Final Project Report

Mode Substitutional Patterns of Ridehailing and Micro-mobility Services

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract
In this study, we explore the heterogeneous impacts of ridehailing on the use of other travel modes using survey data (N=1,438) collected from June to October 2019 (i.e., before the COVID-19 pandemic) across three regions in southern U.S. states: Phoenix, Arizona; Atlanta, Georgia; and Austin, Texas. We apply a latent-class cluster analysis to indicators of changes in the use of various travel modes as a result of ridehailing adoption, with covariates of socioeconomics, demographics, a land-use attribute, and individual attitudes. We identify four distinctive latent classes of behavioral changes in response to the use of ridehailing. About half of ridehailing users in the sample (49.7%) are found to behave as *Mobility augmenters*, who use ridehailing rarely, in addition to other travel modes, and do not change their travel routines much as a result of the adoption of this mobility service. The second largest class includes *Exogenous changers* (24.5%), whose members report many changes in their use of various travel modes, but which can be largely explained by other reasons. *Private car/taxi substituters* (15%) frequently hail a ride, and as a result, reduce their use of private vehicles while making more trips by public transit and active modes, as the result of using ridehailing. Interestingly, *Transit/active mode substituters* (10.8%) often use ridehailing, likely for trips that they previously made by public transit or active modes, and consequently reduce their use of these less-polluting modes while enjoying enhanced mobility. This study reveals substantial heterogeneity in ridehailing impacts, which were masked in previous studies that focused on average impacts, and it suggests that policy responses should be customized by users' socioeconomics and residential neighborhoods.

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EXECUTIVE SUMMARY

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INTRODUCTION

Ridehailing refers to on-demand ride services that users can request in real-time and pay for via a smartphone app. Under the hood, transportation network companies (TNCs) broker rides, matching customers requesting a ride and drivers: the largest TNCs include Uber and Lyft in the United States, Didi Chuxing in China, and Grab in Southeast Asia. Since its first launch in San Francisco in March 2009, the number of annual trips served by Uber has continuously increased, reaching seven billion trips world-wide during the year 2019 alone (Uber, n.d.). More than 20% of U.S. adults are estimated to use ridehailing services (Young & Farber, 2019).

Researchers and transportation professionals have examined the user base of ridehailing and its impacts on travel behavior and transportation systems, to obtain insights for effective policy responses. Regarding user characteristics, previous studies found that (frequent) users are predominantly young, well-educated, and wealthy individuals living in dense parts of large metropolitan areas (Deka & Fei, 2019; Gehrke et al., 2019; Rayle et al., 2016; Young & Farber, 2019). However, recent statistics suggest that the gaps in ridehailing adoption among segments in the population (e.g., college graduates vs. others) have reduced in size over time as ridehailing market penetration increases (Jiang, 2019).

As for ridehailing impacts, many studies have explored whether ridehailing substitutes or complements public transit. Summary statistics show that ridehailing users tend to make more transit trips than non-users (Das, 2020; NASEM, 2016); however, causality might work in both directions. Studies claim that ridehailing's role as a substitute for or a complement to public transit use depends on the type of transit services. For example, ridehailing is found to more often substitute for the use of bus and light rail services, while it tends to more often complement commuter rail (Babar & Burtch, 2020; Clewlow & Mishra, 2017). Another study reveals that Uber complements public transit services operated by small agencies in large metropolitan areas, but it substitutes for the use of public transit in other cases (Hall et al., 2018). As for other modes, while studies find negative impacts of ridehailing on taxis (Contreras & Paz, 2018; Tirachini & del Río, 2019; Young & Farber, 2019), other studies present mixed findings regarding its impacts on the use of active modes (Alemi et al., 2018; Circella & Alemi, 2018; Young & Farber, 2019). In addition, ridehailing is found to increase vehicle miles traveled (VMT) at the system level and contribute to traffic congestion, through deadheading miles, substitution of non-motorized modes, and induced demand (Henao & Marshall, 2019b; Jiao et al., 2020; Schaller, 2017, 2018, 2021; Castiglione et al., 2017; Castiglione et al., 2018; Tirachini & Gomez-Lobo, 2020). However, ridehailing helps reduce demand for parking by replacing private-vehicle trips (Henao & Marshall, 2019a). As for longer-term mobility choices, the entry of ridehailing into cities has contributed to increasing new car sales in Chinese cities, while decreasing them in U.S. cities (Guo et al., 2019). Last but not least, ridehailing impacts on road safety are mixed. While ridehailing decreases driving under the influence (Young & Farber, 2019), it is likely to increase traffic fatalities for vehicle occupants and pedestrians because of increased use of vehicles (Barrios et al., 2020).

In recent studies, researchers examined how different subgroups in the population react to the adoption of ridehailing. In one study, the authors identify three segments in the population – drivers, riders, and walkers – and examine how each of them changes their behavior in response to ridehailing (Lee et al., 2019). Interestingly, ridehailing leads drivers to greater use of ridehailing and public transit for trips formerly made by private vehicles. In comparison, ridehailing allows riders and walkers to make more trips in general because of enhanced mobility brought by ridehailing. Another study employs a latent-class cluster analysis (LCCA), with which its authors identify three unobserved classes in a sample of ridehailing users in fall 2015 in California (N=482)

(Alemi et al., 2020). Their behavioral changes in response to ridehailing adoption differ across classes. For instance, the majority of Urban travelers (53% of the sample) reduced use of most travel modes, almost all Car users (37%) reduced driving, and many Transit/TNC riders (10%) reduced driving while making more trips by transit. A follow-up LCCA study with a larger sample of ridehailers (N=1,268) in fall 2018 in California identified three classes with respect to modal impacts (Etezady et al., 2020): Substituters (23% of the sample) reduced their use of most other modes; Personal car augmenters (56%) seldom used other modes in the first place and mostly kept using their own car at the same level; and Multimodal augmenters (21%) reported little impact of ridehailing on their modal style except for noticeable reductions in personal cars and taxis. While informative, these previous studies focus more on the distinctive types of ridehailing impacts, but less on class-specific user profiles, which greatly help put heterogeneous modal impacts in context.

With a few exceptions, most studies so far have looked at the substitution effects of the last trip made by ridehailing and/or the sample-average effects of ridehailing, but such average effects may mask considerable heterogeneity among subgroups in the sample (Hall et al., 2018). Moreover, many studies that take potential heterogeneity into account employ two-step approaches, with which authors first define subgroups, and next examine travel behaviors for each subgroup. The definition of the subgroups is often arbitrary, or driven by the convenience of identifying categories of travelers based on exogenous segmentation (e.g. by income, or by the neighborhood of residential location), and the differences in the observed travel behaviors across subgroups may fail to reveal the true extent of heterogeneity in the sample. In addition, many studies did not control for individual attitudes, which are as important as conventional variables in accounting for changes in travel behavior after ridehailing adoption.

In this study, we examine whether (and how) ridehailing substitutes or complements the use of other travel modes. In so doing, with a latent-class cluster analysis, we identify unobserved groups with similar behavioral patterns within each group, but heterogeneous patterns across different groups. For each of these groups, we examine the profiles of its members in great detail to derive implications for policy and planning. Last but most importantly, this study focuses on the southern U.S., in which public transit is not as prevalent as in large metropolitan areas, and ridehailing is often the only viable alternative for those without access to private vehicles.

The remainder of the report is organized as follows. The next section presents methods and data in detail, followed by a third section that presents the main results of the analyses. The fourth section discusses the implications, contributions, and limitations of this work, and the last section concludes with a summary of the findings from this study and directions for future research.

METHOD & DATA

In this study, we employ a latent-class cluster analysis (LCCA), which allows us to identify unobserved groups (i.e., classes) with behaviors that are as homogeneous as possible within each class, but heterogeneous across different classes. LCCA consists of two sub-models – a measurement model and a membership model – and it estimates these sub-models simultaneously. The measurement model conceives indicators to be outputs of (unobserved) class membership and computes class-specific averages for these indicators in a way that differences in these averages across classes are maximized. The membership model computes probabilities of individual cases belonging to one class or another, and in this study it does so with explanatory variables (i.e., active covariates). Selected explanatory variables found not to have statistically significant coefficients in the model estimation are instead used as inactive covariates to help identify the unique profiles of the members of each class.

In this study, we focus on individual-level heterogeneity (in self-reported changes in mode use after ridehailing adoption), which in itself is not observable, but is assumed to be associated with observed variables. In other words, we do not directly observe distinctive forms of mode-use changes; however, we identify them from self-reported changes in the frequency with which individuals use various travel modes (i.e., indicators) and individuals' characteristics (i.e., covariates). In so doing, our chosen analytical approach takes a different approach from deterministic market segmentation (e.g., K-means clustering), which *deterministically* assigns individual cases to certain groups. The deterministic approach assumes that the relevant heterogeneity is based on variables that are observable and known, whereas LCCA permits heterogeneity on the basis of unobserved, or latent, characteristics. The latter approach requires a strong assumption about the parameter distributions, and it often lacks implications for planning and policy.

To introduce the LCCA model, let the indicator y_{it} denote the type of change in the use of a means of travel t ($t \in \{1, 2, ..., 8\}$) made by individual i after she began to use ridehailing services. In this study, y_{it} takes one of four values, or changes: "*[respondents] changed [the frequency of using a means of travel t] but for reasons not related to ridehailing*; *[or they] use [a means of travel t] less often*; *about the same*; or *more often*." We denote these changes as m_t ($m_t \in \{1, 2, 3, 4\}$). In addition, we assume that there are K distinctive patterns of changes in the use of various means of travel in the population, and that each individual i is associated with one and only one of those patterns. The discrete variable c ($c \in \{1, 2, ..., K\}$) indexes these distinctive patterns, or classes, and by definition, c is "latent" because researchers can neither directly observe the classes nor identify the "correct" class of individual i with certainty. Thus, equation (1) allows us to identify these classes in the population, and more importantly, the likelihoods that individuals are associated with them, in a probabilistic manner:

$$\mathrm{P}\left(y_{i1}=m_1, y_{i2}=m_2, \dots y_{i8}=m_8\right) = \sum_{c=1}^{K} \mathrm{P}(c|\mathbf{z}_i) \prod_{t=1}^{8} \mathrm{P}\left(y_{it}=m_t|c\right). \tag{1}$$

$\mathrm{P}\left(y_{i1}=m_1, y_{i2}=m_2, \dots y_{i8}=m_8\right)$ denotes the *unconditional* probability of individual i reporting changes in the use of various means of travel from m_1 to m_8. It can be expressed as a product of the probability of individual i belonging to class c given her attributes $\mathbf{z}_i$, $\mathrm{P}(c|\mathbf{z}_i)$, and the *conditional* probability that y_{it} takes on the value m_t (t = 1, 2, …, 8) conditional on individual i belonging to class c, $\prod_{t=1}^{8} \mathrm{P}\left(y_{it}=m_t|c\right)$.

The first term in equation (1) is the membership model, which takes individual i's attributes $\mathbf{z}_i$ as covariates and computes the probability of individual i belonging to c. Equation (2) expresses the membership model in the conventional multinomial logit form, in which $\mathbf{z}_i$ is an R × 1 vector with z_{ir} being the r^{th} component and z_{i1} set to one, and γ_{cr} is the r^{th} component of coefficient vector $\boldsymbol{\gamma}_c$ (1 × R). For identification, $\boldsymbol{\gamma}_1$ is set to a zero vector.

$$P(c|\mathbf{z}_i)= \frac{\exp(\sum_{r=1}^{R}\gamma_{cr}\, z_{ir})}{\sum_{c'=1}^{K}\exp(\sum_{r=1}^{R}\gamma_{c'r} z_{ir})} \tag{2}$$

The second term of equation (1) is the measurement model, in which class c is modeled as producing values for each of the eight indicators. Each class is associated with a unique octuplet of probabilities for the changes in the use of the 8 means of travel after ridehailing adoption. These probabilities are also computed via the conventional multinomial logit form. Equation (3), $P(y_{it}=m_t|c)$, denotes the probability of individual i choosing change m_t for means of travel t given that she belongs to class c. Specifically, the probability that her use of means of travel t takes on the value m_t given that she belongs to class c is expressed in a logit form with alternative-specific constants $\beta_{m_t}^{t|c}$. For identification, $\beta_{m_t=1}^{t|c}$ is set to zero.

$$P(y_{it}=m_t|c)= \frac{\exp(\beta_{\boldsymbol{m_t}}^{t|c})}{\sum_{\boldsymbol{m_t'}=1}^{M}\exp(\beta_{\boldsymbol{m_t'}}^{t|c})} \tag{3}$$

Figure 1 portrays the relationships among the latent construct of modal change patterns, the indicators, and the active and inactive covariates. Note that we initially include all covariates as active in the membership model, and inspect their statistical significance. Those found not to be significant are transferred to being inactive covariates, which help us identify the member profiles of individual latent classes.

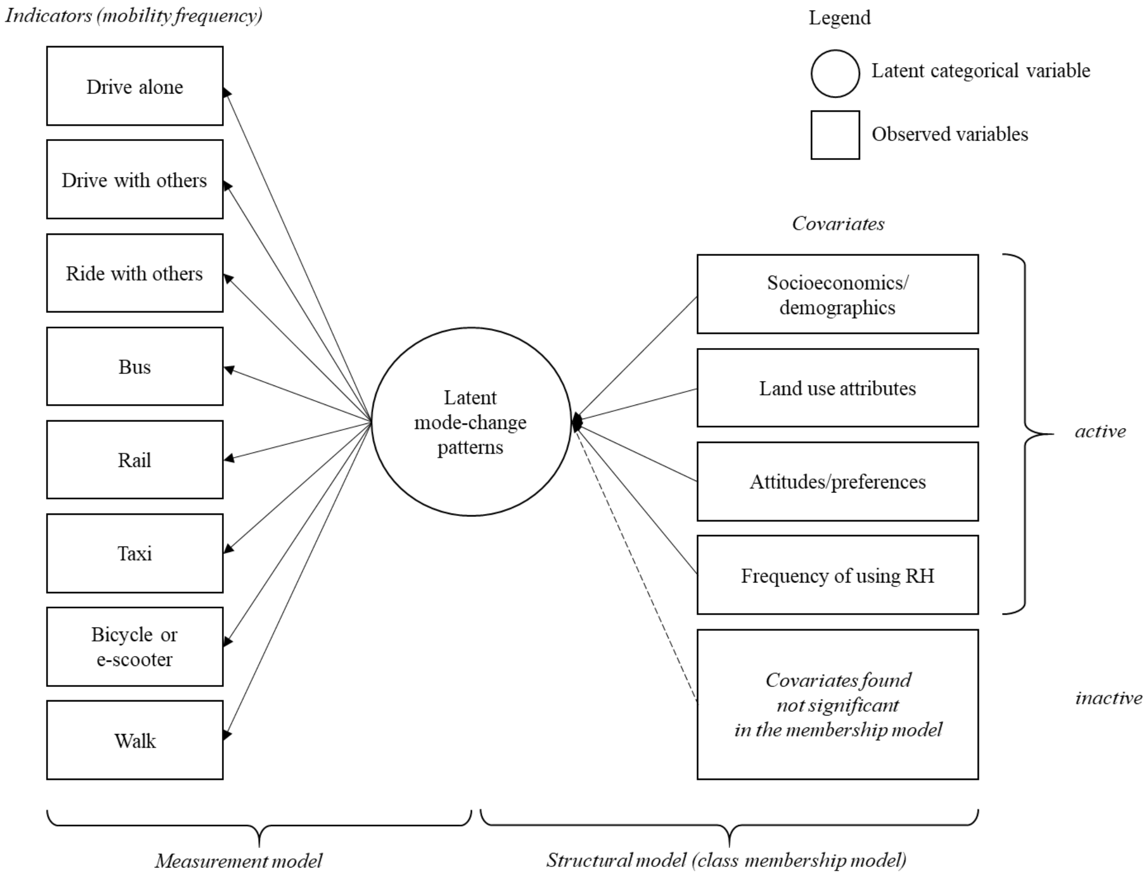

Figure 1 Graphical Representation of the Latent-Class Cluster Analysis with Covariates

We used data from a sample of ridehailing users collected through a multi-region transportation survey with a focus on emerging mobility services, autonomous vehicles, changing lifestyles, and individual attitudes. The survey was administered as part of a joint project carried out by a network of researchers through sending invitations via regular mail or email to randomly selected residents in four metropolitan areas in the southern U.S.: Phoenix, Arizona (AZ); Atlanta, Georgia (GA); Tampa, Florida (FL); and Austin, Texas (TX), between June 2019 and March 2020 (N=3,358). Additional respondents were recruited through social media advertisements in Austin, because of low response rates initially obtained from the other recruitment modes. Since the survey for the Tampa region did not ask about changes in use of light rail after ridehailing adoption, we excluded cases from that region from the analyses in this study. Only the cases in Florida were collected until March 2020. All other cases were collected before or in October 2019, i.e. well before the beginning of the COVID-19 pandemic in the U.S. Accordingly, the data collection of relevance for this analysis was not impacted by the pandemic.

The last column in Table 4 (in the Results section, below) shows the distribution of socioeconomics, demographics, a land-use attribute, and attitudes at the sample level (N=1,438). Two thirds of the sample report using ridehailing rarely; one quarter uses it monthly; and only 8% use it on a weekly basis. The majority of the sample (63.8%) is 25-64 years old. The sample includes more females than males (60.5%), as often happens in surveys. Not surprisingly, most cases are White or non-Hispanic (72.2%), and are well educated (e.g., about two thirds of the sample have at least a Bachelor's degree). The sample includes more workers than non-workers

(71% and 29%), in part because workers tend to adopt ridehailing more than non-workers. Many individuals live in small households and/or households without a child. Also, the sample includes many cases with recent residential relocations. About half the sample earns annual household incomes from $50,000 to $99,999. Only a small fraction (5.5%) live without a car, while more than four fifths (82.6%) live in a household with at least one car per driver. Compared to the population in the combined study areas, our sample includes more individuals between 18 and 24, with a Bachelor's or graduate degree, in a household with 3 or more vehicles, and residing in Austin, TX. Table A1 presents the shares of various sociodemographic groups computed for the study sample (N=1,438), the entire sample (N=3,358), and the population in the study area (N=12,384,973).

As *indicators*, we use responses to a question in the survey asking how ridehailing users changed their use of various means of travel after they had begun to use ridehailing. These means of travel include: drive a private vehicle alone, drive a private vehicle with other passengers, ride in a private vehicle as a passenger, or use bus, light rail, taxi, a bicycle or e-scooter, and walk. Note that the survey asked only about light rail, instead of all rail systems, due to a survey design flaw that was identified only after the data collection was already underway. However, Atlanta is the only region with heavy rail service among the three study areas. As mentioned earlier in this section, for each means of travel, respondents chose one among four options: "I have changed usage, but not because of ridehailing", "I use it less often", "I use it about the same", and "I use it more often". Note that the first option does not tell us whether respondents increased or decreased their use.

As *covariates*, we use socioeconomic and demographic characteristics, land use attributes, attitudes, and self-reported frequencies of using ridehailing. For land use attributes, we compute population density in the residential Census tract, by geocoding reported home addresses, spatially joining geocodes with the Census TIGER shapefiles, and processing information from the American Community Survey 2015-2018 5-year estimates. For attitudes, we factor-analyze two sets of variables that ask respondents to report their agreement with several attitudinal statements on a 5-point Likert-type scale. Table 1 presents the five attitudinal factors included in our analysis.

Table 1 Attitudinal Factors and Statements with High Loadings

Factors	Statements (loadings)
Environmentally-friendly	• I am committed to an environmentally-friendly lifestyle. (0.665) • I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible. (0.597)
Pro-density	• I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area. (0.777) • I prefer to live in a spacious home, even if it is farther from public transportation or many places I go. (-0.684)
Transit-as-reliable	• Public transit is a reliable means of transportation for my daily travel needs. (0.634) • Most of the time, I have no reasonable alternatives to driving. (-0.486)
Tech-savvy	• Learning how to use new technologies is often frustrating for me. (-0.494) • I like to be among the first people to have the latest technology. (0.483)
Ridehailing-as-lifestyle	• Ridehailing services allow me to live with fewer or no cars. (0.558) • The lower cost of shared ridehailing (e.g., uberPOOL, Lyft Share) is worth the additional time picking up and dropping off other passengers. (0.516)

Notes: The first four factors are from an exploratory factor analysis that led to the identification of 8 factors out of 28 attitudinal statements (N=3,339) on various topics including transportation, land use, environmentalism, and lifestyle. Factor loadings were taken from the pattern matrix. The last factor is from another exploratory factor analysis with four factors extracted from 12 attitudinal statements (N=3,415) on various aspects of ridehailing service use. In both cases, SPSS was used to conduct principal axis factoring, with oblimin rotation and Bartlett scores.

RESULTS

After cleaning and excluding ineligible or incomplete cases, we apply LCCA to a sample of 1,438 users in the three southern U.S. regions. To choose an appropriate number of classes, we estimate models from two to ten classes without any active covariates, and examine their goodness-of-fit measures and interpretability. Goodness-of-fit measures (e.g., AIC and BIC) tend to improve as the number of latent classes increases (refer to Table 2), and we find that the four-class solution presents distinctive and interpretable patterns of behavioral changes, with the smallest class being not-too-small. In other words, unlike the case for some of the solutions with more classes, the K = 4 solution does not isolate a small group of *outliers*.

Table 2 Goodness-of-Fit Measures of the Latent-Class Cluster Analysis Models

No. of classes (K)	AIC	BIC	Sample-size adj-BIC	LL	Npar	Share of each class									
						1	2	3	4	5	6	7	8	9	10
1	22252.0	22378.5	22302.3	-11102.0	24	100%	-	-	-	-	-	-	-	-	-
2	16867.5	17125.8	16970.1	-8384.8	49	64.4%	35.6%	-	-	-	-	-	-	-	-
3	15329.7	15719.7	15484.7	-7590.8	74	52.4%	24.5%	23.0%	-	-	-	-	-	-	-
4	14892.9	15414.7	15100.2	-7347.4	99	51.9%	24.5%	12.3%	11.3%	-	-	-	-	-	-
5	14517.7	15171.3	14777.4	-7134.9	124	51.7%	13.8%	12.0%	11.3%	11.1%	-	-	-	-	-
6	14325.8	15111.2	14637.9	-7013.9	149	50.1%	13.2%	11.1%	10.4%	8.6%	6.7%	-	-	-	-
7	14133.5	15050.7	14498.0	-6892.8	174	49.5%	13.0%	10.6%	8.6%	6.8%	5.8%	5.7%	-	-	-
8	14034.2	15083.1	14450.9	-6818.1	199	50.7%	12.3%	8.8%	8.3%	5.8%	5.1%	4.9%	4.0%	-	-
9	13951.9	15132.6	14421.0	-6751.9	224	49.2%	11.2%	8.5%	7.7%	6.1%	5.1%	4.6%	4.0%	3.8%	-
10	13904.8	15217.3	14426.3	-6703.4	249	49.5%	9.7%	8.6%	7.0%	5.6%	4.6%	4.5%	3.8%	3.8%	2.9%

Notes: AIC = Akaike information criterion, BIC = Bayesian information criterion; Sample-size adj-BIC = Sample-size adjusted BIC (n* = (n + 2)/24), LL = final log-likelihood of the model, and Npar = number of parameters.

Behavioral Changes

Table 3 presents behavioral changes in the use of eight travel modes after ridehailing adoption, computed separately for each class, and Figure 2 visualizes these changes. The last column in Table 3 shows behavioral changes at the sample level (N=1,438). For all modes, the majority of respondents did not report changing their mode use patterns. Still, we see noticeable variations in response patterns across modes, even at the samplewide level. For example, only half the sample kept the same level of use for taxis after they began to hail a ride, while about 60-65% of the sample did so for the other travel modes. Not surprisingly, a quarter of the sample reported reductions in taxi use in part because ridehailing is a direct substitute for conventional taxis. As for private vehicles, more respondents reduced driving alone, driving with others, and getting a ride with others than those who increased using these modes. Unfortunately, a similar pattern is also found for public transit and active travel: i.e., more people reduced their use of transit, biking, and walking than those who increased the use of these environment-friendly modes. In the meantime, the survey question allowed respondents to separately report any changes that are *not* attributable to ridehailing (“Changed for other reasons”). In the sample as a whole, the shares of those who selected this option are slightly larger for public transit, taxis, and active modes than for personal vehicles. More specifically, the share of this option for bicycle or e-scooter (24.3%) is higher than those for the other modes, in part because dockless bikesharing and e-scooter sharing services were introduced and widely adopted in dense urban areas in recent years.

Although informative, behavioral changes at the sample level may mask substantial heterogeneity across various (unobserved) groups of individuals in the sample. Thus, we review the reported behavioral changes separately for the members of each class. Note that we name the four classes based on the patterns of changes in mode use that members of individual class underwent after ridehailing adoption. Figure 2 visualizes those patterns of the four classes – *Mobility augmenters, Exogenous changers, Personal car/taxi substituters, and Transit/active mode substituters* – by the order of their class size. First, *Mobility augmenters* are the largest class among the four, accounting for about one half of the sample. Members of this class did not change their use of other travel modes as a result of ridehailing adoption. The only (partial) exception is for taxis, for which the option "about the same" is selected by "only" 87.8% of cases in this class, compared to about 95% for the other travel modes. In fact, 12.1% of this class substitute ridehailing for conventional taxis. The second largest class is *Exogenous changers* (24.5%). Some 50 to 90% of the members of this class reported having changed their use of the various other travel modes for reasons other than ridehailing adoption. Members of this class changed their use of transit and active modes more than private vehicles. After all, the three study regions in this study are built in rather auto-oriented ways, and private vehicles are often the only viable mode for completing certain trips (even to a greater extent than in other regions in the US). About a quarter to a third of this class used private vehicles about the same (drive alone 33.9%; drive with others 30.7%; and ride with others 26.6%). In comparison, much smaller proportions kept similar frequencies for buses, light rail, biking, and walking, ranging from 3.5% to 13.4%.

Personal car/taxi substituters (15.0%) reported behavioral changes in response to ridehailing adoption that are more desirable from a sustainable transportation standpoint (than those of the other classes): i.e., they reduced their use of motorized modes, and increased the use of shared/active modes. About half of this class use private vehicles *less often*, and more than 70% of this class use buses and light rail (73.4% & 77.8%) and biking and walking (78.2% & 71.0%) *about the same*. Interestingly, some cases in this class use buses and light rail (9.9% and 9.5%) and biking and walking (9.0% and 17.9%) *more* since they started using ridehailing. As the smallest class, *Transit/active mode substituters* (10.8%) present behavioral changes for which ridehailing substitutes for most travel modes at the aggregate level, especially more so for shared/active modes than for motorized modes. Members of this class appear to be multimodal travelers who, since they started to use ridehailing, became less multimodal due to a reduction in the number of trips they make by public transit, walking, and biking. More than half of this class reported using private vehicles about the same as before, but only about a tenth of this class reported that they take public transit as often as in the past. In fact, the majority of this class answered that they use public transit (and conventional taxis) less often. As for active modes, 54.9-71.3% walked or biked less often than before they began using ridehailing.

Table 3 Summary Statistics of Indicators by Class (N=1,438)

	Mobility augmenters	Exogenous changers	Private car/taxi substituters	Transit/ active mode substituters	Sample
Class share (%)	49.7%	24.5%	15.0%	10.8%	100%
Class size (n)	714	353	215	156	1,438
Change in driving alone					
Changed for other reasons	1.5%	**47.3%**	14.1%	11.4%	15.7%
Less	1.2%	12.3%	**44.1%**	19.6%	12.3%
Same	**96.0%**	33.9%	35.3%	59.6%	67.7%
More	1.3%	6.5%	6.5%	**9.4%**	4.2%
Change in driving with others					
Changed for other reasons	0.2%	**55.4%**	11.4%	8.1%	16.3%
Less	0.1%	12.0%	**44.0%**	34.4%	13.3%
Same	**99.5%**	30.7%	37.2%	53.8%	68.4%
More	0.2%	2.0%	**7.4%**	3.7%	2.1%
Change in riding with others					
Changed for other reasons	0.6%	**56.6%**	5.3%	5.9%	15.6%
Less	0.5%	14.2%	**48.4%**	41.3%	15.4%
Same	**97.9%**	26.6%	39.0%	48.8%	66.3%
More	1.0%	2.5%	**7.3%**	4.0%	2.6%
Change in taking buses					
Changed for other reasons	1.7%	**79.1%**	3.0%	2.8%	21.0%
Less	2.5%	6.3%	13.7%	**85.2%**	14.0%
Same	**95.4%**	9.5%	73.4%	8.7%	61.6%
More	0.5%	5.1%	**9.9%**	3.3%	3.3%
Change in taking light rail					
Changed for other reasons	0.4%	**90.0%**	1.4%	4.0%	22.9%
Less	0.7%	3.2%	11.2%	**84.5%**	12.0%
Same	**98.9%**	6.5%	77.8%	10.0%	63.4%
More	-	0.3%	**9.5%**	1.6%	1.7%
Change in using taxi					
Changed for other reasons	0.1%	**84.0%**	1.9%	8.8%	21.9%
Less	12.1%	12.6%	35.6%	**85.1%**	23.6%
Same	**87.8%**	3.5%	60.7%	4.8%	54.0%
More	-	-	**1.9%**	1.3%	0.4%
Change in riding a bicycle or e-scooter					
Changed for other reasons	0.2%	**91.7%**	6.6%	7.1%	24.3%
Less	0.2%	2.5%	6.2%	**71.3%**	9.4%
Same	**99.1%**	5.0%	78.2%	19.2%	64.2%
More	0.5%	0.9%	**9.0%**	2.4%	2.1%
Change in walking					
Changed for other reasons	1.6%	**74.2%**	3.0%	4.6%	20.0%
Less	2.5%	6.6%	8.2%	**54.9%**	10.0%
Same	**94.6%**	13.4%	71.0%	32.3%	64.4%
More	1.3%	5.8%	**17.9%**	8.3%	5.6%

Note: Bolded numbers indicate the highest value for each row.

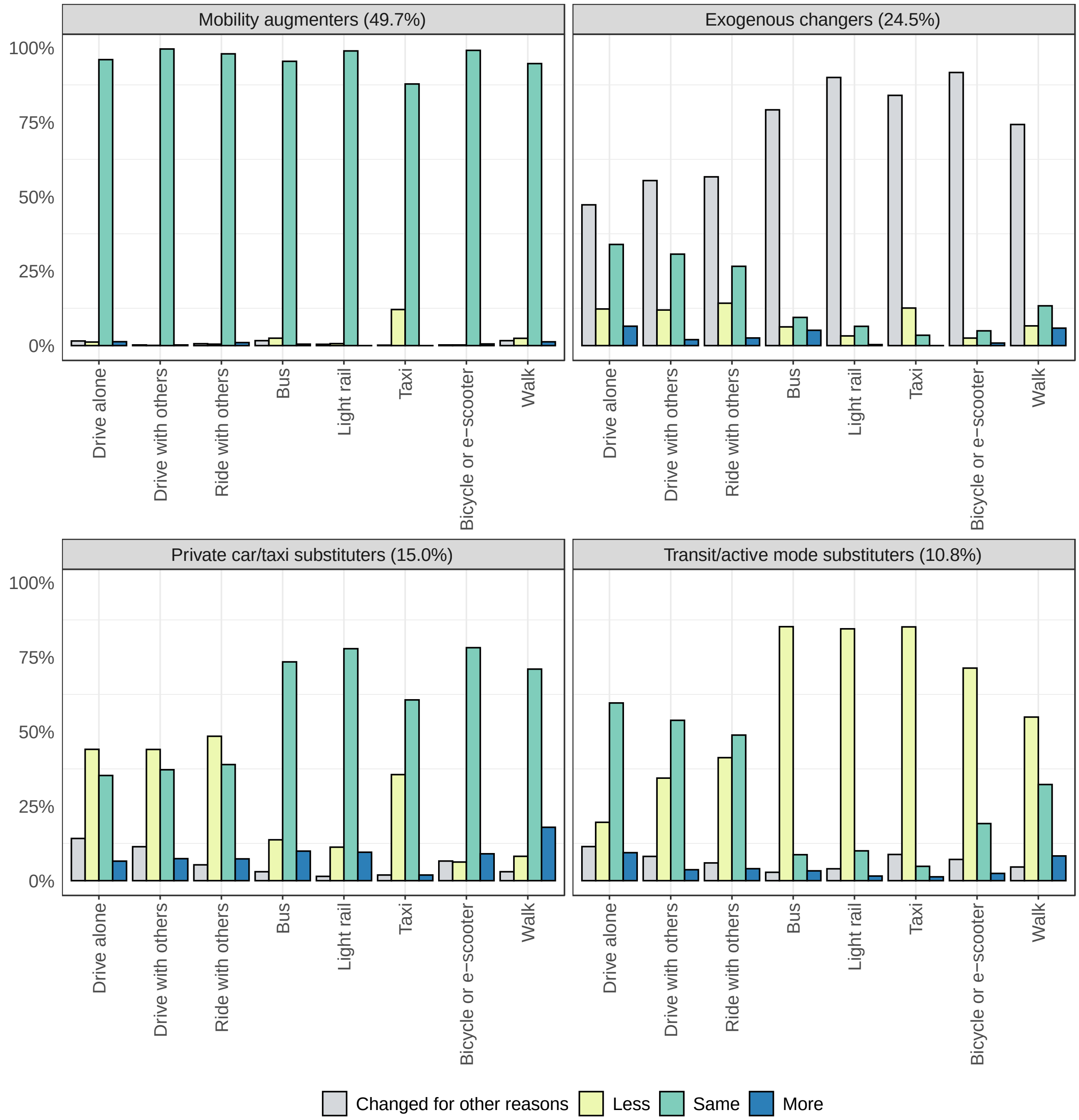

Figure 2 Changes in Use of Various Means of Travel after Ridehailing Adoption by Class (N=1,438)

Class-Specific Profiles

Table 4 presents the socioeconomic, demographic, land-use, and attitudinal profiles of the members of individual classes, through class-specific (posterior) probability-weighted summary statistics (see Appendix for the comparison with the entire survey sample and the general population). Many members of the *Mobility augmenter* class use ridehailing only rarely, which explains why their ridehailing adoption does not affect their travel behavior very much. The members of this class are slightly older than the average individual in the sample. Larger shares of individuals in this class are White or non-Hispanic than in the other classes. Many members of this class are workers and well-educated. In fact, this class includes fewer students than the other classes, and 70% of its members hold Bachelor's or graduate degrees. Many live in households with two or three members, and/or with a child, and two thirds own their home. On average, they live in the least dense neighborhoods among the four classes. Many members of this class have convenient access to their household vehicles, with the majority owning at least one car per driver. The members of this class do not see public transit as being reliable for their daily travel demands, and they do not agree that ridehailing has broad impacts on vehicle ownership.

Exogenous changers include higher portions of the youngest (18-24) and oldest groups (65+), who may be undergoing various life events and thus be changing their travel behavior accordingly. They include a larger portion of members from minority groups including Asians or Pacific Islanders, those of multiple races, and those of Hispanic origin. Members of this class are less educated, in part because some are still studying (i.e., they have not obtained their final degree(s) yet). On average, they live in the dense neighborhoods of the cities, while many earn incomes below $50,000 a year. Interestingly, a third of the members of this class own three or more cars, which appears inconsistent with their income levels. As a possibility, we speculate that seniors and middle-aged individuals in this class drive older or less-expensive cars (e.g., they bought these cars in the past when their income levels were high). In addition, members of this class hold positive attitudes toward urban density, and find public transit to be a reliable option for their daily travel needs.

The *Private car/taxi substituters* have the largest shares of weekly and monthly ridehailing users among the four classes. This class includes predominantly young individuals, with the smallest share of those who are 65 years old or older, and a higher-than-average share of men. The members of this class are better educated than average, with only a small share having just a grade/high school education. With the highest residential density on average (among the four classes), many members live in dense neighborhoods. This class has a large share of high-income earners, but many live without a car (10%), presumably often as a lifestyle choice. On average, members of this class score the highest on four attitudes out of the five tested in our analysis. In other words, they tend to be pursuing environmentally friendly lifestyles, pro-density, positive toward public transit, open to the possibility of ridehailing affecting their car ownership, and technologically savvy. Their high frequency of using ridehailing, urban or carless lifestyles, and attitudes explain their behavioral changes in positive directions.

Transit/active mode substituters include many weekly and monthly users of ridehailing (in combination comprising more than 40% of the class), and the highest share of those ages 25-44. Compared to the other classes, this class has a larger share of females, larger shares of African Americans and those of Hispanic origin, and larger shares of single-person households or those living without a child. About half of this class relocated in the past two years, do not own their home, and/or live in less-dense neighborhoods. Members of this class live with limited access to vehicles (i.e., fewer cars than household drivers), and they view ridehailing as having the potential for less car-oriented lifestyles. Their limited access to private vehicles, combined with suburban living, appears to explain their behavioral changes: ridehailing allows them to make trips in more convenient ways, which may have been made by public transit or active modes in the past. Thus, members of this class reduced their use of all modes, and more so for less-polluting modes.

Table 4 Summary Statistics of Covariates by Class (N=1,438)

	Mobility augmenters	Exogenous changers	Private car/taxi substituters	Transit/ active mode substituters	Sample
Class share (%)	49.7%	24.5%	15.0%	10.8%	100%
Class size (n)	714	353	215	156	1,438
Frequency of using ridehailing					
Rarely	**78.2%**	63.5%	30.6%	58.0%	65.3%
Monthly	20.0%	26.1%	**49.0%**	29.2%	26.8%
Weekly	1.8%	10.4%	**20.4%**	12.7%	7.9%
Age					
18-24	21.1%	**28.7%**	28.6%	27.4%	24.8%
25-44	33.5%	28.1%	37.4%	**39.9%**	33.4%
45-64	**32.7%**	29.4%	29.1%	23.7%	30.4%
65 or older	12.7%	**13.8%**	4.9%	9.0%	11.4%
Gender (n = 1,427) <Inactive>					
Male	38.5%	39.3%	**43.9%**	35.5%	39.2%
Female	60.6%	60.4%	55.8%	**62.7%**	60.1%
Did not answer	0.9%	0.3%	0.3%	**1.8%**	0.8%
Race (n = 1,387) <Inactive>					
White or Caucasian	**74.1%**	62.5%	70.3%	64.9%	69.7%
Black or African American	8.1%	11.3%	6.6%	**13.1%**	9.2%
Native American	0.2%	0.6%	0.3%	**2.5%**	0.6%
Asian or Pacific Islander	10.0%	**14.9%**	14.0%	12.6%	12.1%
Other	1.0%	**2.3%**	1.6%	0.7%	1.4%
Multi race	3.5%	**3.9%**	2.9%	3.6%	3.5%
Did not answer	3.1%	**4.5%**	4.2%	2.7%	3.5%
Ethnicity (n = 1,437) <Inactive>					
Not of Hispanic/Latino origin	**87.0%**	77.2%	83.9%	74.3%	82.8%
Of Hispanic/Latino origin	11.2%	20.8%	13.6%	**21.5%**	15.0%
Prefer not to answer	1.8%	1.7%	2.5%	**4.2%**	2.2%
Did not answer	-	**0.3%**	-	-	0.1%
Educational attainment <Inactive>					
Up to high school	6.1%	**10.4%**	5.8%	8.8%	7.4%
Some college	23.8%	**30.1%**	24.5%	26.2%	25.7%
Bachelor	37.6%	36.9%	38.7%	**39.5%**	37.8%
Graduate	**32.5%**	22.6%	31.0%	25.4%	29.1%
Work/study status <Inactive>					
Worker	**61.5%**	46.5%	58.0%	57.1%	56.8%
Worker/student	12.8%	16.0%	**16.3%**	13.7%	14.2%
Student	9.2%	**18.7%**	16.0%	17.3%	13.4%
Neither	16.5%	**18.8%**	9.7%	11.9%	15.6%
Household size <Inactive>					

	Mobility augmenters	Exogenous changers	Private car/taxi substituters	Transit/ active mode substituters	Sample
Class share (%)	49.7%	24.5%	15.0%	10.8%	100%
Class size (n)	714	353	215	156	1,438
Single	21.5%	23.7%	25.2%	**27.9%**	23.3%
Two members	**36.5%**	33.6%	35.8%	33.3%	35.3%
Three members	**16.1%**	14.6%	10.5%	12.7%	14.5%
Four members or more	25.9%	28.2%	**28.5%**	26.0%	26.8%
Live with a child or not <Inactive>					
Don't live with a child	78.8%	82.8%	83.3%	**85.8%**	81.2%
Live with a child	**21.2%**	17.2%	16.7%	14.2%	18.8%
Housing tenure (n = 1,435) <Inactive>					
Owner	**65.1%**	52.5%	51.6%	49.9%	58.3%
Not owner (e.g., renter)	34.6%	47.2%	48.4%	**50.1%**	41.4%
Did not answer	0.3%	**0.3%**	0.0%	-	0.2%
Recent relocation (n = 1,429) <Inactive>					
Not in the past 2 years	**61.8%**	57.0%	57.5%	52.7%	59.0%
In the past 2 years	37.7%	41.9%	42.0%	**47.3%**	40.4%
Did not answer	0.5%	**1.1%**	0.6%	0.0%	0.6%
Density (resident/sq.km.)	1,761	2,406	**2,437**	1,951	2,041
Income					
Below $50,000	19.7%	**33.1%**	29.8%	29.7%	25.6%
From $50,000 to $99,999	**53.9%**	48.4%	43.1%	51.0%	50.6%
$100,000 or more	26.4%	18.5%	**27.0%**	19.3%	23.8%
# of cars in the household <Inactive>					
Zero cars	3.9%	6.0%	**10.0%**	5.4%	5.5%
One car	22.6%	27.2%	23.5%	**31.6%**	24.8%
Two cars	**43.2%**	35.2%	37.3%	32.6%	39.2%
Three or more cars	30.3%	**31.6%**	29.1%	30.4%	30.5%
Access to car (n = 1,350) <Inactive>					
No cars/driver	2.9%	5.1%	**6.3%**	4.0%	4.1%
Fewer than one car/driver	9.6%	14.8%	14.4%	**15.2%**	12.2%
One car/driver	**65.8%**	58.0%	56.1%	55.1%	61.3%
More than one car/driver	17.7%	14.8%	12.8%	**17.8%**	16.3%
Did not answer	3.9%	7.3%	**10.3%**	7.8%	6.1%
Attitudes and preferences					
Environmentally-friendly	-0.01	0.13	**0.45**	0.05	0.10
Pro-density	0.13	0.23	**0.84**	0.19	0.27
Transit-as-reliable	-0.30	0.33	**0.41**	0.27	0.02
Ridehailing-as-lifestyle	-0.28	0.23	0.41	**0.47**	0.03
Tech-savvy <Inactive>	0.24	0.23	**0.57**	0.25	0.29
Region <Inactive>					
Phoenix, AZ	20.1%	**21.0%**	17.8%	18.8%	19.8%
Atlanta, GA	**39.1%**	30.4%	35.3%	32.6%	35.7%
Austin, TX	40.8%	**48.7%**	46.9%	48.6%	44.5%

Notes: Numbers shown are counts, shares, or means, as appropriate. Bolded numbers indicate the highest value for each row.

Factors Affecting Class Membership

Table 5 shows the membership model, which illuminates the factors affecting the probabilities of individuals belonging to one class or another. Specifically, it summarizes the active covariates that were found to have statistically significant effects after testing the full set of variables introduced in Table 4. Note that the reference category is *Mobility augmenters*, and all estimated coefficients should be interpreted accordingly. Interestingly, not many sociodemographic variables are found statistically significant once ridehailing frequency and attitudes are controlled for. That is, socioeconomic and demographic characteristics of ridehailing users have limited ability in explaining the likelihood of an individual reporting a certain bundle of ridehailing impacts.

Among the sociodemographic variables that are statistically significant, we find age, income, and density at residence. Those who are 65 years old or older are *more* likely (than those who are 18 to 24 years old) to belong to the *Exogenous changer* class, whose members tend to change their use of all modes for reasons not related to ridehailing. In addition, those with middle or high incomes are *less* likely (than those with incomes below $50,000) to belong to the *Exogenous changer* class. This is consistent with the profile of this class, many of whom are either 18-24 or 65+, economically constrained, and likely to undergo life events. In the meantime, those living in *denser* neighborhoods are *less* likely to belong to the *Transit/active mode substituter* class, many of whom live in suburbs while having limited access to cars, and substitute ridehailing more for public transit and active modes.

The ways that ridehailing frequency and attitudes influence class membership probabilities are informative. Monthly and weekly ridehailing users (compared to those who use ridehailing rarely) are *more* likely to belong to one of the three classes other than *Mobility augmenters*. This pattern is more pronounced for *Exogenous changers*, for which parameter estimates are larger (for "Weekly") in magnitude than those for the other two classes or very close to the largest (for "Monthly"). Those who pursue environmentally friendly lifestyles are *more* likely to be *Private car/taxi substituters* than *Mobility augmenters*. Likewise, those who prefer dense urban neighborhoods with convenient access to transit tend to be *Private car/taxi substituters* more than *Mobility augmenters*. Those who consider transit as a viable means of transportation for their travel needs are *more* likely to belong to any of the other three classes than to *Mobility augmenters*. Again, this tendency is more pronounced for *Private car/taxi substituters*. Lastly but most importantly, those who see the potential of ridehailing for less car-oriented lifestyles are *more* likely to be *Transit/active mode substituters* or *Exogenous changers* than *Mobility augmenters*. Note that members of these classes on average take more ridehailing trips than *Mobility augmenters*. That is, it may be the case either that more frequent use of ridehailing helps users realize its potential for lifestyle changes, or (perhaps more likely) that those who want or need to adopt less car-oriented lifestyles are actively adopting ridehailing more often. In either case, we find significant associations between attitudes on ridehailing and certain behavioral changes attributable to ridehailing.

Table 5 Class Membership Model (base: Mobility augmenters, N=1,438)

Variables	Exogenous changers	Private car/taxi substituters	Transit/active mode substituters
Share	24.5%	15.0%	10.8%
(Intercept)	-0.69***	-2.27***	-0.67
Age (reference: 18-24)			
25-44	-	-	-
45-64	-	-	-
65 or older	0.49**	-	-
Income (reference: below $50,000)			
From $50,000 to $99,999	-0.32**	-	-
$100,000 or more	-0.53**	-	-
Residential population density	-	-	-0.17**
Frequency of ridehailing (reference: rarely)			
Monthly	1.65**	1.70***	0.70**
Weekly	6.03***	3.01***	2.07***
Attitudes and preferences			
Environmentally friendly	-	0.22**	-
Pro-density	-	0.33***	-
Transit-as-reliable	0.28***	0.32**	0.22**
Ridehailing-as-lifestyle	0.09*	-	0.26***

Notes: *Significant at the 10% level, **significant at the 5% level, and ***significant at the 1% level

DISCUSSION

In this section, we first discuss the implications of our main findings both theoretically and practically, and then comment on their contributions to the literature and limitations. First, and not surprisingly, regarding the impact of ridehailing on the use of other travel modes, ridehailing *frequency* appears to matter. Although the market penetration of ridehailing services in the U.S. and many other countries has continually increased over time, most people exploit ridehailing only to a limited extent, and their use of other travel modes does not appear to be affected considerably. For instance, *Mobility augmenters* (comprising half the sample) exhibit almost no change to other modes in relation to ridehailing use, in part because they use it only rarely, possibly out of town or in special circumstances (e.g., for travel to/from an airport, or when their own car is under repair). When it comes to the connection between frequency and behavioral changes, we expect attitudes to have a moderating role. For example, we find a positive association between ridehailing frequency and positive mode changes for those with less car-oriented lifestyles. Thus, when frequent ridehailing and supportive attitudes (and ideally, land uses that are conducive to transit/active travel) are combined together, individuals could better adjust their travel routines in ways to reduce environmental impacts.

Second, the way ridehailing affects travel behavior is not homogeneous, but varies by *context* (e.g., who the users are, and where they reside). Ridehailing allows *Private car/taxi substituters* to become less auto-oriented. After all, their neighborhoods, work/school, and frequent destinations are better connected by public transit and active modes than those for the other classes. Also, members of this class hold positive attitudes towards urban density, public transit, and less car-dependent lifestyles. In contrast, *Transit/active mode substituters* reduce their use of all eight modes as a result of ridehailing adoption, but they do so more for public transit and active modes. A plausible explanation is the following. *Transit/active mode substituters* may have had to take public transit and/or make multimodal trips due to limited access to cars. Then, ridehailing provides door-to-door transportation, and removes the need for multimodal trips. To the extent this is true, ridehailing improves the mobility of car-deficient households, especially those in suburbs, at the cost of increasing the environmental impacts of transportation.

Third, *attitudes* are key to explaining why users react to ridehailing adoption differently. The membership model in Table 5 shows that attitudes are more often significant than are sociodemographic variables. This finding appears to have a timely implication. Under the current COVID-19 pandemic, attitudes appear to be changing (at least in the short term), especially those related to travel modes (e.g., private vehicles vs. public transit), development patterns (e.g., suburbs vs. dense mixed-use), and new mobility services and technology (e.g., bike/scooter sharing vs. pooled ridehailing). Note that desirable behavioral changes (those by *Private car/taxi substituters*) are associated with positive attitudes towards public transit, compact development, and less auto-oriented lifestyles. Thus, one could speculate that, under the current public health crisis, given that ridehailing use is declining, its impacts on the use of other modes are likely to be in a less desirable direction (e.g., a reduction in the share of *Private car/taxi substituters* in the population).

We identify three main contributions of our analysis. First, our chosen indicators allow us to model ridehailing impacts in comprehensive and accurate ways. They are not limited to impacts that are specific to the last trip (a common approach in the literature), but instead focus on overall impacts, which cover both direct and indirect consequences related to ridehailing adoption. They also allow separating out changes that take place during the same time period but are not attributable to ridehailing (through the option "Changed but for other reasons"). Second, we control for individual attitudes, which are not often observed/taken into account in studies based on household travel surveys and large trip-level data. Attitudes help determine the statistical significance and (relative) magnitude of policy variables (e.g., land use) in accounting for behavioral changes, and enable us to better simulate changes in class shares under hypothetical scenarios (e.g., increasing aversion to urban density during the COVID-19 pandemic). Third, the geographic reach of our study covers parts of the U.S. that are less often analyzed with respect to the adoption of emerging mobility services, and particularly regions that are far more auto-dominated than the transit-rich urban areas that often constitute the focus of attention. Last but most importantly, our approach reveals heterogeneity in mode-use changes in response to ridehailing adoption among various classes of users. With this approach, not only are we able to identify distinctive patterns of behavioral changes, but also to examine their shares in the sample and among various groups of ridehailing users (e.g., young urbanites vs. middle-aged suburbanites). These findings help inform planners and policymakers and can support the development of policies and programs that are customized to local contexts and characteristics of the users of these services.

Several policy implications can be drawn from this study. First, although our results are unweighted and might not be considered perfectly representative of the population, our study shows how the *environmentally-positive* impacts of ridehailing adoption appear to be quite limited to a small subset of users. We conclude that transportation planners should not expect the positive impacts of TNCs on traffic congestion and environmental sustainability to be sizable. Note that this subset of users tends to be young, residing in dense neighborhoods in the central city (without owning cars), and positive towards environmental protection, density, public transit, and technology. Planners may encourage this group to remain longer in the urban core, maintaining their positive substitution patterns and even increasing their share in the population, by further improving access to various businesses and places along their routine destinations and travel routes, and increasing the levels of service for alternative modes.

Note that this study suggests that *Transit/active mode substituters*, many of whom live in suburbs with limited access to cars, are better off by enhanced mobility via ridehailing; however, this benefit comes with environmental costs. Thus, planners need to examine the travel demand of suburban dwellers, especially those with limited access to public transit and private vehicles. The provision of affordable housing in those suburbs close to regional transit systems, and support for the first/last-mile trip (e.g., via local feeder buses or docked shared bikes) will help these suburbanites keep their multimodal travel patterns, even with occasional ridehailing trips. Also, local municipalities can work with mobility companies to provide incentives for intermodal trips (e.g., fare discounts and easy booking/reservation) so that ridehailing does not replace the entire journey, while solving the first/last mile problem.

The ways that attitudes lead to behaviors are mediated/moderated by land-use attributes. How strongly behaviors are accounted for by attitudes depends on how conducive/challenging one's environment is to the use of alternative means of travel, even if people hold pro-transit, pro-sharing, and pro-environment attitudes. For this, planners should work in ways that make alternatives to the use of cars increasingly available, easy to use and integrated with other modes. Further, ways to promote such alternatives as socially desirable should be prioritized, eliminating the stigma for these alternatives as literally an "inferior good".

Attitudes are usually not policy variables; however, we see a few effective approaches based on our understanding of the central role of attitudes in shaping travel behavior. Planners and policymakers usually do not explicitly aim to achieve attitude "conversion" when promoting sustainable travel behavior. In addition, researchers do not yet have definitive answers on the ways in which attitudes might change in response to external factors. Still, studies and anecdotal evidence suggest that education, past exposure, and mobility culture are among factors accounting for individuals holding specific attitudes, in the context of sustainable transportation (Klinger & Lanzendorf, 2016; Macfarlane et al., 2015; Smart & Klein, 2018). Based on the findings from our study, we advise planners to consider educational campaigns (e.g., health benefits of active travel), information distribution (e.g., where/how to take transit, walk, and bike nearby, especially for recent movers from dense neighborhoods with transit/active-mode-oriented mobility culture), and the designation of zones with limited vehicle traffic (i.e., promotion of "local" mobility culture). We expect these measures to help individuals continue to hold "positive" attitudes on dense development and alternative modes of travel or to shift previous attitudes in desirable directions.

This study has some limitations. First, our chosen mode change indicators are not error-free. Our analysis is based on self-reported changes in the use of travel modes, and not on objectively-measured quantities (e.g., via GPS data). Thus, it is possible that some respondents misrepresent their behavioral changes, either because of inaccurate memory or biases toward/against ridehailing. Also, the survey asked about the direction of change in frequency of use, but not about specific frequencies/lengths/ durations of the trips by various modes, before and after ridehailing adoption. Thus, we are unable to assess the *amounts of changes* in either direction, only the *share of people* making such changes. In addition, we employ a proxy measure for the built environment because of data limitations. That is, residential density captures the built environment of one's neighborhood, not that of the origins and destinations of ridehailing trips an individual makes. Second, attitudes may be endogenous to behavioral changes. Since attitudes are measured at the time of the survey administration, it is not clear whether positive attitudes toward ridehailing are causes or effects of positive mode use changes (e.g., those made by *Private car/taxi substituters*), or both. As an alternative research design, a panel study with attitudes measured at multiple time points would allow modeling behavioral changes as a function of attitudes measured at *previous* time points. Third, ridehailing supply and demand have been evolving at a fast pace, especially more so during the ongoing pandemic, and their *current* impacts on travel behavior may already differ from the findings of this study, although the relationships among frequency, attitudes, and land use are likely to hold true in a qualitative sense.

CONCLUSION

In this study, we investigate the heterogeneity in self-reported changes in the use of various travel modes in response to ridehailing adoption among a sample (N=1,438) of users in three regions of the southern U.S.: Phoenix, AZ, Atlanta, GA, and Austin, TX. We apply a latent-class cluster analysis to indicators of changes in travel mode use with covariates of socioeconomics, demographics, a land-use attribute, and individual attitudes.

We find four classes of users with distinctive behavioral changes in response to ridehailing adoption. About half of the sample (49.7%) belong to *Mobility augmenters*, whose members use ridehailing rarely, and do not report many changes to their use of various travel modes. The second largest class is *Exogenous changers* (24.5% of the sample), whose members undergo many changes in their mode use, but for reasons other than ridehailing adoption. In comparison, *Private car/taxi substituters* (15% of the sample) frequently hail a ride, and as a result, tend to reduce their use of private vehicles while making trips more often by public transit and active modes. Interestingly, *Transit/active mode substituters* (10.8%) often use ridehailing, likely for trips that they previously made by public transit or active modes, and report a reduction in their use of less-polluting modes while enjoying enhanced mobility. Regarding future research, researchers need to improve measurements, collect and analyze panel data, and capture ridehailing impacts that are likely to evolve as its supply and demand do.

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APPENDIX: COMPARISON OF COVARIATES FOR STUDY SAMPLE, ENTIRE SURVEY, AND GENERAL POPULATION[1]

	Study sample	Entire survey (excluding FL)	Population in the entire survey study areas[2]
Class size (n)	1,438	3,098	12,384,973
Frequency of using ridehailing			
Weekly	7.9%	4.5%	-
Monthly	26.8%	15.3%	-
Rarely	65.3%	40.0%	-
Never used the service	-	40.2%	-
Age			
0-17	-	-	
18-24	24.8%	19.3%	12.4%
25-44	33.4%	24.2%	38.0%
45-64	30.4%	32.2%	40.2%
65 or older	11.4%	23.6%	9.4%
Did not answer	-	0.7%	-
Gender (n = 1,427) <Inactive>			
Male	38.5%	41.2%	49.2%
Female	60.6%	57.7%	50.8%
Did not answer	0.9%	1.1%	-
Race (n = 1,387) <Inactive>			
White or Caucasian	69.7%	71.7%	65.5%
Black or African American	9.2%	7.8%	18.8%
Native American	0.6%	0.6%	1.8%
Asian or Pacific Islander	12.1%	9.7%	5.4%
Other	1.4%	1.5%	5.2%
Multi race	3.5%	3.6%	3.3%
Did not answer	3.5%	5.0%	-
Ethnicity (n = 1,437) <Inactive>			
Not of Hispanic/Latino origin	82.8%	83.6%	77.5%
Of Hispanic/Latino origin	15.0%	13.2%	22.5%
Prefer not to answer	2.2%	2.6%	-
Did not answer	0.1%	0.6%	-
Educational attainment <Inactive>			
Up to high school	7.4%	9.3%	33.2%[3]
Some college	25.7%	28.9%	29.2%
Bachelor	37.8%	36.4%	23.7%

Graduate	29.1%	25.0%	13.9%
Did not answer	-	0.4%	-
Work/study status <Inactive>			
Worker	56.8%	50.7%	52.0%[4]
Worker/student	14.2%	11.6%	-
Student	13.4%	11.2%	26.5%[4]
Neither	15.6%	26.6%	-
Household size <Inactive>			
Single	23.3%	21.5%	27.0%
Two members	35.3%	38.3%	32.9%
Three members	14.5%	14.2%	15.6%
Four members or more	26.8%	26.1%	24.4%
Live with a child or not <Inactive>			
Don't live with a child	81.2%	83.4%	66.5%
Live with a child	18.8%	16.6%	33.5%
Housing tenure (n = 1,435) <Inactive>			
Owner	58.3%	66.9%	62.1%
Not owner (e.g., renter)	41.4%	32.6%	35.0%
Did not answer	0.2%	0.5%	2.9%
Recent relocation (n = 1,431) <Inactive>			
Not in the past 2 years	59.0%	68.3%	-
In the past 2 years	40.4%	30.8%	-
Not in the past 1 year[5]	-	-	82.6%
In the past 1 year	-	-	16.2%
Did not answer	0.6%	0.9%	1.2%
Density (resident/sq.km.)	2,041	1,733	239[6]
Income			
Below $50,000	25.6%	26.3%	36.4%
From $50,000 to $99,999	50.6%	54.3%	31.2%
$100,000 or more	23.8%	18.6%	32.4%
Did not answer	-	0.8%	-
# of cars in the household <Inactive>			
Zero cars	5.5%	4.0%	5.6%
One car	24.8%	23.3%	34.2%
Two cars	39.2%	39.7%	39.4%
Three or more cars	30.5%	32.9%	20.7%
Did not answer	-	0.0%	-
Access to car (n = 1,350) <Inactive>			
No cars/driver	4.1%	2.8%	5.6%[7]

Fewer than one car/driver	12.2%	12.9%	38.0%
One car/driver	61.3%	60.5%	46.1%
More than one car/driver	16.3%	18.5%	10.3%
Did not answer	6.1%	5.3%	-
Attitudes and preferences			
Environmentally-friendly	0.10	0.01	-
Pro-density	0.27	0.01	-
Transit-as-reliable	0.02	0.01	-
Ridehailing-as-lifestyle	0.03	0.01	-
Tech-savvy <Inactive>	0.29	0.00	-
Region <Inactive>			
Phoenix, AZ	19.8%	33.2%	40.5%
Atlanta, GA	35.7%	30.5%	42.5%
Austin, TX	44.5%	36.4%	17.1%

Notes: 1. Numbers shown are counts, shares, or means, as appropriate. Bolded numbers indicate the highest value for each row.

2. For population-representative statistics for the entire survey study areas (excluding FL), the 2015-2019 American Community Survey (ACS) 5-year estimates are retrieved and processed for those counties included in the survey study areas.

3. The total population for this ACS categorical variable is those 25 years old or more.

4. ACS asked whether one is employed or not and whether one is enrolled in school separately, and did not report the intersection of employment and school enrollment status. Thus, for population statistics in this table, students are the percent of population that enrolled in school, and workers are the percent of population that were employed, and the two variables are not independent from each other.

5. Our survey asked about relocation within the past 2 years, while ACS asked about it within the past 1 year.

6. For the sample, density is computed for respondents' residential census tracts, and for the population statistics, it is processed for the total area of all counties.

7. For the sample, we define access to car by the number of cars divided by the number of drivers in the household. In comparison, for the population statistics, it denotes the number of cars divided by the number of adult members in the household. The U.S. Census ACS does not release the number of drivers in the household.