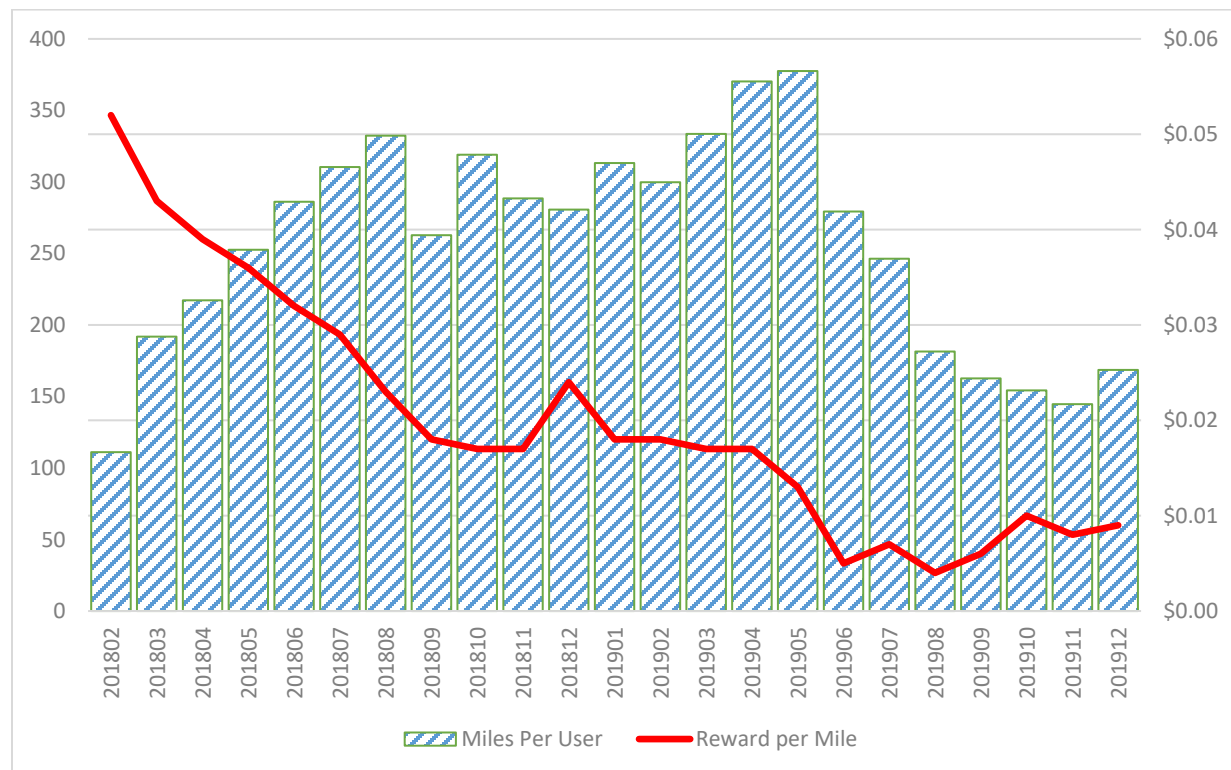


Figure 12. Diagram. Total miles per user per month compared to average rewards per mile. (Source: Middle Tennessee State University Data Science Institute)

According to Hytch™, it is concerned about attrition of app users and interested in finding the lowest cost rewards that sustain desired behavior. Minimizing attrition is important to realizing long-term benefits of applications. Normal attrition rates have hovered at or below 1 percent per month. An attrition rate of 1 percent per month means that half of the participants would have dropped out in 50 months, or that the average participant is, under normal conditions, expected to stay in the system for about four years. But when user rewards have, in some instances, been eliminated entirely for many trips (excluding carbon emission offsets, which have continued), participation drop off is substantial. As can be seen in table 13, and also in figure 13 use fell immediately following a large reduction in reward levels in June 2019. The share of users taking their last trip using the app grew each month after the reduction in rewards, reaching 4.4 percent in November 2019. A high positive correlation of 0.73 was found with the elimination of rewards and permanent disengagement from the app. (This finding was made through Middle Tennessee State University Data Science Institute running a correlation matrix, which indicates the mutual strength of the relationship between two variables, from -1 to +1, known as the coefficient of correlation.)

Table 13. Counts and percentages for no reward and last trip (Source: Middle Tennessee State University Data Science Institute)

Year Month	Total Trips	No Reward Trip Count	No Reward Percent	Last Trip Count	Last Trip Percent
2019 Jan	41,795	5,369	12.8%	348	0.8%
2019 Feb	38,253	4,258	11.1%	248	0.6%
2019 Mar	44,212	6,045	13.7%	444	1.0%
2019 Apr	41,067	4,135	10.1%	398	1.0%
2019 May	38,347	8,538	22.3%	408	1.1%
2019 Jun	21,898	13,259	60.5%	426	1.9%
2019 Jul	14,533	6,991	48.1%	313	2.2%
2019 Aug	10,997	7,842	71.3%	377	3.4%
2019 Sep	7,940	3,825	48.2%	288	3.6%
2019 Oct	6,382	2,763	43.3%	234	3.7%
2019 Nov	6,084	2,987	49.1%	269	4.4%
2019 Dec	4,713	2,453	52.0%	186	3.9%
TOTAL	276,221	68,465	24.8%	3939	1.4%

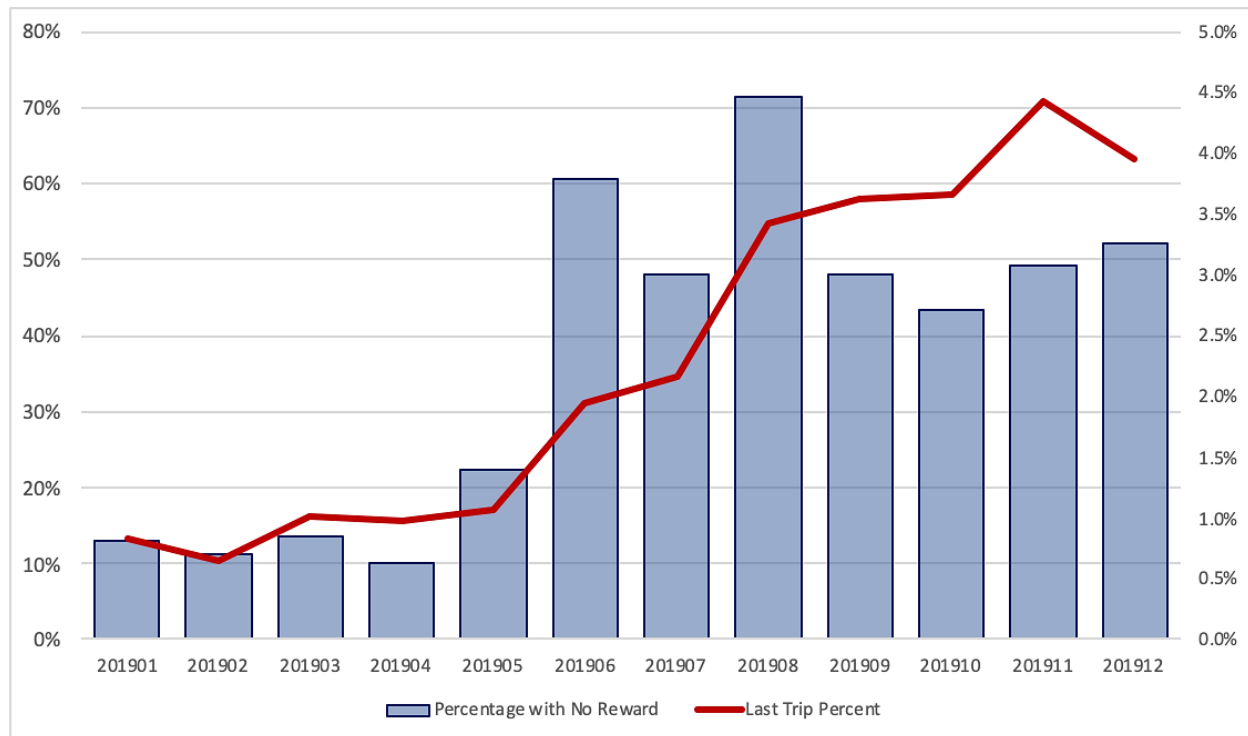


Figure 13. Percentage of trips with no rewards and last trips per month. (Source: Middle Tennessee State University Data Science Institute)

Responses to varying reward amounts may be considered a “natural experiment,” where the differing conditions faced by participants were due to factors outside of the control of the platform company. Random assignment would be preferable for this research need, since markets, programs, and reward amounts in this natural experiment could vary somewhat, but random assignment would require sufficient planning and budgeting. Despite this note of caution, changes in behavior from the natural experiment, especially within group behavior changes when reward levels have been varied, may be the result of the changes in reward amounts rather than other factors. When examining “within user” data, or changing behavior of individual users over time, the lack of random assignment becomes less of a concern since users are not being compared to others. While, in theory, it is possible that different users might respond differently to changing reward levels, there is no inherent reason that users found to be in one of these three categories (increasing, stable, and decreasing reward levels) would respond differently to changing incentives than would users ending up in other categories.

Data from Hytch™ allows researchers to find correlations between per-mile reward values and user miles that are rewarded. Table 14 is quite instructive in this regard and shows that a reward level of 2 cents per mile appears to yield indistinguishable results in monthly Trips per User from higher reward levels, but substantially better results than for lower reward levels. Monthly average awards of \$7.54 for participants receiving 2 cents per mile, as shown below, appear to be a very affordable cost as compared to other transportation investment options (which are not explored as part of this research).

Table 14. Average rewards per mile per month for a user (Source: Middle Tennessee State University Data Science Institute)

Reward Per Mile¹⁴	User Percentage¹⁵	Distance Per Trip¹⁶	Total Trips Per User¹⁷	Distance Per User¹⁸	Ave. Reward Per User¹⁹
\$0.00	19.6%	24.08	7.86	189.32	\$0.41
\$0.01	25.0%	20.38	15.19	309.43	\$3.30
\$0.02	22.3%	15.51	24.75	383.85	\$7.54
\$0.03	13.6%	13.81	23.57	325.39	\$9.52
\$0.04	7.8%	13.03	23.49	305.99	\$12.00
\$0.05	4.1%	11.57	23.50	271.85	\$13.59
\$0.06	4.4%	9.75	18.31	178.59	\$10.61
\$0.07	1.8%	8.51	15.55	132.38	\$9.15
\$0.08 or more	1.3%	9.80	10.57	103.60	\$10.93

¹⁴ Reward Per Mile – The average reward per mile for a user in a month (for example, if User ID 334 averaged \$0.04 rewards per mile in a given month, they would be counted in the \$0.04 category, which had 7.8% of the months. If the next month, they average \$0.05, they would be counted in the \$0.05 category.

¹⁵User Percentage – Percentage of user months that averaged a particular Reward Per Mile category.

¹⁶ Distance Per Trip – The average miles per trip in a particular Reward Per Mile category.

¹⁷ Total Trips Per User– The total number of trips per user in a particular Reward Per Mile category

¹⁸ Distance Per User – The average miles per user in a particular Reward Per Mile category.

¹⁹ Average Reward Per User - The average rewards per user in a particular Reward Per Mile category.

Table 14 shows that higher average per-mile reward levels correspond to average trip lengths that are shorter than with lower reward levels. Hytch™ explained that some reward sponsors cap reward amounts on a per-trip basis, suggesting that those receiving the highest per-mile rewards were taking shorter trips, where no cap is imposed. Where such a cap exists, the expected manifestation of behavior change resulting from a higher per-mile reward structure would be more trips taken by those inclined to take shorter trips, as such trips would be handsomely rewarded. The data here do not show that result.

Another area of inquiry with the Hytch Rewards™ data requested by FHWA was for Hytch™ to report on individual distance per user and trips per user with rewarded miles where reward levels have, over time, declined noticeably, stayed the same, and increased noticeably. Such an inquiry may help formulate the most cost-effective strategies for allocating reward funds and could answer the following FHWA questions:

1. For users offered reward levels that remain constant, how, if at all, do distance per user and trips per user change over time (and can participation duration effects be separated from seasonality effects)?
2. Does starting with higher reward levels lead to higher initial distance per user and trips per user than starting with lower reward levels? If so, is the higher average maintained even when reward levels are cut?
3. For users where reward levels rise, do distance per user and trips per user rise in a corresponding fashion?
4. Does the manner and timing of reward redemption affect behavior? For example, if Hytch™ participants were required to be eligible for a minimum of \$10 in rewards prior to redemption, would users become more responsive to incentives as they neared redemption eligibility?

To begin to answer FHWA's questions, Hytch™ reviewed its data and shared a number of products the company generated from its data. The data and related products showed expected seasonal effects (e.g., travel picks up after the winter months). The reduction in reward miles when per-mile rewards dipped below 2 cents was also very apparent. Overall, though, clear patterns were difficult to discern. Future controlled experiments may be able to answer these questions.

Hytch's™ existing data could help guide such controlled experiments. To answer the third question above (i.e., "For users where reward levels rise, do distance per user and trips per user rise in a corresponding fashion?"), Hytch™ has only a very small number of users to whom this condition applied. Nonetheless, the data, shown in the table below, suggest that there might be something worthy of further exploration.

For this sample, table 15 shows that increasing reward levels appear to correlate with increased average miles per user. This is particularly apparent beginning in week 12 of 2019, or two weeks after average reward per mile jumped (and continued edging up in subsequent weeks). The rewards increased in weeks where seasonal driving might have increased, which might account

for a bit of the shift, but results from this small sample were far higher than would likely be due to seasonality. Nevertheless, caution in interpreting the data is advised. The number of week-over-week users varied, sometimes substantially. After some time, reward miles declined despite per-mile reward levels remaining high, so it is an open question as to whether behavior changes are sustained. These data suggest that providing increasing reward levels to a greater number of participants (randomly assigned) in a future study could make for a worthy test even though, as noted earlier, higher per-mile reward levels were not correlated with higher numbers of reward trips across the entire study population.

Table 15. Weekly totals for a Hytch™ rewards partner (Source: Middle Tennessee State University Data Science Institute)

Year-Week	Week Start Date	Total Active Users	Average Reward/Mile	Average Miles Per User	Ave. Miles Change Per User %
2019-06	2/3/19	9	0.031	98.44	-50%
2019-07	2/10/19	7	0.029	140.76	48%
2019-08	2/17/19	10	0.030	126.94	18%
2019-09	2/24/19	8	0.031	149.79	14%
2019-10	3/3/19	9	0.054	136.71	-36%
2019-11	3/10/19	11	0.059	134.28	-3%
2019-12	3/17/19	11	0.067	209.34	214%
2019-13	3/24/19	12	0.070	172.75	-6%
2019-14	3/31/19	11	0.077	154.07	-20%
2019-15	4/7/19	8	0.077	250.57	-16%
2019-16	4/14/19	12	0.076	222.64	40%
2019-17	4/21/19	14	0.072	187.18	-2%
2019-18	4/28/19	10	0.074	161.53	-26%
2019-19	5/5/19	12	0.087	162.23	40%
2019-20	5/12/19	12	0.084	137.95	-11%
2019-21	5/19/19	8	0.087	139.47	-39%

CHAPTER 4. SHARED RIDE USE UNDER DIFFERENT SCENARIOS

This chapter formulates various scenarios that could encourage use of higher-occupancy modes. This chapter incorporates research presented in chapters 2 and 3 on the use of shared rides in the context of transportation network companies (TNC) and carpooling apps, respectively, as well as a literature review on the effect of parking price on the use of single occupancy vehicles (SOV) travel (described below). To evaluate the effect of these scenarios on ridesharing behavior, this chapter explains how changes in trip cost and travel time affect mode choice for various market segmentations. This research could be used to support policy and practice for the decision-makers responsible for urban and regional travel by testing and quantifying the impact of ridesharing incentives.

SCENARIO DETAILS

The four scenarios described in this chapter are designed to explore how incentivizing higher vehicle occupancy could result in reducing vehicle miles traveled (VMT). The scenarios are not intended to be based on specific policy mechanisms since there may be different ways for the relative cost and travel time scenarios to occur depending on local contexts. The scenario inputs do not represent all potential policy mechanisms that could impact modal choice.

Each scenario is intended to fit into a broader policy scenario framework that also includes market segments (e.g., trip type, origin, destination, and traveler characteristics) and city settings (i.e., the 15 large markets studied in chapter 1). Scenario impacts differ by both market segment and city. This chapter summarizes findings of the scenario analysis, particularly shifts in vehicle occupancy and VMT. This section introduces the basic details of the four scenarios.

Overview of Scenarios

The four scenarios described in table 16 are intended to address multiple modes of urban travel, including private SOV travel, private vehicle carpool, public transit, and shared or private TNC use. Each scenario represents a change in relative time or cost of modes as a strategy for supporting use of higher-occupancy vehicles, whether private, TNC, or transit. For each policy, table 16 presents the following information:

- The basis for considering the scenario, such as per-trip, per-mile, or cordon-based.¹
- The data source(s) needed to analyze the policy (i.e., the TNC survey research described in chapter 1, the app-based carpooling research described in chapter 2, or external literature review).

¹ A cordon could delineate an airport area, a downtown, an important highway link, or any other zone or facility. Cordon-based policies could be applied to some or all vehicles entering, all trips terminating (for-hire or privately-owned and parked), or only vehicles garaged in a zone.

The scenarios laid out here can be combined with one another in further stages of the analysis. In this study, it is assumed that combinations of scenarios would result in additive effects.

Table 16. Overview of scenarios considered for analysis.

	Scenario	Basis	Data Source
1	Increase cost savings for shared transportation network company (TNC) trips relative to private TNC trips	Dollar per mile	TNC survey findings (Chapter 2)
2	Reduce travel time penalty for shared TNC trips relative to private TNC trips	Minute per trip	TNC survey findings (Chapter 2)
3	Increase price differential between private vehicle car trips and all other modes	Dollar per trip	Literature review
4	(Experimental) Reward shared personal vehicle car trips but not private car trips	Dollar (or points) per trip	App-based carpooling findings (Chapter 3)

Scenario 1: Increase cost savings for shared transportation network company trips relative to private transportation network company trips

This initial scenario applies only to for-hire and TNC rides, specifically to the price difference between private and shared for-hire or TNC rides. This difference could be influenced through a number of mechanisms, including but not limited to fees (or rebates) on private TNC and for-hire rides. This price difference can be understood on a per-mile or a per-trip basis but is modeled in this research in terms of dollars per mile, in order to control for differences in trip lengths. Price differences apply to individual travelers or traveler parties. The expected effect of such a scenario would be to increase occupancy of TNC trips. This scenario is feasible to implement from a technical perspective and possible to model using the output of the TNC survey research described in chapter 2 (see figure 5).

Scenario 2: Reduce travel time penalty for shared transportation network company trips relative to private transportation network company trips

Unlike scenario 1, this scenario applies to time rather than cost. Under this scenario, shared TNCs would enjoy faster and more reliable travel times. While it is difficult to affect travel times in a consistent way, transportation facilities and policies (e.g., exclusive access to dedicated travel lanes or enforced delay on private TNC trips) could provide mechanisms for improving the relative travel time of shared TNC trips. Another possible mechanism for influencing relative travel time would be for a city to set a limit on the number of private TNC trips that may be underway at a given time through a metering system.² When private rides are in high demand, users would then have the option to wait for a private ride or skip the “virtual queue” by accepting a shared ride (for which there is no cap). Naturally, this supply-side policy could also have the effect of increasing the cost of private TNC rides, but it is difficult to predict exactly

² This could be implemented as a percentage of a TNC’s time per hour that could be allocated to private trips in order to avoid restricting growth of upstart TNCs or competition between TNCs to secure all the allowable private trips within an hour.

how the private sector would react to such a policy. Whatever the case may be, public agencies would likely require audit authority of TNCs and the ability to penalize violations in order to enforce this mechanism.

Whatever the exact mechanism may be, the expected impact of this scenario is to discourage single-occupancy travel by TNC (or for-hire vehicle). Like scenario 1, it is possible to model the impact of this policy using the output of the TNC survey research described in chapter 1. As with scenario 1, travel time difference is modeled in terms of minutes per mile, in order to control for differences in trip lengths (see figure 7).

Scenario 3: Increase price differential between private vehicle car trips and all other modes

Unlike scenarios 1 and 2, this scenario applies to the relative cost of private vehicle trips. It corresponds to mechanisms such as providing all residents of an area a refundable transportation expense allowance and then deducting from this allowance a per-trip fee on non-shared private vehicles crossing into or parking within a specific cordoned area. The fees could function as a fee for all trips and a rebate for verified carpools. The expected effect of such a scenario would be to increase travel by transit, carpool, TNC, and nonmotorized modes. This scenario is feasible to implement from a technical perspective and possible to model using a review of relevant literature.

To use studies of parking and non-parking driving costs as a proxy for this scenario, Shoup offers a useful starting point; the study reviewed seven studies conducted between 1969 and 1991 that analyzed the effect of employer-paid parking on SOV commute rates³. The review found that when employers in the analyzed areas paid for parking, 67 percent of employees drove alone. When employees paid for parking themselves in the same areas, the drive-alone rate dropped to 42 percent. Price elasticity for the various employment sites ranged from -0.08 to -0.23, with a mean of -0.15. This elasticity suggests that reducing the price of parking by 10 percent would increase the number of vehicle trips to work by 1.5 percent. However, elasticity—the ratio of percent change in demand to percent change in price—cannot be calculated if the starting price is zero (e.g., free parking), as any price increase would be one of infinity percent. Therefore, these elasticities were not calculated as logarithmic arc elasticity, but rather as linear arc elasticity (also known as midpoint elasticity). Linear arc elasticity approximates the average elasticity between two points along a demand curve. In this case, the percent change in price is defined as the absolute change in price divided by the average of the before and after prices. Because each case study examined the results of raising parking prices from zero to a market price, the change in market price is equal to the market price, and the average of the two prices (zero and market) is always half the market price.

Concas and Nayak conducted a meta-analysis of parking price elasticity using 25 studies that included in total 169 elasticity variables. This review found elasticity values -6.22 to zero, with a mean value of -0.482.⁴ The authors also developed a model to explain the variation in elasticity

³ Shoup et al (2005)

⁴ Concas, S. and Nayak, N. (2012). “A Meta-analysis of Parking Pricing Elasticity.”

estimates based on factors such as geographic location, estimation method, and data type. Their model, applied to estimate an elasticity for the United States (using econometric techniques), yielded a parking elasticity of -0.39. Similarly, Farber and Weld point to an average value of -0.30 based on an econometric analysis of public parking price responses in Eugene, OR.⁵ Finally, Litman⁶ conducted an extensive literature review of transportation elasticities and generally found that the demand for vehicle trips with respect to parking price ranges from -0.1 to -0.3.

The Trip Reduction Impacts of Mobility Management Strategies (TRIMMS) model from the Center for Urban Transportation Research at the University of South Florida uses elasticities like these alongside a wide range of other data sources in order to estimate the impacts of various travel demand management (TDM) strategies. Specifically, TRIMMS evaluates strategies directly affecting the cost of travel, such as parking pricing or tolling, in terms of outputs like changes in mode share, trips, and VMT. Among the strategies included in the TRIMMS tool is the ability to test increased per-trip costs for drive-alone automobile trips—a scenario very similar to scenario 3 as proposed in this research. For this strategy, the TRIMMS tool cites Hymel et al. and Concas and Nayak for their demand elasticity values for non-parking costs (-0.047) and parking costs, respectively (-0.39).^{7,8}

Considering all these studies and reviews together, this research relies upon a benchmark travel price elasticity of -0.30 for drive-alone trips. This elasticity value affects all travel costs. Because of the prevalence of employer-paid or otherwise free parking, a parking price elasticity calculation is impossible in the case of many trips (as noted above, it is not possible to make an elasticity calculation with a starting condition of zero for price or quantity demanded). For that reason, all pricing is included within the bundle of travel costs (i.e., an arc elasticity function with an elasticity of -0.30 considers the change in vehicle travel in relation to the driving costs as derived from the literature review above).

As noted above, the chosen elasticity affects all trip costs, which this paper calculates for each of the metropolitan areas included in the TNC survey, as shown in table 17. These per-trip costs provide a necessary starting point to estimate the effect of dollar-based increases in travel costs for drive-alone trips in scenario 3 using the elasticity estimate described above.

⁵ Farber, M. and Weld, E. (2013). Econometric Analysis of Public Parking Price Elasticity in Eugene, Oregon.

⁶ Litman, T. (2013). *Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior*.

⁷ Hymel, K.M., Small, K.A., and Van Dender, K. (2010). “*Induced Demand and Rebound Effects in Road Transport*.”

⁸ Concas, S. and Nayak, N. (2012).

Table 17. Average cost of drive-alone trips in study cities, with and without parking costs.
(Sources: City Observatory Price of Parking, Shoup (2005), National Household Travel Survey (2017))

Metropolitan Area	Monthly Parking Cost	% Workers Parking for Free	Avg. Trip Distance (mi)	Average Trip Cost	Avg. Trip Cost w/ Parking
Atlanta	\$80	95%	16.3	\$7.31	\$7.51
Austin	\$140	92%	12.6	\$5.66	\$6.19
Boston	\$458	93%	10.6	\$4.77	\$6.30
Chicago	\$309	93%	11.9	\$5.36	\$6.39
Denver	\$170	91%	10.1	\$4.55	\$5.28
Las Vegas	\$58	98%	11.6	\$5.21	\$5.27
Los Angeles	\$125	92%	13.7	\$6.17	\$6.64
Miami	\$98	91%	15.9	\$7.15	\$7.57
Nashville	\$128	92%	15.2	\$6.84	\$7.33
New York City	\$770	86%	9.1	\$4.08	\$9.21
Philadelphia	\$325	94%	9.7	\$4.38	\$5.31
Portland	\$197	95%	10.2	\$4.59	\$5.06
San Francisco	\$320	81%	9.6	\$4.31	\$7.20
Seattle	\$288	92%	12.0	\$5.39	\$6.48
Washington, D.C.	\$429	86%	10.8	\$4.87	\$7.73
All Study Cities	\$352	90%	11.7	\$5.26	\$6.88

Note: Average trip cost is calculated by multiplying average trip distance by \$0.45/mile (AAA 2016 driving costs)

Table 18 applies the values in table 17 to an estimated initial drive-alone mode share calculated from NHTS 2017 data (also used in the analytic model as described below). Table 18 is a sample of the effect of increasing drive-alone costs using the -0.30 elasticity value used in TRIMMS. Researchers could use these values to analyze the effect of this scenario on mode choice and VMT, with travel converted from private car travel assigned proportionally to other modes based upon their initial mode shares.

Table 18. Sample effect of increasing relative per-trip drive-alone costs on drive-alone mode share according to Trip Reduction Impacts of Mobility Management Strategies elasticity estimate of -0.30. (Source: Federal Highway Administration)

Geography	Initial Mode Share	Initial Trip Cost	\$1	\$2	\$3	\$4	\$5
All Study Cities	54.2%	\$6.88	53.4%	52.5%	51.6%	50.6%	49.6%

Experimental Scenario 4: Reward Personal Vehicle Carpool Trips but Not Private Car Trips

Unlike the scenarios discussed above, experimental scenario 4 applies only to private vehicle trips. Under this policy, drivers and potential passengers who participate in a carpooling platform application would be offered incentives to carpool through a point (or cash) rewards program, with points that could, for example, be exchanged for gift cards at restaurants and retailers. Alternatively, verified carpool participants could also receive refunds on charges that apply to SOV under a feebate scheme. The expected outcome of this scenario is conversion of private SOV trips to carpool trips.

Expanding upon the analysis presented in chapter 3, it would be possible, for illustrative purposes only, to show how if the data from one of the app-based platforms had been from a large randomized control experiment it could be used for additional analysis. Thus, this scenario is being presented as an experimental scenario.

In the experimental scenario, the approach described in the following paragraph is used to calculate the elasticity of incentives. In the future, this scenario analysis could be updated with other estimates of elasticity with respect to carpool rewards programs as data become more widely available.

Using the Metropia™ data (with the important caveat that this experimental scenario assumes that the observed behaviors associated with a particular incentive can be attributed only to that incentive), the elasticity of incentives to participation is similar for carpool passengers and drivers. Specifically, a 1 percent increase in incentives producing a 0.24 percent, 0.27 percent, and 0.24 percent increase in weekday carpool passenger/driver participation for the study cities of Tucson, El Paso, and Austin, respectively.

Taking the median (0.24 percent) as an assumed elasticity, a 0.01 percent increase in app-based points then translates to a 0.0024 percent increase in the probability of carpooling. Because the explanatory variable is a percentage increase and not absolute increase, the rough observed levels of points awarded provides a baseline for understanding this increase. As presented in chapter 3, roughly 60 points are awarded for each trip between the driver and the passenger. These points can be translated into dollars on a conversion rate of 1,200 points to \$5. Based on 60 points per trip, this translates to a price difference of \$0.25. Finally, a 1 percent increase in \$0.25 translates to a cash increase of \$0.0025. If a \$0.0025 reward increases the probability of carpooling by 0.0024 percent, the relationship between these values is roughly one-to-one. As such, the analysis of this scenario assumes that each \$0.25 increase in rewards increases the probability of sharing by 0.25 percent, or that each \$1 increase in rewards increases the probability of sharing by 1 percent.

Using these experimental scenario findings (or any alternative dataset and analytical framework) entails making an assumption about the proportion of the population that would agree to participate in a carpool incentive program entailing user monitoring and attempted engagement. For the sake of analysis, this participation rate is set to 25 percent, but could be adjusted to any other rate. Determining a potential value of the participation rate with confidence may involve significant market research.

Use of the Scenarios in the Analytic Model

Together, the three scenarios and the experimental scenario address multiple modes (i.e., private SOVs, carpool, and private/shared TNC travel) and multiple dimensions of mode choice (i.e., cost and time). However, each of the scenarios reallocate trips from one mode to another in different ways, based on the assumptions explained above. Figure 14, figure 15 and figure 16 explain how the scenarios differ from one another according to a mode choice decision tree. Dark red boxes in each scenario represent the modal choices directly affected by each scenario. (In scenarios 1 and 2, for example, we treat the share of people using a TNC as fixed, and that only the choice of shared TNC versus private TNC is influenced by the incentive. Experimental scenario 4 is similar, but with private vehicle trips. Only scenario 3 distributes trips from private vehicles or TNCs to other modes: transit, bike, and walk.)

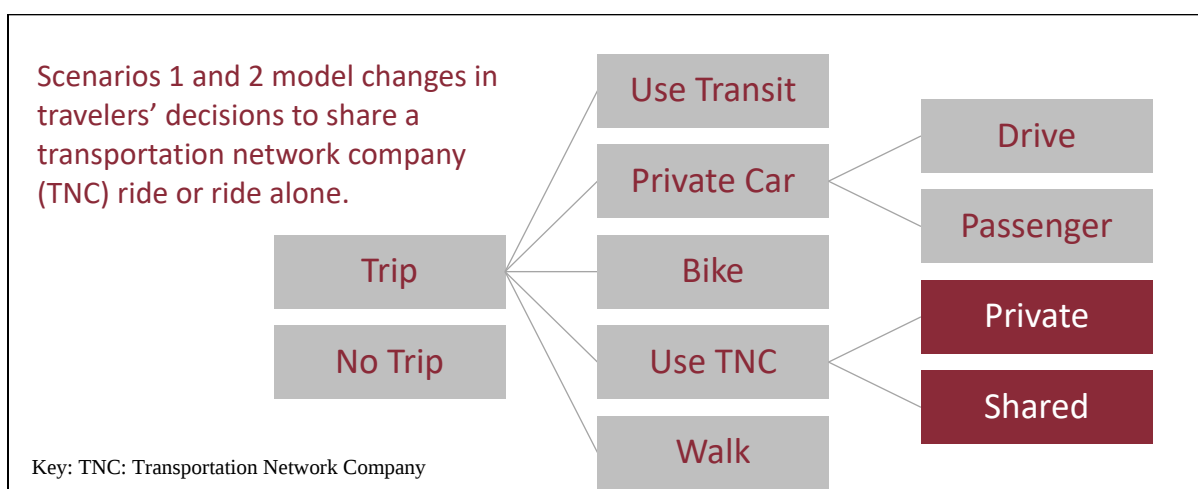


Figure 14. Graphic. Explanation of modes and decisions affected by scenarios 1 and 2.
(Source: Federal Highway Administration)

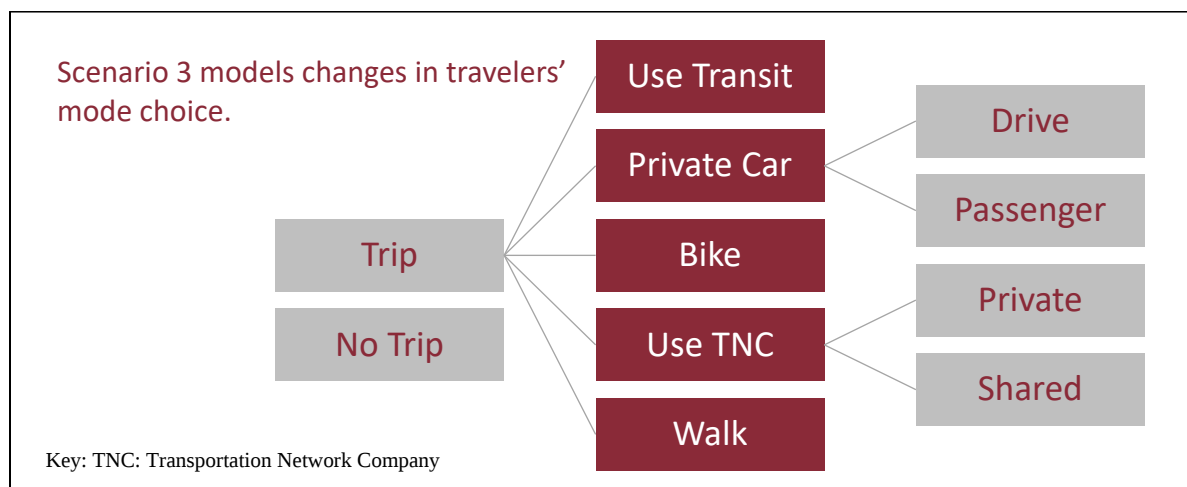


Figure 15. Graphic. Explanation of modes and decisions affected by scenario 3.
(Source: Federal Highway Administration)

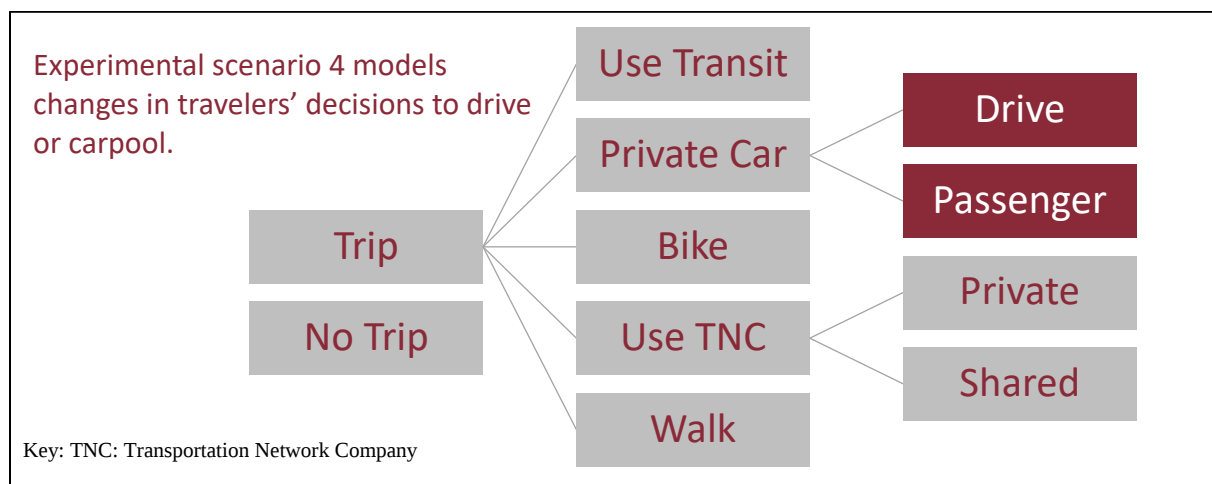


Figure 16. Graphic. Explanation of modes and decisions affected by experimental scenario 4. (Source: Federal Highway Administration)

The analytic model presented in the following section is able to estimate the effects of these scenarios on particular market segments. The analytic model can also show how policy impacts would likely differ by city based on considerations such as average trip distances.

ANALYTIC MODEL FOR SCENARIO ASSESSMENTS

The scenario analysis results presented in the following section are built upon an analytic model constructed in R and available at [Intelligent Transportation Systems \(ITS\) CodeHub](https://github.com/usdot-its-codehub), U.S. Department of Transportation's (USDOT) portal for open-source ITS code. Readers can download the code from the ITS CodeHub⁹ and run the analytic model to further explore the findings of the research in this report. The model allows the user to conduct their own tests, such as of a preferred policy scenario at a particular price point, for the fifteen cities included in the model. The model allows the user to explore the findings of the research described in chapters 2 and 3 as applied to the scenarios defined above.

The model can be used to explore changes in mode choice that might be observed if the relative time and price of various transportation modes were to change. The model allows testing of the scenarios that were developed from the research that the Federal Highway Administration (FHWA) explored on price and time but does not analyze all the potential policies that could impact modal choice. Despite the lack of perfect information on interactions between scenarios, the model offers the user the ability to test more than one scenario concurrently. For example, the user may apply scenarios for changes affecting personal cars and ridehailing simultaneously.

⁹ Direct link to the project repository: <https://doi.org/10.21949/1520429>

Analytic Model Inputs and Assumptions

The “Scenarios” tab allows the user to apply different levels and combinations of the scenarios (see figure 17). A slider bar is provided for each of the scenarios. The maximum value of each slider bar is determined according to the limits of the research into the effects of each scenario (e.g., price differences between private and shared TNC rides of greater than \$4 per mile were not queried and so the analytic model was designed to not allow inputs outside of this range).

The “Segments” tab allows the user to narrow the scenario analysis by geography, population segment, and time of day (see figure 17). The “Geography” menu allows the user to select between the 15 study cities analyzed in Chapter 1 or to select “All Study Cities.” The “Population Segment” menu allows the user to select between the segments for which models were re-estimated, as described in chapter 1 (i.e., annual income, relative gross office and industrial employment density for the market at the trip origin and destination, regional centrality index by transit at the trip origin and destination, and trips to/from airports or other intermodal hubs). Finally, the user can also toggle between peak period trips (i.e., trips beginning between 8:00 and 9:59 a.m. or 4:00 p.m. and 6:59 p.m.) or all trips. All segments affect the number of trips and amount of VMT included in the model outputs, with each additional segmentation reducing the number of trips affected. Population segment sizes are calculated using data from NHTS 2016 and from the TNC survey.

The “Customize Initial Mode Shares” tab allows the user to input customized initial mode shares (by person trip) for analysis (see figure 17). By default, mode shares are derived from National Household Travel Survey 2016 data. However, the user may override this starting point with more current or localized information. Any mode share may be entered as long as the sum of the shares is 100 percent. Throughout the analytic model, “mode share” refers to person trips.

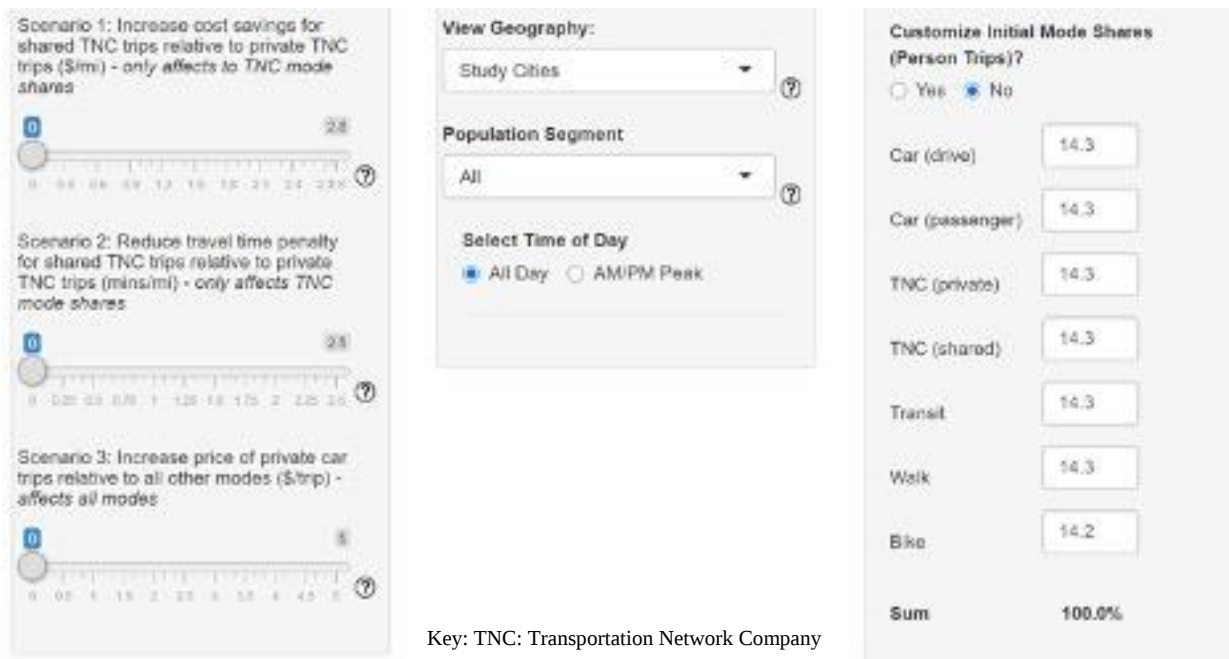


Figure 17. Image. Screenshots, from left to right: “Scenarios” sidebar tab, “Segments” sidebar tab, and “Customize Initial Mode Shares” sidebar tab. (Source: Federal Highway Administration)

The user can override these defaults using the slider bars. The question mark boxes provide citations or explanations for each of the assumptions. For convenience, these explanations are listed below:

- Trips Affected by Car Pricing Policies:** This value affects the impact of scenario 3, which impacts private car trips. This value can be used to tailor the scenario definition to be specific to the type of policy instrument applied. For example, a 100 percent value here means that the price difference would affect all vehicle trips for the selected segment. A lower share would be appropriate for a smaller cordon, or parking surcharge-based policy instrument (as not all parking is controlled). This assumption can also represent policy instrument leakage, since some number of vehicles may find their way around parking or cordon charges according to specific limitations or exemptions of any ultimate policy. In consideration of this effect, the default value is 70 percent.
- Penetration of Carpooling Incentive Apps:** This value represents the share of travelers that would opt in to using a carpooling app, which supports the use of reward incentives. The default value is 25 percent.
- Vehicle Occupancy for Carpool Trips (*before* applying scenarios):** This value represents the occupancy of carpool trips prior to the application of scenario 3 and/or Experimental scenario 4, which would be expected to impact the occupancy of carpool trips. The default starting occupancy of carpool trips is 2.05 people per vehicle.
- Vehicle Occupancy for Carpool Trips (*after* applying scenarios):** This value represents the new occupancy after applications of scenario 3 and/or experimental

scenario 4. If, for example, there is a conversion of 2-person carpools to 3-person carpools as the result of the scenarios, then this value should be expected to increase. If the user assumes that all new carpool trips are created from former SOV trips, then this value can be set equal to vehicle occupancy for carpool trips *before* applying the scenarios. The default starting occupancy of carpool trips is 2.05 people per vehicle.

- **Shared TNC Overlap Rate:** This value captures the percent of trips in which a user who opts in to sharing is matched with another rider (defaulted to 50 percent) and the percent of their trip where two parties are in vehicle (defaulted to 70 percent). Multiplying these two values together results in a starting value of 35 percent. It is needed to translate TNC mode share and trip distance into VMT. This value is within the range of plausible values suggested by Schaller.¹⁰ Another paper from Tachet et al. developed a formula predicting a related quantity they call shareability: the fraction of individual trips that can be shared within a tolerable threshold of delay.¹¹ Using data on taxi trips in several cities in the United States and abroad, the authors computed a universal shareability curve based on a few basic characteristics, including trips per hour per area, providing evidence that shareability (a proxy for the shared TNC overlap rate) should increase along with spatiotemporal trip density. For that reason, an overlap rate greater than 35 percent may be feasible at greater levels of opt-in to shared TNC rides and also in cities with relatively high densities.
- **TNC Non-Passenger Miles:** This value represents the share of TNC VMT without a passenger (i.e., cruising and deadheading). It is needed to translate TNC mode share and trip distance into VMT. The starting value of 42 percent is drawn from Balding et al.¹²
- **Pool Circuity:** This value represents the additional distance that a shared TNC trip travels to accommodate matched parties when compared with a private TNC trip's more direct route. It is needed to translate TNC mode share and trip distance into VMT. The starting value is assumed to be 10 percent.
- **Carpool Circuity:** This value represents the additional distance a carpool driver would travel to pick up his/her passenger relative to driving alone directly to his/her destination. It is needed to translate carpool mode share into VMT. The starting value is assumed to be 10 percent.

Interpreting Analytic Model Outputs

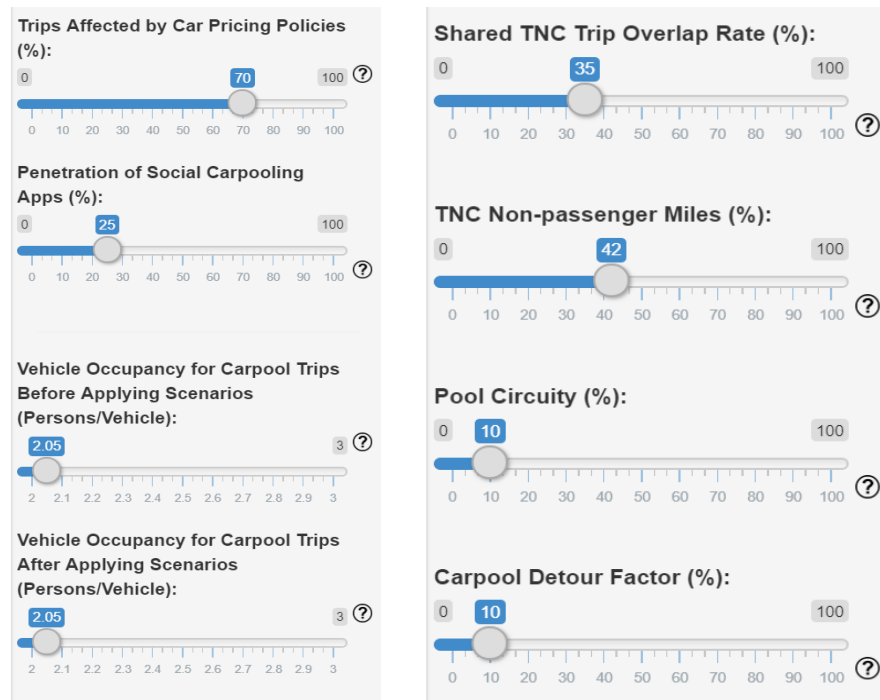
The analytic model processes the inputs described above (and shown in figure 18) and produces two primary outputs in its main panel: a table of values and a histogram of mode shares before and after the application of the scenario(s) being tested. (See figure 19.) The bars in the histogram represent the values presented in the “Initial Share” and “New Share” columns of the table. The figure also summarizes the change in VMT associated with the changes in mode share. Note that VMT is presented as “N/A” for several modes: passenger in private car, transit,

¹⁰ Schaller, B. (2018).

¹¹ Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S.H., and Ratti, C. (2017). “*Scaling Law of Urban Ride Sharing.*”

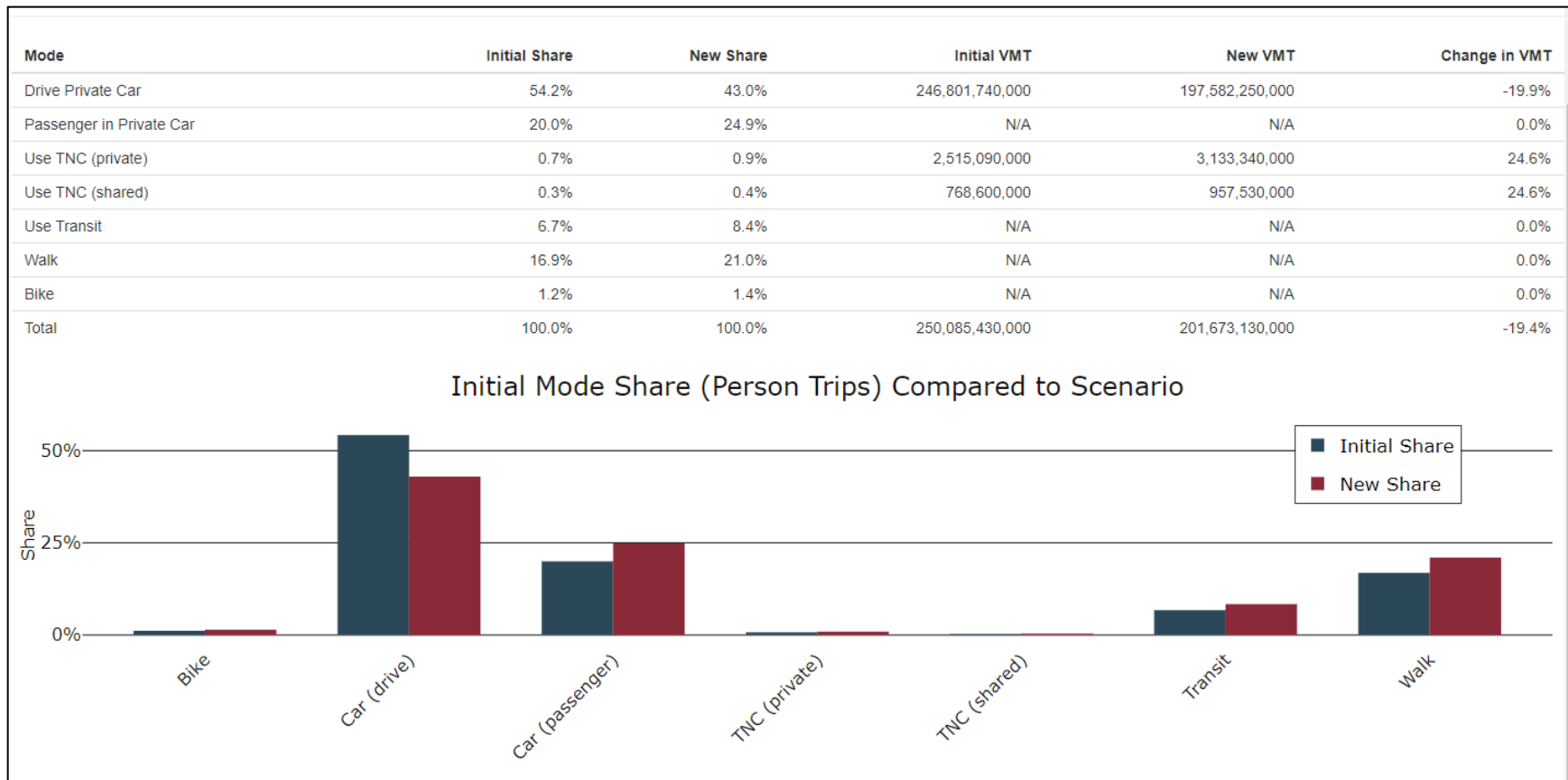
¹² Balding, M., Whinery, T., Leshner, E., and Womeldorff, E. (2019).

walk, and bike. VMT associated with private car passenger trips is combined with private car VMT in the top row of the output table. Walking and biking require no motor vehicle travel. Transit VMT is omitted from this analysis because VMT per passenger mile traveled is so low in high-occupancy transit so as to be considered negligible, and transit VMT is unlikely to change significantly with changes in transit vehicle occupancy.



Key: TNC: Transportation Network Company

Figure 18. Image. Screenshot of slider bars features in “Assumptions” sidebar tab.
(Source: Federal Highway Administration)



Key- TNC: Transportation Network Company, VMT: Vehicle Miles Traveled

Figure 19. Graph. Sample output of analytic model for illustrative purposes. (Source: Federal Highway Administration)

Limitations of the Analytic Model

This analytic model is intended to assess the mode choice implications of relative price and travel time differences between single-occupancy/single-party and carpool/shared trips. These differences sometimes result from public policy but could also stem from market dynamics or corporate pricing policy. The analytic model is agnostic as to the source of these differences.

As noted in chapter 2, the results of the TNC survey research built into the analytic model are limited by the trip alternative questions asked in the survey. That is, the study did not produce the data to evaluate the effects of price and time differences that exceed those presented in table 3 (i.e., maximum shared TNC discount of 75 percent). It is not possible, for example, for the analytic model to assess the effects of free shared TNC trips on the rate at which people choose to use shared TNCs. For that reason, the maximum allowable input values for scenarios 1 and 2 are capped at \$2.80/mile and 2.5 minutes/mile respectively. These limits are calculated by multiplying the highest level of price difference (75 percent) or travel time difference (approximately 65 percent) included in the survey by the observed average price per mile (\$3.30) or travel duration per mile (3.9 minutes).

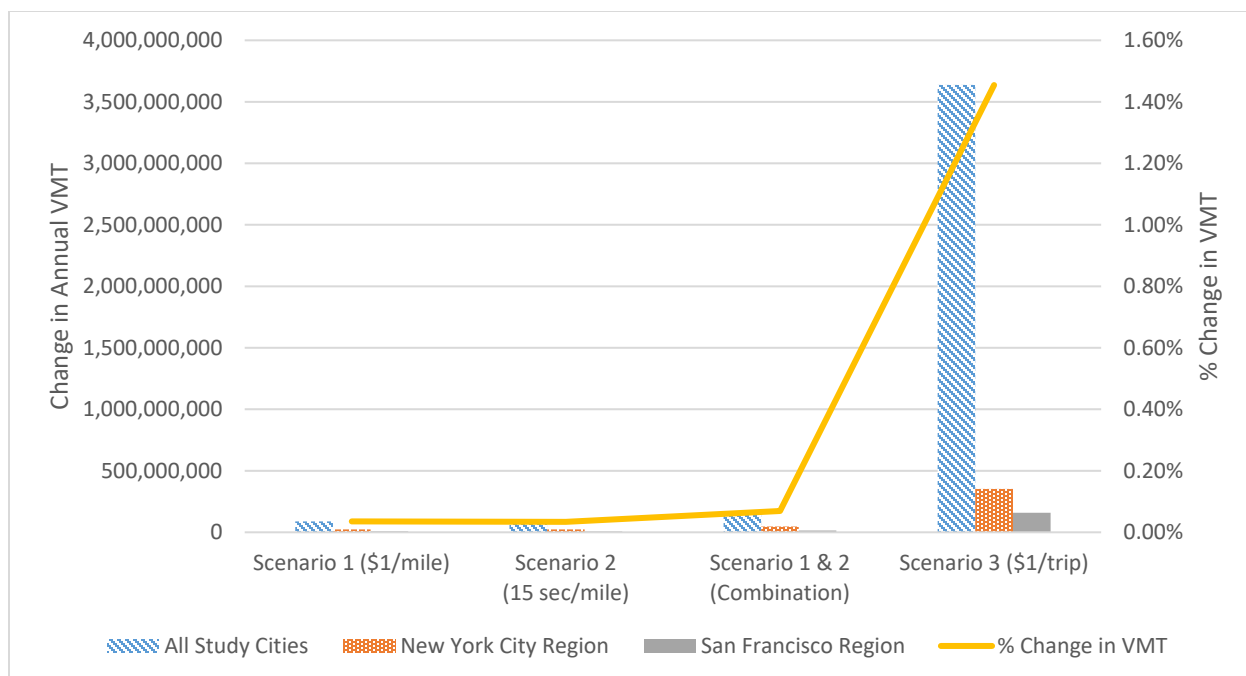
Except for scenario 3, interactions across all modes are not considered. As shown in figure 14, the first and second scenarios reallocate trips between TNCs (private and shared) and as shown in figure 15, the third scenario reallocates only between private vehicles (drive alone or carpool). These reallocation patterns should still provide interesting insights and may not be too far from accurate, because (1) travelers typically seem to make decisions between personal cars, for-hire vehicles, transit, and active transportation before making decisions about shared versus private personal cars and for-hire vehicles; and (2) the relative prices of the first-order choices remain the same regardless of changes within the categories.

In scenario 3, “Drive Private Car” trips are reallocated to other modes according to initial mode share. For this scenario (and the others), the research does not consider either induced demand or, conversely, that some people may choose not to travel if mode characteristics change.

Finally, the analytic model is built on a number of assumptions that are explained in pop-up question mark text in the “Assumptions” tab and described above. These assumptions may be updated within the analytic model if better, more current, and/or more localized information becomes available.

SCENARIO ANALYSIS RESULTS

The following section uses the analytic model described above to assess the VMT impact of various scenario applications in multiple cities and across multiple population segments. Figure 20 presents a high-level summary of the effect of various levels for three scenarios, plus a combination of scenarios 1 and 2.



Key: VMT- Vehicle Miles Traveled

Figure 20. Graph. Effect of scenarios on vehicle miles traveled (total change and percent change). (Source: Federal Highway Administration)

Key findings displayed in figure 20 include:

- Although it would involve a substantial increase in the price per mile differential, it is possible to influence TNC riders with price differences (i.e., scenario 1). A \$1/mile price difference increase between private and shared TNC rides would reduce VMT in the 15 study cities by roughly 88 million miles per year.
- Scenario 2 can achieve a similar reduction in VMT (roughly 85 million miles per year) at the level of 15 seconds of travel time saved per mile for shared rides. This parity implies a very high value of time for TNC users overall.
- Because TNC trips comprise a small share of overall VMT, even in cities with relatively heavy use, such as New York City and San Francisco, policies targeted at TNCs have a relatively small impact on overall VMT (at least at current levels of TNC usage).
- Although population segments are not shown in Figure 20, the effectiveness of changes in differences in price and travel time for TNC trips is relatively greater for specific segments, such as trips starting in dense office districts (for price) and trips ending in dense office districts (for travel time).
- Compared to TNC-specific scenarios (i.e., scenarios 1 and 2), scenario 3 has a broader reach and a greater impact on VMT. A relative price increase of \$1/trip for all private car trips (compared with carpool trips in private vehicles) would result in annual VMT savings of approximately 3.6 billion miles across the 15 study cities (about 1.5 percent of annual VMT in those cities).

- Price differences applied to private car travel affect many more trips and have far greater VMT impacts than such differences applied to TNC travel (at least with current levels of private car and TNC usage).

The following sections present greater detail on the effect of each of the three scenarios.

Scenario 1: Lower Relative Prices for Shared Transportation Network Company Trips

Table 19 tests the effect of scenario 1 on VMT. The analytic model allows the user to test the scenario at any price level from \$0.05 to \$2.80 per mile. The results in Table 19 present the effect of a \$1/mile increase in the price difference between private and shared TNCs—a meaningful, but realistic increase in the difference in price between these two modes. The effect of a higher or lower price difference on VMT would scale linearly to the size of the price difference and effect presented here. The table presents the results for all trips (on the left) and for trips starting in dense office districts (on the right). This segment was chosen because trips in that segment were shown to be more sensitive to this price difference (as described in Figure 5). Table 19 also presents three geographies. The table only presents TNC VMT (and total VMT by all modes) because scenario 1 does not affect private vehicle, transit, walk, or bicycle modes.

As expected, table 19 shows that the effect of scenario 1 on VMT is more than twice as great for trips starting in dense office districts (i.e., annual VMT savings of 0.09 percent compared to 0.04 percent for all trips). Due to the higher initial share of TNC trips, the effect of scenario 1 on VMT is proportionally higher in New York City and San Francisco than for the study cities taken as a whole (i.e., VMT reductions of 0.06 to 0.07 percent compared to 0.04 percent). Considering all trips in all study cities, a \$1 additional price difference (per mile) between private and shared TNCs would reduce VMT by roughly 88 million miles per year by reducing private TNC VMT by 12.3 percent and substituting shared TNCs for that travel.

Scenario 2: Faster Relative Travel Time for Shared Transportation Network Company Trips

Table 20 shows the effect of scenario 2 on VMT. The analytic model allows the user to test the scenario at any level up to 2.5 minutes per mile. The results in table 20 present the effect of a 15 seconds/mile travel time difference reduction (between private and shared TNCs), a VMT impact roughly equivalent to the \$1/mile impact shown in table 19. As with scenario 1, the effect of a higher or lower travel time difference on VMT would scale linearly to the size of the difference tested. The table presents the results for all trips (on the left) and for trips ending in dense office districts (on the right). This segment was chosen because trips in that segment were shown to be more sensitive to this time difference (as described in figure 7). The table only presents TNC VMT (and total VMT by all modes) because scenario 2 does not affect private vehicle, transit, walk, or bicycle modes.

As expected, table 20 shows that the effect of scenario 2 on VMT is greater for trips ending in dense office districts (i.e., annual VMT savings of 0.05 percent compared to 0.03 percent for all trips). Due to the higher initial share of TNC trips, the effect of scenario 2 on VMT is

proportionally higher in New York City and San Francisco than for the study cities taken as a whole (i.e., VMT reductions of 0.06 to 0.07 percent compared to 0.03 percent). Considering all trips in all study cities, a 15 seconds per mile travel time difference reduction between private and shared TNCs would reduce VMT by roughly 85 million miles per year by reducing private TNC miles by 11.9 percent and substituting shared TNC travel for that difference.

Table 19. Effect of \$1/mile price difference for shared transportation network company trips across three geographies, for all segments, and for trips starting in dense office districts. See scenario 1. (Source: Federal Highway Administration)

Geo- graphy	All Trips						Trips Starting in Dense Office Districts				
	Use TNC Mode	Initial Share (%)	New Share (%)	Initial Vehicle Miles Traveled (VMT)	New VMT	Change in VMT (%)	Initial Share (%)	New Share (%)	Initial VMT	New VMT	Change in VMT (%)
All Study Cities	Private	0.7	0.6	2,515,090,000	2,205,760,000	-12.30	0.7	0.5	418,770,000	285,120,000	-31.90
	Shared	0.3	0.4	768,600,000	989,770,000	28.80	0.3	0.6	127,970,000	223,540,000	74.70
	Total	1.0	1.0	3,283,690,000	3,195,530,000	-2.7	1.0	1.1	546,740,000	508,660,000	-6.96
	Total all modes	100.0	100.0	250,085,430,000	249,997,270,000	-0.04	100.0	100.0	41,640,200,000	41,602,110,000	-0.09
New York City Region	Private	1.2	1.1	636,050,000	550,980,000	-13.40	1.2	0.8	105,910,000	69,150,000	-34.70
	Shared	0.7	0.8	251,180,000	312,010,000	24.20	0.7	1.1	41,820,000	68,100,000	62.80
	Total	1.9	1.9	887,230,000	862,990,000	-2.73	1.9	1.9	147,730,000	137,250,000	-7.09
	Total all modes	100.0	100.0	33,012,550,000	32,988,310,000	-0.07	100.0	100.0	5,496,720,000	5,486,240,000	-0.19
San Francisco Region	Private	1.0	0.9	197,710,000	171,030,000	-13.50	1.0	0.7	32,920,000	21,390,000	-35.00
	Shared	0.6	0.7	80,544,000	99,070,000	23.80	0.6	0.9	13,320,000	21,560,000	61.90
	Total	1.6	1.6	278,254,000	270,100,000	-2.93	1.6	1.6	46,240,000	42,950,000	-7.12
	Total all modes	100.0	100.0	11,728,310,000	11,720,710,000	-0.06	100.0	100.0	1,952,810,000	1,949,530,000	-0.17

Key: TNC: Transportation Network Company

Table 20. Effect of 15 seconds/mile reduced travel time difference between private and shared transportation network company trips across three geographies, for all segments, and for trips ending in dense office districts. See scenario 2 (affects only shared transportation network company modes). (Source: Federal Highway Administration)

Geo- graphy	All Trips						Trips Ending in Dense Office Districts				
	Use TNC Mode	Initial Share (%)	New Share (%)	Initial Vehicle Miles Traveled (VMT)	New VMT	Change in VMT (%)	Initial Share (%)	New Share (%)	Initial VMT	New VMT	Change in VMT (%)
All Study Cities	Private	0.7	0.7	2,515,090,000	2,216,610,000	-11.90	0.7	0.6	681,120,000	572,670,000	-15.90
	Shared	0.3	0.4	768,600,000	982,020,000	27.80	0.3	0.4	208,150,000	285,690,000	37.30
	Total	1.0	1.1	3,283,690,000	3,198,630,000	-2.6	1.0	1.0	889,270,000	858,360,000	-3.48
	Total all modes	100.0	100.0	250,085,430,000	250,000,360,000	-0.03	100.0	100.0	67,726,220,000	67,695,310,000	-0.05
New York City Region	Private	1.2	1.1	636,050,000	553,960,000	-12.90	1.2	1.0	172,250,000	142,420,000	-17.30
	Shared	0.7	0.8	251,180,000	309,880,000	23.40	0.7	0.9	68,020,000	89,350,000	31.40
	Total	1.9	1.9	887,230,000	863,840,000	-2.64	1.9	1.9	240,270,000	231,770,000	-3.54
	Total all modes	100.0	100.0	33,012,550,000	32,989,160,000	-0.07	100.0	100.0	8,940,210,000	8,931,710,000	-0.10
San Francisco Region	Private	1.0	0.9	197,710,000	171,970,000	-13.00	1.0	0.8	53,540,000	44,190,000	-17.50
	Shared	0.6	0.7	80,544,000	98,400,000	23.00	0.6	0.8	21,660,000	28,350,000	30.90
	Total	1.6	1.6	278,254,000	270,370,000	-2.83	1.6	1.6	75,200,000	72,540,000	-3.54
	Total all modes	100.0	100.0	11,728,310,000	11,720,980,000	-0.06	100.0	100.0	3,176,170,000	3,173,510,000	-0.08

Key: TNC: Transportation Network Company

Combination of Scenarios 1 and 2: Greater Price Differential and Less Time Differential

Table 21 presents the impacts on VMT, at the level of \$1/mile and 15 seconds per mile, respectively. These effects were chosen to represent a realistic, multifaceted approach to reduction of TNC VMT. As before, the table presents the results for all trips (on the left) and for trips ending in dense office districts (on the right), and for three geographies.

Because it is assumed in this study that the effects of travel time and price differences are linear for the values tested in the study, combining scenarios 1 and 2 simply adds the effect of the two scenarios together. As expected, table 21 shows a VMT effect greater than either scenario 1 or scenario 2 alone, for all cities and for any segment. Considering all trips in all study cities, a \$1 additional price difference between private and shared TNCs combined with a 15 second/mile travel time advantage would reduce VMT by roughly 173 million miles per year.

Table 21. Effect of both a \$1/mile increased price difference and a 15 seconds/mile reduced travel time difference between private and shared transportation network company trips across three geographies, in all segments (left) and trips ending in dense office districts (right). See scenarios 1 and 2 (affects only transportation network company modes). (Source: Federal Highway Administration)

Geo- graphy	All Trips						Trips Ending in Dense Office Districts				
	Use TNC Mode	Initial Share	New Share	Initial Vehicle Miles Traveled (VMT)	New VMT	Change in VMT	Initial Share	New Share	Initial VMT	New VMT	Change in VMT
All Study Cities	Private	0.7	0.6	2,515,090,000	1,907,280,000	-24.20	0.7	0.5	681,120,000	486,040,000	-28.60
	Shared	0.3	0.5	768,600,000	1,203,190,000	56.50	0.3	0.5	208,150,000	347,630,000	67.00
	Total	1.0	1.1	3,283,690,000	3,110,470,000	-5.3	1.0	1.0	889,270,000	833,670,000	-6.25
	Total all modes	100.0	100.0	250,085,430,000	249,912,200,000	-0.07	100.0	100.0	67,726,220,000	67,670,620,000	-0.08
New York City Region	Private	1.2	0.9	636,050,000	468,890,000	-26.30	1.2	0.8	172,250,000	118,600,000	-31.10
	Shared	0.7	1.0	251,180,000	370,700,000	47.60	0.7	1.1	68,020,000	106,380,000	56.40
	Total	1.9	1.9	887,230,000	839,590,000	-5.37	1.9	1.9	240,270,000	224,980,000	-6.36
	Total all modes	100.0	100.0	33,012,550,000	32,964,910,000	-0.14	100.0	100.0	8,940,210,000	8,924,920,000	-0.17
San Francisco Region	Private	1.0	0.8	197,710,000	145,290,000	-26.50	1.0	0.7	53,540,000	36,720,000	-31.40
	Shared	0.6	0.9	80,544,000	117,470,000	46.80	0.6	0.9	21,660,000	33,690,000	55.50
	Total	1.6	1.7	278,254,000	262,760,000	-5.57	1.6	1.6	75,200,000	70,410,000	-6.37
	Total all modes	100.0	100.0	11,728,310,000	11,713,380,000	-0.13	100.0	100.0	3,176,170,000	3,171,380,000	-0.15

Key: TNC: Transportation Network Company

Scenario 3: Increase Price Difference of Private Car Trips and All Other Modes

Table 22 shows the effect of scenario 3 on VMT, at a level of \$1/private car trip. The effect on VMT presented here (a 1.45 percent reduction in VMT across all study city regions) is greater than the effect observed in either of the TNC scenarios (scenarios 1 and 2), where VMT reductions ranged from 0.03 percent to 0.17 percent. Considering all trips in all study city regions, a \$1/trip relative price increase for “Drive Private Car” would reduce VMT by roughly 3.6 billion miles per year. This effect is greater than the VMT reductions of scenarios 1 and 2 because scenario 3 affects many more trips; while driving alone accounts for 54.2 percent of trips in the study city regions, private TNC trips account for less than 1 percent in the study city regions.

Unlike the previous tables in this section, this table presents the results only for all trips as the scenario effect studied is not shown to vary between population segments. That is, although the amount of VMT within a segment does differ (i.e., there are more total trips than trips to the airport), the analytic model assumes that a \$1/trip price increase for private car travel would have a proportional effect on any segment.

Table 22 presents three geographies. Unlike the other tables in this section, this table presents VMT for all modes because scenario 3 shifts trips from private vehicles to other modes: TNC, transit, walk, and bicycle.

Table 22. Effect of \$1/trip relative increase in the price of private car trips compared to all other modes (affects all modes), in all segments for three different geographies. See scenario 3. (Source: Federal Highway Administration)

Geography	Mode	Initial Share (%)	New Share (%)	Initial Vehicle Miles Traveled (VMT)	New VMT	Change in VMT (%)
All Study Cities	Drive private car	54.2	53.4	246,801,740,000	243,103,410,000	-1.50
	Passenger in private car	20.0	20.4	N/A	N/A	0.00
	Use transportation network company (TNC) (private)	0.7	0.8	2,515,090,000	2,561,550,000	1.85
	Use TNC (shared)	0.3	0.3	768,600,000	782,790,000	1.85
	Use TNC (total)	1.0	1.1	3,283,690,000	3,344,340,000	1.85
	Use transit	6.7	6.9	N/A	N/A	0.00
	Walk	16.9	17.2	N/A	N/A	0.00
	Bike	1.2	1.2	N/A	N/A	0.00
	Total	100.0	100.0	250,085,430,000	246,447,760,000	-1.45
New York City Region	Drive private car	42.1	41.6	32,125,320,000	31,765,270,000	-1.12
	Passenger in private car	16.4	16.5	N/A	N/A	0.00
	Use TNC (private)	1.2	1.2	636,050,000	641,400,000	0.84
	Use TNC (shared)	0.7	0.7	251,180,000	253,290,000	0.84
	Use TNC (total)	1.9	1.9	887,230,000	894,690,000	0.84
	Use transit	13.0	13.1	N/A	N/A	0.00
	Walk	25.5	25.7	N/A	N/A	0.00
	Bike	1.2	1.2	N/A	N/A	0.00
	Total	100.0	100.0	33,012,550,000	32,659,960,000	-1.07
San Francisco Region	Drive private car	48.6	48.5	11,450,610,000	11,287,400,000	-1.43
	Passenger in private car	22.0	22.3	N/A	N/A	0.00
	Use TNC (private)	1.0	1.0	197,710,000	200,500,000	1.41
	Use TNC (shared)	0.6	0.6	80,000,000	81,120,000	1.40
	Use TNC (total)	1.6	1.6	277,710,000	281,620,000	1.41
	Use transit	7.1	7.2	N/A	N/A	0.00
	Walk	18.8	19.1	N/A	N/A	0.00
	Bike	1.9	1.9	N/A	N/A	0.00
	Total	100.0	100.0	11,728,310,000	11,569,020,000	-1.36

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CHAPTER 5. IMPLICATIONS FOR CITIES

Reducing vehicle miles of travel has the potential to unlock a wide range of benefits for cities: alleviating congestion, improving travel time and travel time reliability for all road users, reducing vehicle emissions and energy use, supporting economic growth, and preventing crashes. Furthermore, shared rides offer direct benefits to several groups: lower, split costs for travelers and economized costs for transportation service providers.¹

Because vehicle occupancy has a significant impact on the number of vehicles on the road, cities have an interest in encouraging higher-occupancy travel as a means of reducing vehicle miles traveled (VMT). Cities have a multitude of mechanisms for reducing VMT, from encouraging high-occupancy or active modes to pricing private vehicle travel. However, a major challenge for cities is predicting the effectiveness of various policy mechanisms on VMT reduction. Understanding this effectiveness is critical for cities because many policy mechanisms may also present challenges for transportation agencies and changes in costs for the traveling public. This study provides cities with information on the impacts of four changes in modal travel characteristics that could relate to potential policy mechanisms:

1. Increase cost savings for shared transportation network company (TNC) trips relative to private TNC trips.
2. Reduce travel time penalty for shared TNC trips relative to private TNC trips.
3. Increase price differential of private car trips relative to all other modes.
4. Reward carpooling trips but not private car trips.

Chapter 4 analyzes the first three scenarios (the fourth being experimental) and finds that changes to the relative price of single occupancy vehicle (SOV) travel (i.e., driving alone rather than with a passenger) offer the greatest opportunity for reduction in VMT. The reason for this impact is that SOV travel accounts for the majority of VMT and person trips in the United States. Scenario 3 asks what the impact would be if SOV travel were relatively more expensive than private vehicle carpool trips. The study finds, for example, that a \$1/trip relative price increase for drive-alone trips could potentially save over 3.5 billion vehicle miles annually in the 15 markets studied in this report. More modest, or more targeted, interventions could also reduce VMT by focusing on particular geographies or population segments.

Chapter 3 explored carpooling incentives and the sharing of rides facilitated through carpooling apps, which informed an experimental scenario 4, discussed in chapter 4, and was provided for illustrative purposes only. In the future, this scenario analysis could be updated with other estimates of elasticity with respect to carpool rewards programs as data, such as through future randomized control trials, become more widely available.

¹ Merlin, L.A. (2019). “*Transportation Sustainability Follows From More People in Fewer Vehicles, Not Necessarily Automation.*”

Scenarios 1 and 2 draw upon the results of chapter 1 to test the impact of lower relative prices and faster relative travel time for shared TNC trips, respectively. The impact of these scenarios on VMT is much smaller than scenario 3 because TNCs currently represent a very small portion of total trips and total VMT (about 1 percent of all person trips in the study city regions, compared to private vehicles' much larger share of person trips in the study city regions: roughly 55 percent as a driver and a further 20 percent as a passenger). Nonetheless, these scenarios do have an impact on VMT—an impact that might have an outsized influence on congestion if TNC trips also occur in the most congested areas of a region at the most congested times. Specifically, scenario 1 finds that a \$1/mile increase in price difference between private and shared TNCs could potentially reduce VMT by roughly 88 million miles per year by reducing private TNC VMT by 12.3 percent and substituting shared TNCs for that travel. This corresponds to an annual VMT savings of about 0.04 percent across all 15 study city regions. The relative effect is twice as high if the scenario is applied only to trips starting in dense office districts.

The scenario 2 example shown above demonstrates that a 15 seconds/mile decrease in travel time difference between private and shared TNCs would result in a VMT impact roughly equivalent to the \$1/mile tested in scenario 1. In both scenario 1 and scenario 2, the effect of a higher or lower price/travel time difference on VMT scales linearly to the size of the difference tested. Considering all trips in all study city regions, a 15 seconds per mile reduction in travel time difference between private and shared TNCs could potentially reduce VMT by roughly 85 million miles per year by reducing private TNC miles by 11.9 percent and substituting shared TNC travel for that difference.

CHAPTER 6. POTENTIAL FOR FUTURE RESEARCH

The research presented in this report spans several topics: carpooling apps, ridesharing via transportation network companies (TNC), private vehicle trip pricing, and the impacts of sharing on vehicle miles traveled (VMT). In each of these areas, the report points to several avenues for future research.

Chapter 2 describes this report's methodology for a stated-preference study anchored off real TNC trips with revealed preferences to simulate other potential decisions. Using stated-preference surveys anchored on real trips taken—because they incorporate the genuine context of trips—can likely provide much more accurate results than do stated-preference surveys more generally. While this research takes several steps forward in explaining TNC travel choices, it also points to several avenues for building on and expanding upon its findings.

First, the data presented here is only a snapshot in time of a TNC user base that is growing and changing rapidly. As this user base evolves and TNCs alter their services, this analysis could be updated to reflect the point-in-time reality of travel behavior. Longitudinal/panel research would support an understanding of how sharing behavior changes over time.

Second, this study did not have data to evaluate the effects of price and time differences that exceed those presented in table 3 (i.e., maximum shared TNC discount of 75 percent). It is not possible, for example, to use data from the TNC survey to analyze the effects of *free* shared TNC trips on the rate at which people choose to use shared TNCs. Further research could test the impact of truly free shared TNC rides on mode choice.

Third, the TNC survey results do not address interactions across all modes. For that reason, this study can estimate how price and time affect a user's choice between a private and shared TNC ride, but it cannot estimate how price and time affect a user's choice among TNCs, transit, driving, carpooling, walking, bicycling, or any other mode. Similarly, the study provides no data to consider how TNC characteristics affect a user's decision to take a trip in the first place. Additional multimodal discrete choice analysis is necessary to properly nest these decisions within an integrated mode choice model.

Regarding the analysis presented in chapter 3, the exploration of carpooling apps points to the potential benefit of additional research into the impacts of campaigns that promote carpooling, and specifically randomized controlled experiments on the impacts of incentives, and the altering of such incentives, on carpooling rates.

Regarding the analytic model that enables scenario assessments as presented in chapter 4, assessments could be improved and expanded on in several ways. If data and analysis become available, the analytic model could be updated to analyze the effects of more extreme price and travel time differences between private and shared TNC trips (currently, the maximum allowable input values for scenarios 1 and 2 are capped at \$2.80/mile and 2.5 minutes/mile, respectively).

Further, if data supporting additional discrete choice analysis were available, the analytic model could be updated to consider interactions across all modes for each scenario. By posting the model on the [Intelligent Transportation Systems \(ITS\) CodeHub](#),¹ FHWA enables collaborative development and improvements to the model. Readers are permitted and encouraged to collaboratively share any updates, modifications, and improvements to the model as new data sources or city-level information changes.

This research report does not explore factors (beyond cost and travel time) that, according to other research, sometimes make people averse to sharing a vehicle with strangers, such as safety, privacy, and convenience. The impact of each of these factors, if better understood, might suggest additional approaches for policymakers to increase the public's willingness to share rides, whether in private vehicles or through TNC services.

¹The direct link to the project information on ITS CodeHub is <https://doi.org/10.21949/1520429>

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